

The Finance Uncertainty Multiplier*

Iván Alfaro[†]

Nicholas Bloom[‡]

Xiaoji Lin[§]

January 10, 2019

Abstract

We show how real and financial frictions amplify the impact of uncertainty shocks. We build a model with real frictions, and find adding financial frictions roughly doubles the impact of uncertainty shocks. Higher uncertainty alongside financial frictions induces the standard real-options effects on investment and hiring, but also leads firms to hoard cash, further reducing investment and hiring. We then test the model using a panel of US firms and a novel instrumentation strategy for uncertainty exploiting differential firm exposure to exchange rate and price volatility. Using common proxies for financial constraints, we show that ex-ante financially constrained firms cut investment and other real inputs more intensively than unconstrained firms following an uncertainty shock. These results highlight why in periods with greater financial frictions 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 Zhanhui Chen, Nicolas Crouzet, Ian Dew-Becker, Simon Gilchrist, Po-Hsuan Hsu, Howard Kung, Gill Segal, Toni Whited, and the seminar audiences at the Adam Smith Conference, AEA, AFA, Beijing University, BI Norwegian Business School, CEIBS, Econometric Society, European Finance Association, Georgetown University, London Business School, Macro Finance Society Workshop, Melbourne Institute Macroeconomic Policy Meetings, Midwest Finance Association, Minneapolis Fed, NY Fed, Society for Nonlinear Dynamics and Econometrics, Stanford, The Ohio State University, UBC Summer Finance Conference, University College London, UCSD, University of North Carolina at Chapel Hill, University of Southern California, 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.

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

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

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

1 Introduction

This paper 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 other periods - like the Brexit vote or 2016 US election - are accompanied by economic growth? Second, as [Stock and Watson \(2012\)](#) noted, uncertainty shocks and financial shocks are highly correlated. Therefore, are these the same shock, or 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, firms face both real and financial frictions. On the real side, investment incurs fixed costs,¹ and on the financing side, when internal funds are not enough to finance optimal investment raising external funds also involves a fixed cost². Therefore, firms manage liquidity by saving in cash.³ 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, delivering a rich set of testable predictions.

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 2.6%, but with *only* real frictions a drop of 1.2%.

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 2.6% and 1.9% respectively, but jointly reduce output by 3.4%.

¹See, for example, [Bertola and Caballero \(1990\)](#), [Davis and Haltiwanger \(1992\)](#), [Dixit and Pindyck \(1994\)](#), [Caballero, Engel, and Haltiwanger \(1995\)](#), [Abel and Eberly \(1996\)](#), [Cooper and Haltiwanger \(2006\)](#), etc.

²See, for example, [Moyen \(2004\)](#), [Hennessy and Whited \(2005\)](#), [Hennessy and Whited \(2007\)](#), [Bolton, Chen, and Wang \(2011\)](#) etc.

³See, for example, [Froot, Scharfstein, and Stein \(1993\)](#), [Bolton, Chen, and Wang \(2013\)](#), [Eisfeldt and Muir \(2016\)](#), etc.

We summarize these two results in the Table below. We report a peak drop in aggregate output of 1.2% (top left box) from the calibrated model that only exhibits real frictions and an uncertainty shock. Adding financial frictions (bottom left box) multiplies the impact of an uncertainty shock to 2.6% . Finally, further adding a financial shock (while keeping the uncertainty shock) increases the impact to a drop in output of 3.4% (bottom right). So collectively going from the classic uncertainty model to one with financial frictions and simultaneous financial shocks roughly triples the impact of uncertainty shocks, and can help explain why uncertainty shocks during periods like 2007-2009 were associated with large drops in output.

Key results in simulation

	Uncertainty shock	Uncertainty + financial shocks
Real frictions	1.2%	n/a
Real+financial frictions	2.6%	3.4%

Notes: Results from simulations of 30,000 firms in the calibrated model (see section 3.4).

Alongside the negative impact of uncertainty and finance shocks on investment and employment the model also predicts these shocks will lead firms to accumulate cash and reduce equity payouts, as higher uncertainty causes firms to take a more cautious financial position. As Figure 1 shows this is consistent with macro-data. It plots the quarterly VIX index - a common proxy for uncertainty - alongside aggregate real and financial variables. The top two panels show that times of high uncertainty (VIX) are associated with periods of low investment and employment growth. The middle two panels show that cash holding is positively associated with the VIX, while dividend payout and equity repurchase are negatively related to the VIX. The bottom panel also considers debt and shows that the total debt (the sum of the short-term and long-term debt) growth is negatively related with the VIX, implying firms cut debt when uncertainty is high.

The rich yet complex extensions required to model: (a) real and financial frictions, and (b) uncertainty and financial shocks, required us to make some simplifying assumptions. First, we

ignore labor adjustment costs - including these would likely increase the impact of uncertainty shocks, since labor accounts for 2/3 of the cost share in our model. Second, we ignore general equilibrium (GE) effects - including these would likely reduce the impact of uncertainty shocks by allowing for offsetting price effects. As a partial response to this we also run a pseudo-GE robustness test where we allow interest rates, prices (of output and capital) and real wages to move after uncertainty shocks following typical changes observed in the data, and find our results on the negative impact of uncertainty-finance shocks on output are about 20% smaller but qualitatively similar.⁴ Furthermore, we model external funds as a whole while do not distinguish specific marginal sources of financing (e.g., debt vs. equity) in the baseline model, since this would dramatically increase the complexity of the financial modeling. In an extension with collateralized debt and costly equity issuance we show uncertainty shocks generate similar results. Finally, we show that allowing firms to hold cash is important for shaping firms' investment and employment behavior. It enables firms to reduce the number of times they make costly external equity issuances, which raises firm valuations but also leads to more prolonged recoveries from shocks as they smooth out capital reinvestment.

The second part of the paper tests this model using a micro-data panel of US publicly-listed firms. We examine the response to uncertainty shocks of tangible and intangible investment, employment, sales, cash, debt and equity dividend payouts. We start off by taking concerns over endogeneity seriously in estimating the effects of uncertainty⁵, and thus propose a novel instrumentation strategy for uncertainty that exploits differential industry-level non-directional exposure to exchange rate, factor price, treasury, and policy uncertainty. Our identification strategy, which builds on the classic Bartik instrumentation, works well in delivering strong first-stage F-statistics and passing the Hansen over-identification tests. We find that higher uncertainty significantly and *causally* reduces investment (in tangible and

⁴One reason from the limited impact of GE is that wages and real interest rates do not move substantially over the cycle (e.g. [King and Rebelo \(1999\)](#)), and second increased uncertainty widens the Ss bands so that the economy is less responsive to price changes (e.g. [Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry \(2016\)](#)).

⁵See, for example, [Nieuwerburgh and Veldkamp \(2006\)](#), [Bachmann and Moscarini \(2012\)](#), [Pastor and Veronesi \(2012\)](#), [Orlik and Veldkamp \(2015\)](#), [Berger, Dew-Becker, and Giglio \(2016\)](#), and [Falgelbaum, Schaal, and Taschereau-Dumouchel \(2016\)](#), for models and empirics on reverse causality with uncertainty and growth.

intangible capital), hiring and sales growth, while also leading firms to more cautiously manage their financial policies by increasing cash holdings yet cutting dividends, debt, and stock-buy backs - all of which are consistent with the model and broad macro data. More importantly, classifying firms into broad groups of *ex-ante* financially constrained and unconstrained firms, we show that investment of constrained firms responds more intensively to uncertainty shocks than unconstrained firms, thus find empirical support for the model prediction that financial frictions amplify the impact of uncertainty shocks. Moreover, consistent with the model we also find strong amplification effects of financial frictions for intangible capital investment, cost of goods sold, sales, and debt. In short, we find that uncertainty matters (causally) for a broad mix of real inputs and outputs of production, yet matters even more in the presence of heightened financial frictions. Lastly, our instrumented estimates are likely a lower bound of the effects on average firms in the economy in response to uncertainty shocks - e.g., the average US firm is much smaller and prone to binding financial constraints than the publicly traded firms tested in the paper.

Related literature Our paper builds on three broad literatures. First, the uncertainty literature studying the interaction of uncertainty and adjustment costs for investment and employment.⁶ This emphasizes the "real options" effects of uncertainty, which describes how firms act more cautiously on their real activities in the presence of uncertainty and real adjustment costs. We contribute to this literature empirically by providing *causal* empirical support to identify the impact of uncertainty on investment and employment by using a novel instrumentation

⁶Classic papers on uncertainty and growth included [Bernanke \(1983\)](#), [Romer \(1990\)](#), [Ramey and Ramey \(1995\)](#), [Leahy and Whited \(1996\)](#), [Guiso and Parigi \(1999\)](#), [Bloom \(2009\)](#), [Bachmann and Bayer \(2013\)](#), [Fernandez-Villaverde, Quintana, Rubio-Ramirez, and Uribe \(2011\)](#), [Fernandez-Villaverde, Guerron-Quintana, Kuester, and Rubio-Ramirez \(2015\)](#), and [Christiano, Motto, and Rostagno \(2014\)](#). One more closely related paper that studies the causal impact of uncertainty shocks using a related exposure approach is [Stein and Stone \(2013\)](#). Several other papers also look at uncertainty shocks - for example, [Bansal and Yaron \(2004\)](#) and [Segal, Shaliastovich, and Yaron \(2015\)](#) look at the consumption and financial implications of uncertainty, [Handley and Limao \(2012\)](#) look at uncertainty and trade, [Ilut and Schneider \(2014\)](#) model ambiguity aversion as an alternative to stochastic volatility, and [Basu and Bundick \(2017\)](#) examine uncertainty shocks in a sticky-price Keynesian model, and [Berger, Dew-Becker, and Giglio \(2016\)](#) study news vs uncertainty. A related literature on disaster shocks - for example, [Rietz \(1988\)](#), [Barro \(2006\)](#), and [Gourio \(2012\)](#) - is also connected to this paper, in that disasters can be interpreted as periods of combined uncertainty and financial shocks, and indeed can lead to uncertainty through belief updating (e.g. [Orlik and Veldkamp \(2015\)](#)).

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

Second, the finance literature on firms' financial management of liquidity. The notion of liquidity management goes back at least to [John Maynard Keynes \(1936\)](#) who argued that precautionary cash saving and financing constraints are closely linked if financial markets are imperfect.⁷ This literature highlights how firms will hoard cash in the presence of uncertainty and *financial* adjustment costs - i.e., costs of issuing debt and/or equity. This is a "cash options" equivalent to a "real options" effect (the idea that having cash in the firm preserves the option to issue debt or equity in the future). We extend this literature by showing how the combination of "real options" and "cash options" from real and financial adjustment costs respectively combine together to multiply the impact of uncertainty shocks on firms' real (investment and hiring) and financial (cash and external financing) behavior.⁸

Finally, our paper is also closely related to the recent literature on financial frictions and business cycles.⁹ 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 to the extent that they should not be considered individually, rather jointly. Related work that links uncertainty and financial frictions includes the following. [Gilchrist, Sim, and Zakrajsek \(2014\)](#) study the relationships between uncertainty, investment and credit spreads.

⁷[Meltzer \(1963\)](#), [Miller and Orr \(1966\)](#), and [Baumol \(1970\)](#) are earlier examples emphasizing the transaction motive of firms to hold cash. The recent development in the finance literature on liquidity management and financial constraints include the theoretical work by [Froot, Scharfstein, and Stein \(1993\)](#), [Holmstrom and Tirole \(1998\)](#), [Riddick and Whited \(2009\)](#), [Bolton, Chen, and Wang \(2011\)](#), [Bolton, Wang, and Yang \(Forthcoming\)](#), etc., and the empirical work by [Almeida, Campello, and Weisbach \(2005\)](#), [Bates, Kahle, and Stulz \(2009\)](#), [Pinkowitz, Stulz, and Williamson \(2013\)](#), etc., [Almeida, Campello, Cunha, and Weisbach \(2014\)](#) provides a survey of the literature.

⁸There is a large literature, for example, [Rajan and Zingales \(1995\)](#), [Gomes \(2001\)](#), [Welch \(2004\)](#), [Hennessy and Whited \(2005\)](#), [DeAngelo, DeAngelo, and Whited \(2011\)](#), [Rampini and Viswanathan \(2013\)](#), [Chen, Wang, and Zhou \(2014\)](#), and [Chen \(2016\)](#) that study the impact of various frictions on firms' financing policies.

⁹For example, [Sharpe \(1994\)](#) shows that financial leverage propagates the impact of demand shocks on firms' employment over business cycles; [Alessandri and Mumtaz \(2018\)](#) and [Lhuissier and Tripier \(2016\)](#) show in VAR estimates a strong interaction effect of financial constraints on uncertainty. More generally, [Gilchrist and Zakrajsek \(2012\)](#), [Jermann and Quadrini \(2012\)](#), show that financial frictions are important to explain the aggregate fluctuations for the recent financial crisis. [Caggiano, Castelnuovo, and Figueres \(2017\)](#) show that uncertainty shocks have a bigger impact during recessions. [Giroud and Mueller \(2017\)](#) show that establishments with higher financial leverage cut employment more in response to negative local consumer demand shocks.

They show that financial frictions magnify the effects of uncertainty through changes in credit spreads. [Christiano, Motto, and Rostagno \(2014\)](#) imbed agency problems associated with financial intermediation as in [Bernanke, Gertler, and Gilchrist \(1999\)](#) into a monetary dynamic general equilibrium model; they find volatility shocks are important in driving the business cycle. [Arellano, Bai, and Kehoe \(2016\)](#) build a DSGE model with frictions in labor and financial markets. They show that uncertainty shocks lead to higher default risk and credit spreads, which cause firms to further cut employees. Although we share with [Gilchrist, Sim, and Zakrajsek \(2014\)](#), [Christiano, Motto, and Rostagno \(2014\)](#) and [Arellano, Bai, and Kehoe \(2016\)](#) the idea that financial frictions amplify the impact of uncertainty shocks, our work differs in three important ways. First, we develop an identification strategy to estimate the *causal* impact of uncertainty and financial shocks on firms. The set of variables examined in our paper that causally respond to uncertainty shocks not only covers but largely expands the variables studied in prior work (e.g., we look at financial responses in addition to traditional real responses). Addressing endogeneity is important given potential bias and inconsistency in estimating the effects of uncertainty when using metrics based on financial measures like stock-returns¹⁰. Second, we use common proxies for financial constraints proposed in the finance literature to provide empirical evidence for the multiplier prediction of the model. We use firm information a full 5 years in the past to classify firms into ex-ante financially constrained and unconstrained groups. We show that *ex-ante* financially constrained firms cut investment substantially more (in a causal way) than unconstrained firms in response to uncertainty shocks, and thus confirm a FUM effect in the data. Third, we include cash in our model, and thus allow firms to have an additional dimension over which to respond to uncertainty by holding greater cash balances. Thus, our model allows a richer examination of the impact of uncertainty under “cash-options”. Modeling cash is important given that cash holdings have increased in both the US, Europe and a number of OECD countries, and among

¹⁰The typical prior approach in this literature to instrumentation - for example [Leahy and Whited \(1996\)](#), [Bloom, Bond, and Reenen \(2007\)](#) and [Gilchrist, Sim, and Zakrajsek \(2014\)](#) - is to use lagged values of uncertainty as instruments in OLS regressions. We propose instruments that capture exogenous variation in uncertainty in a 2SLS framework.

other potential reasons such increase is attributed to rising uncertainty (Pinkowitz, Stulz, and Williamson (2013), Pinkowitz, Stulz, and Williamson (2016), Chen, Karabarbounis, and Neiman (2017)).

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 data. In section 5 we present the empirical findings on the effects of uncertainty shocks on both real and financial activity of firms. Section 7 concludes.

2 Model

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

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

$$Y_t = \tilde{Z}_t K_t^\alpha L_t^{1-\alpha}, \quad (1)$$

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

$$Q_t = BP_t^{-\varepsilon}, \quad (2)$$

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

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

Wages are normalized to 1 denoted as \bar{W} . Given employment is flexible, we can obtain optimal labor.¹¹ 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

$$z_{t+1} = \rho_z z_t + \sigma_t \varepsilon_{t+1}^z, \quad (4)$$

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

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

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

Physical capital accumulation is given by

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

¹¹Pre-optimized labor is given by $(\frac{b}{\bar{W}} Z_t^{1-a-b} K_t^a)^{\frac{1}{1-b}}$.

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:

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

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

We also assume that there is a fixed production cost (F_t) which depends on lagged productivity, $F_t = f Z_{t-1}$ with $f > 0$ as a constant¹². Firms need to pay this cost regardless of investment and hiring decisions every period, and is important for motivating firms to hold cash to cover costs of production.¹³ Hence firms' operating profit (Π_t) is revenue minus wages and fixed cost of production, given by

$$\Pi_t = S_t - \bar{W} L_t - F_t. \quad (8)$$

2.2 Cash holding

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

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

¹²We started by wanting to assume fixed cost are a function of lagged revenue S_{t-1} , i.e., $F_t = \tilde{f} S_{t-1}$. This is both to reflect the fact the overheads are likely related to prior size, and numerically to avoid large firms outgrowing fixed costs. However, this poses a numerical challenge because it requires carrying an extra highly partitioned state variable S_{t-1} . Hence, we make the approximation that $F_t = f Z_{t-1}$ - that is fixed costs are a function of lagged productivity. The justification is that lagged sales are highly correlated with lagged productivity (correlation of 0.96 in the model since K_{t-1} and L_{t-1} are both highly correlated with Z_{t-1}), and lagged productivity is an existing state variable so this does not increase computational burden.

¹³Without this the only reason firms hold cash is to fund investment expenditures, which means firms with a low probability of investing (large K firms and/or those with low productivity) do not hold cash.

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

2.3 External financing costs

The final part of the model concerns the external financing costs. We do not model financial intermediation costs endogenously associated with asymmetric information as in [Myers and Majluf \(1984\)](#) or agency frictions in [Jensen and Meckling \(1976\)](#). Instead we choose to summarize the costs of external financing in a reduced form way as in [Hennessy and Whited \(2005\)](#) and [Bolton, Chen, and Wang \(2011\)](#). Specifically, when the sum of investment in capital, investment adjustment cost and investment in cash exceeds the operating profit, firms can take external sources of funds as a last resource. The financing costs include both direct costs (for example, flotation costs - underwriting, legal and registration fees), and indirect (unobserved) costs due to asymmetric information and managerial incentive problems, among others.¹⁴

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

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

Furthermore, external financing costs vary over time and across firms, consistent with [Erel,](#)

¹⁴These 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%.

Julio, Kim, and Weisbach (2012) who show that firms' access to external finance markets also changes with macroeconomic conditions.¹⁵ The micro-foundations of time-varying financing conditions include endogenous time-varying adverse selection problems in Eisfeldt (2004), Kurlat (2013), and Bigio (2015) who show that uncertainty increases the adverse selection cost from external financing, agency frictions varying over time as in Bernanke and Gertler (1989) and Carlstrom and Fuerst (1997), and time-varying liquidity as in Pastor and Stambaugh (2003). Furthermore, empirically, Choe, Masulis, and Nanda (1993) find that the adverse selection costs measured as negative price reaction to seasoned equity offering announcement is higher in contractions and lower in expansions, suggesting changes in information symmetries between firms and investors are likely to vary over time.¹⁶

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

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

We do not explicitly model the sources of the external financing costs. Rather, we attempt to capture the effect of the costs in a reduced-form fashion. In addition, we make general assumptions about the financing costs which include all kinds of costly external financing activities, namely, costs associated with all marginal sources of financing for firms when payouts are negative.¹⁷ Specifically, the external financing costs Ψ_t are assumed to scale with firm size as measured by the revenue:

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

¹⁵Kahle 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.

¹⁶In addition, Lee and Masulis (2009) show that seasoned equity issuance costs are higher for firms with poor accounting information quality.

¹⁷In the robustness section we extend the model by explicitly modelling two common marginal external financing channels separately, i.e., costly external equity and collateralized debt. We show that our result on finance uncertainty multiplier effect remains robust.

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

Finally, note that the marginal external financing cost depends on both time-varying financing condition η_t and time-varying uncertainty σ_t , which captures the fact that periods of high external financing costs are associated with heightened uncertainty. This assumption is consistent with the empirical evidence that uncertainty (proxied by the VIX) and external financing costs (proxied for by the total external financing costs constructed by [Eisfeldt and Muir \(2016\)](#), the SLOOS Index of lending standards and the Baa-Aaa credit spread) are highly positively correlated.¹⁸ In addition, [Caldara, Fuentes-Albero, Gilchrist, and Zakrajsek \(2016\)](#) document that change in VIX and change in CDS spread are positively correlated. As such, we assume $\phi(\eta_t, \sigma_t) = \eta_t + \lambda$ with $\lambda > 0$ when $\sigma_t = \sigma_H$, and $\phi(\eta_t, \sigma_t) = \eta_t$ when $\sigma_t = \sigma_L$, to capture the positive correlation between financing cost and uncertainty shock in the data.

2.4 Firm's problem

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

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

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

3 Main results

This section presents the model solution and the main results¹⁹. We first calibrate the model, then we simulate the model and study the quantitative implications of the model for the

¹⁸We provide detailed analysis for this result in Section 3.1.

¹⁹See <https://people.stanford.edu/nbloom/> for the full Matlab code to replicate all results.

relationship between uncertainty shocks, financial shocks, and firms’ real activity and financial flows.

3.1 Calibration

The model is solved at a quarterly frequency. Table 1 reports the parameter values used in the baseline calibration of the model. The model is calibrated using parameter values reported in previous studies, whenever possible, or by matching the selected moments in the data. Below we briefly discuss how we calibrate the parameters of the baseline model. Appendix Section B provides a detailed discussion of the calibration for some of the key parameters.

To generate the model’s implied moments, we simulate 3,000 firms for 1,000 quarterly periods. We drop the first 800 quarters to neutralize the impact of the initial condition. The remaining 200 quarters of simulated data are treated as those from the economy’s stationary distribution.

Firm’s technology and uncertainty parameters. We set the share of capital in the production function at $1/3$, and the elasticity of demand ε to 4 which implies a markup of 33%, toward the upper end of estimates for price–cost markups in Hall (1988). The capital depreciation rate δ is set to be 3% per quarter. The discount factor β is set so that the real firms’ discount rate $r_f = 5\%$ per annum, which implies $\beta = 0.988$ quarterly. Return on cash saving is assumed to be less than the risk-free rate due to the tax disadvantage of carrying cash for firms or agency frictions associated with cash holding. We calibrate $r_n = 85\%r_f$ to match the average ratios of cash to total assets for firms that hold non-zero cash, which is 5% in Compustat firms.

The fixed investment adjustment cost c_k is set to 1%²⁰ and the fixed operating cost f is set to 20% such that the fixed cost to the average revenue ratio is 15%, consistent with the average SGA-to-sales ratio of 15% in Compustat data. Wage rate \bar{W} is normalized to 1. We set the persistence of firms’ micro productivity as $\rho_z = 0.95$ following Khan and Thomas (2008). Following Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2016), we set

²⁰We have also solved the model with $c_k = 2\%$ and 4% and find the results are robust with these different values of c_k .

the baseline firm volatility as $\sigma_L = 0.051$, the high uncertainty state $\sigma_H = 4 * \sigma_L$, and the transition probabilities of $\pi_{L,H}^\sigma = 0.026$ and $\pi_{H,H}^\sigma = 0.94$.

Financing cost parameters. As noted, there are two types of financing costs: transaction costs and information costs which is unobservable, and there are no empirical estimates for the total financing cost. We set the baseline external financing cost parameter $\eta_L = 0.005$ and the high financing cost state $\eta_H = 10\eta_L = 0.05$.²¹ We use several measures (e.g., the total financing cost index by [Eisfeldt and Muir \(2016\)](#), the SLOOS lending standards, and the Baa-Aaa spread) for firms' cost of external financing to guide us to calibrate the parameter λ which determines the correlation between external financing costs and uncertainty shocks. The correlation between VIX and these measures ranges from 0.42 to 0.72. As such, we set $\lambda = 4\%$ so that the implied correlation between the external financing cost and the uncertainty is 69%, in the middle of the correlation estimates. The calibrated financial costs are on average 1.78% of the sales (conditional on firms taking on external funds), within the range the estimates in [Altinkilic and Hansen \(2000\)](#) and [Hennessy and Whited \(2005\)](#). 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.²²

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

²¹We have also solved the model with $\eta_H/\eta_L = \{2, 5, 8, 16, 20\}$ and find the quantitative results remain broadly robust.

²²We also solved the model with different transition probabilities for financial shocks, e.g., $\pi_{L,H}^\eta = 5\%$ and $\pi_{H,H}^\eta = 95\%$. The quantitative result is similar to the benchmark calibration.

their median grid points and the financial shock at the low state.²³ In the real-only model, optimal investment displays the classic Ss band behavior. There is an investing region when the firm size (capital) is small, an inaction region when the firm size is in the intermediate range, and an disinvestment region when the firm is large. Moreover, the Ss band expands with higher uncertainty due to the real-option effects inducing greater caution in firms investment behavior. Turning to the benchmark model we see that the Ss band associated with high uncertainty state is bigger than the low uncertainty state, similar to the real-only model. However, optimal investment in the benchmark model displays a second flat region, which arises when the firm is investing but only financed by internal funds. This happens because firms are facing binding financial constraints ($E_t = 0$), and are not prepared to pay the fixed costs of raising external equity.

Overall, this shows two results. First, how real and financial constraints interact to expand the central region of inaction in Ss models. Second, how uncertainty leads to a greater increase in the width of the Ss bands with real and financial adjustment costs, which is the mechanism driving the financial uncertainty multiplier.

3.3 Benchmark model result

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

Table 2 starts in Row A by presenting the results from the real data (discussed in section 5) as a benchmark. As we see investment, employment and equity payouts significantly

²³Note 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.

drop after an increase in uncertainty while cash holdings rises.²⁴ Row D below presents the benchmark simulation results (Real+ stochastic financial frictions), and finds similar qualitative results with drops in investment, employment (due to “real options” effects of uncertainty), and drops in equity payouts and rising cash holdings (due to “cash options” effects of uncertainty). In Row B we turn to the classic real frictions only model and see that the impact of uncertainty on investment and employment growth falls from -0.073 to -0.042 and -0.026 to -0.014 respectively. This implies a finance-uncertainty-multiplier of 1.7 ($= 0.073/0.042$) for investment and 1.9 ($= 0.026/0.014$) for employment. So introducing financial frictions to the classic uncertainty model roughly doubles the impact of uncertainty shocks.

In Row C we instead simulate a model with real frictions and non-stochastic financial frictions (Real+nonstochastic financial frictions), and interestingly we still see significant drops in investment and employment and increases in cash holdings. The finance-uncertainty-multiplier for investment and employment is 1.4 and 1.5 , respectively. Dividends rises but small in magnitude. Hence, "stochastic financial frictions" and "nonstochastic financial frictions" models have similar implications that uncertainty shocks reduce investment, employment and increases cash holdings. But "stochastic financial frictions" model has larger real (investment and employment) and financial impacts (cash and dividend).

In Row E we also simulate a model with just stochastic financial frictions. We get small positive impacts on investment and employment (due to positive Oi-Hartman-Abel effects of uncertainty without offsetting negative real options effects), but large positive impact on cash and negative impact on dividends (due to cash options effects). Finally, Row F models firms with no adjustment costs, resulting in very small positive Oi-Hartman-Abel impacts on investment and employment, no cash impacts, and larger dividend impacts due to more fluctuations in equity payouts.

²⁴All results in this table are significant at the 1% (with firm-clustered standard errors), hence we do not report t-statistics for simplicity.

3.4 Impulse responses

To simulate the impulse response, we run our model with 30,000 firms for 800 periods and then kick uncertainty and/or financing costs up to its high level in period 801 and then let the model to continue to run as before. Hence, we are simulating the response to a one period impulse and its gradual decay.

Uncertainty shocks Figure 3 plots the impulse responses of the real and financial variables of the benchmark model to a pure uncertainty shock. Starting with the classic “real adjustment cost” only model (black line, x symbols) we see a peak drop in output of 1.2% and a gradual return to trend. This is driven by drops and recoveries in capital, labor and TFP. Capital and labor drop and recover due to real-option effects leading firms to pause investing (and thus hiring by the complementarity of labor and capital), while depreciation continues to erode capital stocks. TFP falls and recovers due to the increased misallocation of capital and labor after uncertainty shocks - higher uncertainty leads to more rapid reshuffling of productivity across firms, which with reduced investment and hiring leads to more input misallocation. Dividend payout rises because firms with excess capital disinvest more with high uncertainty and hence payout more.

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 2.6%, 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 1.4% peak drop in output. This is driven by a similar drop in capital as financial adjustment costs leads firms to hoard cash after an uncertainty shock, while labor also drops (since this is complementary with capital), as does TFP due to less investment and hiring raising misallocation. The one notable difference in the impact of uncertainty shocks with

real vs financial adjustment costs is the time profile on output, capital and labor. Real adjustment costs lead to a sharp drop due to the Ss band expansion which freezes investment after the shock, but with a rapid bounce-back as the Ss bands contract and firms realize pent-up demand for investment. With financial costs the uncertainty shock only reduces investment by firms with limited internal financing, but this impact is more durable leading to a slower drop and recovery.

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

Starting first with real adjustment costs only (black line, x symbol) we see no impact because there are no financial adjustment costs in this model. Turning to the financial frictions but no real frictions model (blue line, circle symbols) we see only small impacts of financial shocks of 0.4% on output. The reason is with financial (but no real) frictions firms can easily save/dis-save in capital, so they are less reliant on external equity. Firms increase cash holdings and cut dividend payout due to increased financing costs. Finally, in the benchmark model (red line, triangle symbols) we see that, as before, the impact is roughly twice the size of the no financial costs model, with a drop in output of up to 1.9%, with similar falls in capital and labor. The reason is intuitive - if financial costs are temporarily increased firms will postpone raising external finance for investment, which reduces the capital stock and hence labor (by complementarity with capital). Moreover, cash holding and dividend payout display sharper and more persistent rise and drop, respectively. TFP also shows a more modest drop due to the increase in misallocation (as investment falls), although this is smaller than for an uncertainty shock as firm-level TFP does not increase in volatility.

Combined uncertainty and financial shocks As [Stock and Watson \(2012\)](#) suggest combined financial and real shocks are a common occurrence, and indeed these both occurred in 2007-2009, so we examine the impact of this in Figure 5.²⁵ This plots the impact in the

²⁵We see spikes in capital, labor and output here and in Figures 3 and 4 as well. This is the echo effect caused by fixed costs analyzed in [Gourio and Kashyap \(2007\)](#).

benchmark model of an uncertainty shock (blue line, circle), a financial shock (blue line, + 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. But collectively their impact is significantly larger and more persistent - for example, the drop in output from an uncertainty or financial shock alone is 2.6% and 1.9% respectively, while jointly they lead to an output fall of 3.4%. 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 will come closer to explaining the magnitude of this recession.

3.4.1 Robustness

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

Changes in parameter values We start by evaluating one-by-one changes a series of the parameter values listed in Table 2. The broad summary is that while the quantitative results vary somewhat across different parameter values, the qualitative results are robust - uncertainty shocks lead to drops and rebounds in output, capital and labor (alongside rises in cash and drops in equity payouts), and these are roughly doubled by adding in financial adjustment costs.

In particular, we raise the high financing-cost-state-to-low-cost-state ratio (η_H/η_L) from 10 to 20 (while keeping the low financial cost state $\eta_L = 0.005$). This leads to a bigger drop in output and a much slower recovery as it is now more expensive for constrained firms to finance investment (magenta 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 the transition probability matrix to be symmetric, i.e., $\pi_{L,H}^\eta = 0.05$ and $\pi_{H,H}^\eta = 0.95$, which implies that

financial shocks expected every 5 years and that the high financing cost state is more persistent. As we see (green line, circles) this leads to a very similar drop and similarly slow recovery from the uncertainty-finance shock because the finance shocks is now more persistent.

We also try reducing the fixed production cost (f) to 30% of the lagged productivity rather than 20% in the baseline calibration. We see (blue-dash line, crosses) this produces a slightly bigger drop and almost identical recovery of output to the baseline calibration from the uncertainty-finance shocks because financial constraints are not significantly loosened with a smaller fixed operating leverage. Furthermore, we increase the investment adjustment cost (c_k) to 2% of the sales instead of 1% in the baseline and we see this change also leads to a similar drop of output to the baseline but somewhat faster recovery (yellow line, stars). Lastly, we increase the share of capital in the production function (α) to 1 rather than 1/3 in the baseline calibration. Effectively, the share of labor, the costlessly adjustable input in the baseline, is zero. This implies that all factors (capital here) are costly to adjust. We see that setting $\alpha = 1$ leads to a substantially larger drop in output to around 4.2% (3.4% in the baseline) and a slower recovery after the uncertainty-finance shock (black-dash line, right triangles).

General equilibrium Currently the model is in a partial equilibrium setting. A general equilibrium set-up would require a [Krusell and Smith \(1998\)](#) type of model with its additional loop and simulation to solve for prices and expectations. In prior work, for example [Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry \(2016\)](#), this reduced the impact of uncertainty shocks by around 1/3 but did not radically change their character. The reason is two-fold: first, prices (interest rates and wages) do not change substantially over the cycle, and second the Ss nature of the firms' investment decision makes the policy correspondence insensitive in the short-run to price changes. However, to investigate this we do run a pseudo-GE experiment, whereby we allow prices to change by an empirically realistic amount after an uncertainty shock. In particular, we allow interest rates to be 5% lower, prices (of output and capital) 0.5% lower, and wages 0.3% lower, during periods of high uncertainty. We find

broad robustness of our results on the impact of uncertainty shocks with a slightly smaller drop and somewhat faster rebound (black-dash line with pluses in Figure 6).

Debt model In the baseline model we examine total external financing but do not distinguish debt vs. equity to reduce the state space of the model. We also solve and simulate a model with both debt and equity financing, and as we show in 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 . 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

$$B_{t+1} \leq \varphi K_t. \quad (14)$$

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

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

$$E_t = (1 - \tau) \Pi_t + \tau \delta K_t + \tau r_f B_t - I_t - H_t - G_t + B_{t+1} - (1 + r_f) B_t, \quad (15)$$

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 $\tau = 0.35$ following [Jermann and Quadrini \(2012\)](#). We see in Figure 6 a somewhat smaller initial drop as firms can substitute debt for equity financing (cyan line, stars), and a similarly persistent impact of because of debt hangover. Panel H in Table [A1](#) reports the regression result. We see that slopes of investment rate and employment growth are quantitatively close to those in the benchmark model. Furthermore, the debt model also implies the firms cut debt when uncertainty is high (results not tabulated), consistent with the evidence in the data.

4 Data, instruments, and addressing endogeneity

This section discusses the data sources used for the empirical tests of the model. It also details the construction of the instruments used in addressing potential endogeneity concerns in measuring the effects of firm-level uncertainty shocks.²⁶

4.1 Data

Stock returns are from CRSP and annual accounting variables are from Compustat. The sample period is from January 1963 through December 2016. Financial, utilities and public sector firms are excluded (i.e., SIC between 6000 and 6999, 4900 and 4999, and equal to or greater than 9000). Compustat variables are at the annual frequency. Our main firm-level empirical tests regress changes in real and financial variables on 12-month lagged changes in uncertainty (i.e., lagged uncertainty shocks), where the lag is both to reduce concerns about contemporaneous confounding endogeneity and because of natural time to build delays. Moreover, our main tests include both firm and time (calendar year) fixed effects. The regressions of changes in outcomes on lagged annual changes in uncertainty restricts our sample to firms with at least 3 consecutive non-missing data values. The firm fixed effect further

²⁶A full replication file for data construction and regressions is available on <https://people.stanford.edu/nbloom/>.

restricts this to firms with at least 4 non-missing data values (as it eliminates singletons). To ensure that the changes are indeed annual, we require a 12 month distance between fiscal-year end dates of accounting reports from one year to the next. We drop any firm-year observations having zero or negative employment, total assets, and/or sales.

In measuring firm-level uncertainty we employ both *realized* annual volatility from CRSP stock returns and *option-implied* volatility from OptionMetrics. Realized volatility is the standard-deviation of daily cum-dividend stock returns over the course of each firm’s fiscal year (which typically spans roughly 252 trading days).²⁷ For implied volatility we use the 252-day average of daily implied volatility values from OptionMetrics. Data from OptionMetrics is available starting January 1996. Our daily implied volatility data corresponds to at-the-money 365-day forward call options. Additional information about OptionMetrics, Compustat, and CRSP data is provided in Appendix (C).

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

Our main tests include standard controls used in the literature on both real investment and capital structure. In particular, in addition to controlling for the effect on investment of first-moment variables, i.e., the lagged level of Tobin’s Q and the lagged stock return of each firm, we follow the lagged timing and controls in [Leary and Roberts \(2014\)](#) in all of our main

²⁷We 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).

multivariate tests, specifically control for the lagged levels of book leverage, return on assets, firm tangibility, and log sales. The Appendix (C) details the construction of these variables.

4.2 Identification Strategy

Our identification strategy exploits firms' differential exposure to aggregate volatility shocks in energy, currency, policy, and treasuries to identify exogenous changes in firm-level volatility, that are orthogonal to the endogenous components driving firm-level volatility shocks. For example, to identify exogenous variation using oil, the idea is that some firms are very sensitive to oil prices (e.g. mining and energy-intensive manufacturing firms) while others are not (e.g. retailers and business service firms). Upon a rise in oil-price volatility, firms in the former group see a shift in their firm-level volatilities relative to firms in the latter. Similarly, industries differ in their trading intensity with Europe and Mexico (e.g. industrial machinery versus agricultural produce firms), thus firms differ in their exposure to movements in bilateral exchange rate volatility. Likewise, some industries - like defense, health care and construction - are more reliant on Government contracts, so when aggregate policy uncertainty rises (for example, because of elections or government shutdowns) firms in these industries experience greater increases in uncertainty. Our 2SLS estimation exploits these differential exposures to tease out exogenous components in firm-level volatility shocks, while purging them from remaining orthogonal endogenous components.

Our strategy employs a total of 10 different aggregate sources of uncertainty to identify exogenous variation in firm volatility. As our 2SLS tests show below, not only are each of the 10 instruments strongly positively correlated with firm-level volatility shocks, but also remain highly significant at the 1% after controlling for each other (non-redundant relevance for identification). Moreover, having multiple exogenous sources frees us from having to take a stand on which source (if any) might be more important for firms.

Conceptually our estimation approach is similar to the classic Bartik identification strategy, which exploits industry-level differences in exposure to common aggregate shocks. To

construct the 10 instruments we first estimate industry-level sensitivities.

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 firm i in industry j , $sensitivity_i^c = \beta_j^c$ is estimated as follows

$$r_{i,t}^{risk-adj} = \alpha_j + \sum_c \beta_j^c \cdot r_t^c + \epsilon_{i,t} \quad (16)$$

where $r_{i,t}^{risk-adj}$ is the daily risk-adjusted return on firm i (explained below), r_t^c is the change in the price of commodity c , and α_j is industry j ’s intercept. The sensitivities are estimated at the industry level using daily returns of firms that share a same 3-digit Standard Industrial Classification (SIC) code. Estimating the main coefficients of interest, β_j^c , at the SIC 3-digit level (instead of at the firm-level) reduces the role of idiosyncratic noise in firm-level returns, and thus increases the precision of the estimates. Moreover, we allow these industry-level sensitivities to be time-varying by estimating them using 10-year rolling windows of past daily data. Further, as explained below, we exploit these time-varying factor exposures to construct pre-estimated sensitivities and instruments that are free of look-ahead bias concerns in our main regressions, which run second-stage 2SLS specifications of real and financial outcomes on past uncertainty shocks.

The risk-adjusted returns in (16) are the residuals from running firm-level time-series regressions of daily CRSP stock returns on the classical [Carhart \(1997\)](#) four-factor asset pricing model. In particular, using the same 10-year rolling window used in (16) we define firm daily risk-adjusted returns as the residuals of regressing firms’ excess return on the daily Carhart factors:

$$r_{i,t}^{excess} = \alpha_i + \beta_{i,mkt} \cdot MKT_t + \beta_{i,HML} \cdot HML_t + \beta_{i,SMB} \cdot SMB_t + \beta_{i,UMD} \cdot UMD_t + \epsilon_{i,t} \quad (17)$$

where $r_{i,t}^{excess}$ is firm i ’s daily CRSP stock return (including dividends and adjusted for delisting)

in excess of the t-bill rate, MKT is the CRSP value-weighted index in excess of the risk free rate, HML is the book-to-market factor, SMB is the size factor, UMD is the momentum factor. These daily factor data are obtained from CRSP, and proxy for the price of systematic risk to which firms load differentially to compensate for the risk-reward tradeoff in stock returns.²⁸

Thus, by running (17) before the estimation of the sensitivities in (16) we effectively adjust firm-level returns for aggregate risk, which in turn addresses concerns over whether the sensitivities to energy, currencies, treasuries, and policy - β_j^c in equation (16)- are capturing exposures to common risk factors in stock returns rather than exposures to those 10 factors of interest for the instrumentation strategy.

The daily independent variables in (16) 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 Board²⁹, the return on the US 10-year treasury note³⁰, and the growth in economic policy uncertainty from Baker, Bloom, and Davis (2016). For these 10 aggregate market price shocks (oil, 7 currencies, treasuries, and policy) we need not only their daily returns (for calculating the sensitivities β_j^c in equation (16)) but also their *implied* volatilities σ_t^c as measures of aggregate sources of uncertainty for the construction of the 10 instruments, $|\beta_j^c| \cdot \Delta\sigma_t^c$.

Construction of instruments To instrument for firm-level uncertainty shocks, $\Delta\sigma_{i,t}$, we further require data on aggregate uncertainty shocks, $\Delta\sigma_t^c$. Our baseline instruments use option-implied volatility on the aggregate variables. The forward-looking nature of option-implied volatilities is likely to make them better estimates of aggregate uncertainty than using realized volatilities. However, our results are robust to using the latter. We define the

²⁸To reduce role of outliers and increase precision of industry sensitivity estimates we require firms to have a minimum of 500 daily CRSP returns in the rolling windows (i.e., about 2 years of trading return data in US public markets).

²⁹See http://www.federalreserve.gov/pubs/bulletin/2005/winter05_index.pdf . These include: the Euro, Canadian Dollar, Japanese Yen, British Pound, Swiss Franc, Australian Dollar, and Swedish Krona. Each of these trade widely in currency markets outside their respective home areas, and (along with the U.S. dollar) are referred to by the Board staff as major currencies.

³⁰The treasury return is estimated from the first-order approximation of duration, i.e., by multiplying the first difference of the yield by minus 1.

annual uncertainty on oil and 7 currencies using the 252-day average of daily 3 month implied volatilities of crude oil futures contracts and currencies from Thomson Reuters Eikon. For 10-year treasuries, we use the 252-day average of daily implied volatility for the 10-year US Treasury Note from the Cboe/CBOT (ticker TYVIX), and for economic policy we use the 252-day average of weekday US economic policy uncertainty (EPU) from [Baker, Bloom, and Davis \(2016\)](#).³¹ These 10 annual aggregate uncertainty measures, σ_t^c , are used in constructing 10 cross-industry non-directional exposures to aggregate uncertainty shocks, $|\beta_j^{c,weighted}| \cdot \Delta\sigma_t^c$.

We do this in two steps. First, to further address concerns of noisy estimates in (16) we adjust each sensitivity, β_j^c , by its statistical significance at the 5% within each industry. 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, $\omega_j^c = \frac{|t_j^c|}{\sum_k |t_k^c|}$. Thus, we adjust the sensitivities within each industry by their statistical power in (16). 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 5% 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 (16) 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 each of the 10 factors over time. Our weighting scheme exploits both margins by focusing only on the influence of statistically-significant exposures. However, we report in robustness checks that our main results are similar when we use the raw sensitivities, β_j^c , instead of the significance-weighted estimates, $\beta_j^{c,weighted}$, in constructing each of the 10 instruments. Moreover, results are broadly similar if we use a 10% or 1% level of significance in constructing $\beta_j^{c,weighted}$.

³¹In contrast to oil, 7 currencies, and 10-year treasuries EPU volatility is only available in realized form, and not option-implied. Nonetheless, our main results are robust to both using only option-implied volatility data for the 9 variables (excluding EPU) and using realized volatility for all variables.

Second, we construct 10 composite terms $|\beta_{j,t-2}^{c,weighted}| \cdot \Delta\sigma_t^c$, which we refer to as the industry-by-year *non-directional* exposure for uncertainty shocks, where $\Delta\sigma_t^c$ is the annual growth in the aggregate option-implied volatility of the instrument and the first term is the absolute value of the significance-weighted sensitivity explained above but lagged an additional 2 years with respect to the volatility shock $\Delta\sigma_t^c$. The Appendix further details the exact timing and construction of these variables, but in short and to be conservative, we lag the sensitivities estimated in (16) so that they are ex-ante determined and do not overlap with the information entering the aggregate uncertainty shock $\Delta\sigma_t^c$.

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 non-directional exposure for uncertainty shocks, $|\beta_{j,t-2}^{c,weighted}| \cdot \Delta\sigma_t^c$, are the instruments used in our 2SLS regressions that instrument for firm-level uncertainty shocks, $\Delta\sigma_{i,t}$.

In particular, the first stage of our 2SLS regressions run firm level volatility shocks on each of the 10 industry composite terms plus a full set of controls, i.e., $\Delta\sigma_{i,t} = \sum^c \gamma^c \cdot |\beta_{j,t-2}^{c,weighted}| \cdot \Delta\sigma_t^c + X_{i,t} \cdot \gamma^X + \varepsilon_{i,t}$, to obtain predicted firm-level $\widehat{\Delta\sigma_{i,t}}$ uncertainty shock components that are correlated with the aggregate second-moment uncertainty shocks (i.e., our source of identification), but are orthogonal to the idiosyncratic components in firm-level uncertainty shocks, $\varepsilon_{i,t}$, that remain after controlling for a large number of controls $X_{i,t}$ - which include controls for first-moment effects at both the firm- and aggregate-level. The second stage of our 2SLS regressions run one-year ahead real and financial outcomes, e.g., investment rate of firms $\frac{I_{i,t+1}}{K_{i,t}}$, on the uncertainty shocks $\widehat{\Delta\sigma_{i,t}}$ implied by the 1st stage, plus the full set of controls, $X_{i,t}$.

Finally, to tease out the effects of the second moment in our 10 instruments from their first moment, we include as controls the directional exposure to the returns of each instrument (i.e., aggregate first moment controls). That is, in the regressions we include 10 first moment *directional* composite terms $\beta_{j,t-2}^{c,weighted} \cdot r_t^c$.³² These first moment controls help us distinguish,

³²For economic policy uncertainty we measure r_t^c as growth from one year to the next in the 4-quarter

say, the drop in investment rates of firms due to business conditions becoming worse relative to drops caused by increases in uncertainty. Moreover, the time fixed effects included in all of our regressions further control for any aggregate common shock to which all firms are exposed equally every period, i.e., control for any aggregate shock that is colinear with annual time dummies. Moreover, the firm fixed effects in all of our regressions further control for any time-invariant unobservables present at the firm-level that are not captured by our time-varying controls. Furthermore, at the firm-level we also control for firm-level measures of first moment effects, i.e., Tobin’s $Q_{i,t}$ and the CRSP stock return of the firm, $r_{i,t}$. The latter measure helps us account for discount-rate channel effects influencing firm investment and financial dynamics. In all, the large set of controls allows our empirical examination to focus on the cross-sectional effects of the instrumented firm-level uncertainty shocks, $\widehat{\Delta\sigma_{i,t}}$, above and beyond first moment effects.

4.3 Addressing endogeneity

How do our instruments help us address endogeneity concerns in estimating the effects of firm-level uncertainty shocks? To fix ideas we think of two broad reasons for endogeneity concerns, omitted variable bias and simultaneity bias (see [Jeffrey M Wooldridge \(2015\)](#)). For illustration, consider the problem of some unobserved variable in the equation of investment rate of firms. Let’s say this is an unobserved agency friction that affects investment and is correlated with uncertainty shocks at the firm-level (e.g., internal agency frictions between the board and the CEO of the firm lead to under-investment, while also raising uncertainty of the firm). A simple model is $\frac{I_{i,t+1}}{K_{i,t}} = \gamma_0 + \gamma_1\Delta\sigma_{i,t} + \gamma_2friction_{i,t} + \epsilon_{i,t+1}$. If a suitable proxy for $friction_{i,t}$ were available there is no omitted variable concern in estimating γ_1 , by simply running investment rate on $\Delta\sigma_{i,t}$ and the proxy, which delivers a consistent estimator of γ_1 . However, assuming the proxy is not available, then $friction_{i,t}$ is put into the error term, and we are left with the simple regression model $\frac{I_{i,t+1}}{K_{i,t}} = \gamma_0 + \gamma_1\Delta\sigma_{i,t} + \mu_{i,t+1}$, where μ contains

average 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.

friction and $\Delta\sigma_{i,t}$ is therefore endogenous. Of course, an OLS regression gives a biased and inconsistent estimator of γ_1 . Therefore, the need for an instrument $z_{i,t}$ for $\Delta\sigma_{i,t}$.

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

The exclusion restriction requires that our candidate instruments are not correlated with the unobserved *friction* and have no direct effect on investment. In our setting, it's hard to see why firm-specific agency frictions, $friction_{i,t}$, or more broadly firm-specific unobservable that influence idiosyncratic investment rates, would be correlated with the composite terms that capture the non-directional industry-level exposures to aggregate sources of uncertainty, $z_{i,t} = |\beta_{j,t-2}^{c,weighted}| \cdot \Delta\sigma_t^c$. For instance, for the above scenario to happen the idiosyncratic agency frictions at time t would have to be correlated with either 1) shocks to the 3 month option-implied volatility of WTI crude oil futures contracts, $\Delta\sigma_t^{oil}$, and/or 2) the non-directional industry-level exposures to oil, $|\beta_{j,t-2}^c|$. The latter might be of some concern because the exposures involve the industry of each firm. However, recall that the sensitivities $\beta_{j,t-2}^c$ come from estimations done in rolling windows of a long 10 year history of daily returns at the 3-digit SIC industry levels. It's hard to see why the time t level of idiosyncratic frictions would correlate with the ex-ante determined industry-wide exposures in absolute terms, i.e., $|\beta_{j,t-2}^c|$. In addition, the timing setup of the rolling windows guarantees that the 10 year information used in estimating the exposures $\beta_{j,t-2}^c$ does not overlap with any of the dependent or independent variables at time $t+1$ and t in the investment regression. As stated above, the exposures are ex-ante determined at the 3SIC level using information ending 3 full years prior to any of the outcome LHS variables explored in this paper, e.g., $z_{i,2007} = |\beta_{j,2005}^{c,weighted}| \cdot \Delta\sigma_{2007}^c$ used in instrumenting for $\Delta\sigma_{i,2007}$ in the $\frac{I_{i,2008}}{K_{i,2007}}$ regression. For the exclusion restriction not

to hold, firms' *friction* $_{i,2007}$ would have to correlate with industry j 's composite term, i.e., $|\beta_{j,2005}^{c,weighted}| \cdot \Delta\sigma_{2007}^c$, which does not seem likely from an economic standpoint (and to the extent that we have more instruments than the endogenous firm uncertainty variable, we can test for instrument exogeneity using the Hansen over-identification test).

The concern with simultaneity bias is that, for example, firms cut investment upon higher uncertainty ($\uparrow \Delta\sigma_{i,t} \Rightarrow \downarrow \frac{I_{i,t+1}}{K_{i,t}}$), but stock return volatility might also have risen because the market saw earlier *persistent* cuts in investment for the same firm ($\downarrow \frac{I_{i,t-1}}{K_{i,t-2}} \Rightarrow \uparrow \Delta\sigma_{i,t}$), thus begging the question of whether it is uncertainty that affects investment or the opposite, or both. Therefore, a classic endogeneity problem in running the one-way OLS regression, and again the need for an instrument $z_{i,t}$ for $\Delta\sigma_{i,t}$.³³

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

All main empirical tests below, which guide the target data moments for the model of section 2, use the above instrumentation strategy to help us address endogeneity concerns present in related work on uncertainty. Often these concerns are altogether left untreated or generally only use uncertainty lags for identification, e.g., Bloom (2009), Gilchrist, Sim, and Zakrajsek (2014), and Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2016) run OLS in examining the effects of uncertainty. By taking endogeneity seriously in this paper, our results also help shed light on how the size of the effects of uncertainty may differ when endogeneity is treated explicitly.

³³One can certainly include lagged investment rates as controls in the OLS regression of investment rate on lagged uncertainty shocks, and indeed our results are robust to this, but given the cotermination of the variables it does not suffice. The estimator for uncertainty shock effects remains biased and inconsistent.

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.³⁴

5.1 Investment results

Table 3 examines how uncertainty affects future capital investment rates. Column 1 presents the univariate OLS regression results of investment rate on lagged annual *realized* stock return volatility growth. We observe highly statistically significant coefficients (point estimate of -0.032, t-stat of -20.2) on return volatility shocks, showing that firms tend to invest more when their firm-specific uncertainty is low. Column 4 presents the analogue OLS univariate regression results on *implied* volatility shocks (from OptionMetrics). The sign of the coefficient is consistent with realized volatility shocks, but the size is almost three times as large (estimate -0.089, t-stat -10.570), potentially because option-implied volatility may be a better measure of uncertainty as it is forward-looking and likely less prone to endogeneity influences that may be prevalent in realized return volatility.³⁵

These results indicate that uncertainty shocks have real effects on firm investment decisions. However, as explained in section 4.3, inferences from OLS results are likely to suffer from endogeneity bias. Although our use of lagged uncertainty shocks mitigates some of the potentially stronger endogenous effects of contemporaneous uncertainty shocks, there is no guarantee that it fully deals with endogeneity bias implicit in forward looking variables like stock prices to measure uncertainty (e.g., simultaneity bias or measurement error bias given that returns might be controllable to a certain extent by firms based on selective timely news and announcements given to the market). Therefore, we exploit our instrumentation strategy

³⁴See <https://nbloom.people.stanford.edu/research> for the Stata code to replicate all results.

³⁵We reestimate both specifications in columns (1) and (4) on a common sample of 17,481 observations in table (A6) and find similar realized and implied volatility coefficients are -0.033 and -0.080, both significant at the 1%.

to address broad endogeneity concerns using the full set of 10 instruments in the remaining columns of Table 3. In particular, columns 2 and 3 instrument lagged *realized* volatility shocks while columns 5 and 6 lagged *implied* volatility shocks. Columns 2 and 5 are univariate while 3 and 6 are multivariate with a full set of controls at both the firm- and aggregate-levels. In all cases we find that uncertainty shocks lead to significant drops in firm-level investment, with significance at the 1% in the realized specifications.

The instrumented 2SLS point estimates in the univariate specifications are roughly 3 times as large as the univariate OLS counterparts (e.g., columns 2 vs 1 and 5 vs 4), meaning that the OLS estimators commonly used in the literature are likely biased toward zero or the opposite direction, and thus the effects of uncertainty at the micro-level may be larger than previously documented.³⁶ Adding our full set of controls in columns 3 and 6, however, reduces the magnitudes of the effects to comparable sizes (yet larger) to the OLS univariate results. The firm controls include Tobin's Q and stock-returns (as first moment controls), as well as log sales, book leverage, profitability (return on assets), and tangibility to control for financial conditions. The 10 first moment controls of our instruments are also included to account for deteriorating economic conditions and to allow our estimates on uncertainty shocks to focus on the second moment effects. Firm and time fixed effects are included, and conservatively in all specifications we cluster the standard errors at the 3-digit SIC industry (the same level at which factor exposures are estimated). Of course, clustering standard errors at lower levels (e.g., firm) gives a greater significance.

Table 3 indicates that the testable predictions of the model in section 2 on the real effects of uncertainty, indeed, find support in the data using our instrumentation strategy. The data on US publicly listed firms confirm that increases in uncertainty lead to *causal* future reductions in capital investment rates. In terms of magnitudes the results imply that a two-standard deviation increase in realized volatility shocks (see the descriptive statistics in Table A2) reduces investment by between 2.1% to 4% - this using the results from our preferred 2SLS

³⁶This could be because of measurement error (which would attenuate down the OLS coefficient estimates) or positive reverse causality (e.g. large investment projects increasing firm stock-volatility).

multivariate specifications in column (3) and (6), while 3 times as large using the univariate point estimates in (2) and (5)). This is moderate in comparison to firm-level investment fluctuations which have a standard deviation of 24.8%, but is large when considering that annual aggregate investment rates drop between 2% to 6% during recessions as shown in Figure 1.

5.1.1 2SLS first stage results

The 2SLS first stage results for investment are shown in Table 4. Columns (1) and (2) report the first stages for the univariate IV columns (2) and (5) from table 3. We see that the F-statistics indicate a well identified first stage with respective values of 125.3 and 64.66 for the Cragg-Donald (CD) F-Statistics (robust standard-errors), and 14.77 and 11.56 for the Kleibergen-Paap (KP) F statistic (SIC-3 digit clustering). Moreover, each of the 10 instruments is individually positively correlated with firm uncertainty shocks and mostly significant at the 1%. This means that, indeed, each instrument succeeds in identifying exogenous variation in firm uncertainty shocks that arise from different unrelated sources of aggregate uncertainty shocks. Using the motivation of our instruments presented in section 4.2, exogenous variation in uncertainty shocks for firms in, say, the real manufacturing sector seems to stem not only from their exposure to oil uncertainty but at the same time also from exposure to bilateral exchange rate uncertainty affecting input and output prices for imports and exports with major developed countries and the Euro Area, and simultaneously also from exposure to political uncertainty about, say, tariff decisions made by the Executive branch and US State Department.

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

We find similar results when we add the full set of controls, where columns (3) and (4) in Table 4 present the first stage for the multivariate IV regressions of columns (3) and (6) from Table 3. For instance in the 1st stage of our preferred realized volatility specification in column (3), we see that each of the 10 instruments remains individually positively correlated with firm volatility shocks and significant at the 1%. Altogether, we find that even in the presence of a full set of both aggregate and firm-level controls, we see a well satisfied relevance condition, with CD F-statistics of 134.2 and 46.65, and KP F-statistics of 15.04 and 8.07, respectively, and even stronger non-rejected Sargan-Hansen validity tests, with p-values 0.992 and 0.740.

5.2 Intangible capital, employment, cost of goods sold, and sales

Table 5 examines the predictive and *causal* implications of uncertainty shocks on the growth of other *real* outcomes. In particular, Panel A examines investment in intangible capital (as measured by expenditure on general and administration items plus R&D, which extends the approach of [Eisfeldt and Papanikolaou \(2013\)](#)), Panel B examines employment, Panel C examines the cost of goods sold, and Panel D examines sales. In each panel we present the same 6 specification results presented for investment in Table 3, but to preserve space we drop the point coefficient estimates on controls and keep only the estimates on lagged uncertainty shocks.

Regardless of which of the 24 specification we look at, the signs on each of the uncertainty coefficients is negative, thus confirming the real negative effects of uncertainty shocks. Indeed, the four panels show that both realized and implied volatility shocks are negatively related to a broad mix of production inputs: intangible capital investment, employment, and cost of goods sold, and also with a proxy for technological output: sales. Our instrumentation strategy with realized volatility in column (3) gives points estimates that range from a 1 to 1 comparable magnitude with the OLS univariate results in column (1) (e.g., intangible capital investment) to about 5 times as large (for sales).

As with capital investment, these regressions show a strong and well satisfied first-stage relevance condition, with (robust) CD F-statistics and (3digit SIC clustered) KP F-statistics in the range of 89.27 to 134.6 and 12.65 to 14.92, respectively, for our preferred baseline multivariate specification of realized uncertainty shocks in column (3), which includes a full set of controls. Moreover, in terms of significance, regardless of whether we instrument realized or option-implied uncertainty shocks, columns (3) and (6), we see significant drops in intangible capital investment, cost of goods sold, and sales 1-year into the future upon higher uncertainty shocks (with significance at the 5 and 1 percent in all cases). The response of employment (which is only measured yearly and often with heavy rounding in firm reports) is negative but not statistically significant in the multivariate 2SLS tests. Nonetheless, it's reassuring that cost of goods sold, which is a quarterly audited variable that is heavily driven the firm wage bill, does respond significantly and negatively to uncertainty shocks.

Overall, the four panels in Table 5 provide *causal* support for the directional testable predictions of the model in section 2, and confirm that the negative real effects of uncertainty shocks are not limited to capital investment presented in Table 3, but extends to a broader mix of production inputs and outputs. This impact is robust to the presence of extensive controls for first-moment and financial conditions (which are further expanded in robustness check below), and robust to endogeneity concerns addressed by our instrumentation strategy for uncertainty shocks.

5.3 Financial variables

Table 6 examines the predictive and *causal* implications of uncertainty shocks on the growth of *financial* variables. In particular, Panel A examines dividend payout, Panel B total debt, and Panel C cash holdings. Regardless of which of the 18 specifications we look at, uncertainty shocks have significant financial effects on publicly listed firms. All point estimates on uncertainty shocks are significant at the 1% (mostly) or 5%. However, consistent with the model in section 2, the direction of the effects differ depending on which financial variable

is examined. Panel A indicates that firm’s take a more cautious financial approach toward corporate payout upon an increase in uncertainty. Consistent with a precautionary savings motive, firms cut down their cash dividend payouts following a high uncertainty shock. Panel B shows that increases in uncertainty reduce the willingness of firm’s to increase their overall debt going forward (thus a negative effect on debt), while Panel C shows additional evidence of a precautionary savings channel, as cash holdings strongly increase following high uncertainty shocks. This positive effect on the hoarding of cash reserves and short-term liquid instruments is robust to endogeneity concerns, as shown by the significant point estimates at the 5% for both realized and implied volatility shocks in columns 3 and 6.

Moreover, our instrumentation strategy works well for financial variables. For instance, our preferred instrumented specification in column (3) with full set of controls shows that for all 3 financial variables the point estimates are significant at the 5% and 1%, there are strong first stage F-statistics (i.e., robust CD F-statistics above 134.5 and clustered KP F-statistics above 14.8), and we do not reject the Sargan-Hansen over-identifying tests (with p-values in the range of 0.30 to 0.88). In addressing endogeneity concerns, our IV results show that the effects of uncertainty shocks can be substantially larger than those implied by OLS, as seen by the effects ranging from twice as large as predicted by OLS (e.g., payout column 3 vs 1) to 5 times as large (for cash).

In all, Table 6 provides *causal* support for the directional testable predictions of the model in section 2, and confirm that uncertainty shocks not only have real implications (as seen in Tables 3 and 5) but also strong financial effects on publicly listed firms. Moreover, the strong 1st stage results highlight that our instrumental strategy based on exchange rate, policy, and factor price volatility works well for key financial variables of US firms.

5.4 Instrument, functional form, and credit supply robustness

This section presents robustness checks to our instrumentation strategy, checks to uncertainty functional form, and additional controls to our baseline multivariate 2SLS regressions. In

practical terms, our instrumentation strategy relies on identifying cross-sectional exogenous variation in firm volatility shocks, $\Delta\sigma_t^c$, from non-directional exposure to 10 different aggregate volatility shocks, $z_{i,t} = |\beta_{j,t-2}^{c,weighted}| \cdot \Delta\sigma_t^c$. Even though our 1st stage results show strong relevance F-tests and high significance of individual instruments in accounting for non-redundant exogenous variation, a first concern is whether the significance of the uncertainty effects examined to this point go away once we drop any particular instrument from our instrumentation strategy. E.g, do the highly significant effects on investment and cash no longer exist once we exclude Euro-USD exchange rate volatility shocks? Moreover, a second related question is despite the obvious concerns of potential multicollinearity and noise in regression (16), whether our results depend on teasing out the most significant exposures when using the weighted estimates, $|\beta_{j,t-2}^{c,weighted}|$, instead of the raw estimates, $|\beta_{j,t-2}^c|$? We address these two concerns jointly in Appendix Table A3. In particular, column (1) presents the baseline realized 2SLS results (with full set of controls) but using the raw exposures in constructing both the instrumental variables and their corresponding 1st moment aggregate controls, i.e., $z_{i,t} = |\beta_{j,t-2}^c| \cdot \Delta\sigma_t^c$ and first moment directional controls, $\beta_{j,t-2}^c \cdot r_t^c$. Column (1) shows that all real and financial outcomes retain their significance and sign at the 5% in responding to firm-volatility shocks. In columns (2) to (11) we examine whether those results are robust to dropping each instrument one-by-one, starting with the implied volatility of the Canadian Dollar-USD exchange rate in column (2) and ending with the US 10 year treasury note volatility in column (11). Again, all real and financial outcomes retain their significance in response to uncertainty shocks. Moreover, the 1st stage results shown for investment at the bottom of the Table again show strong instrument relevance and validity - as indicated by the robust CD F-test always above 230.1 and the KP F-test above 33.2 in all 11 columns, while the Hansen over-identifying test does not reject in any specification with p-values in the range of 0.42 to 0.67.

Taken together, the results across all columns in Appendix Table A3 indicate that our identification of exogenous variation in firm volatility shocks is not driven by the identification

extracted from one particular instrument, but instead from the combined identification arising from energy, exchange rate, policy, and treasury uncertainty. Moreover, given the robustness of the tests the results suggest that our identification strategy will likely be useful for a wide-range of models of the causal impact of uncertainty on firm behavior.

Another concern is whether the instrumented real and financial results depend on the precise functional form used in measuring our endogenous RHS variable for uncertainty. In Appendix Table A4 we relax our assumption on using annual changes in firm volatility, $\Delta\sigma_{i,t}$, and explore different reasonable transformations of this variable. In particular, columns (1) and (1A) repeat the baseline 2SLS multivariate regression results, with full set of controls, presented in columns (3) and (6) of main Tables 3, 5, and 6, which measure volatility shocks as the annual growth in CRSP realized and OptionMetrics implied volatilities, respectively. Columns (2) and (2A) present the results when using the annual growth in the square of volatility, $\Delta\sigma_{i,t}^2$, columns (3) and (3A) the results for volatility in levels, $\sigma_{i,t}$, (4) and (4A) the square of the level of volatility, $\sigma_{i,t}^2$, and (5) and (5A) the log of the level of volatility, $\log(\sigma_{i,t})$. Regardless of which specification we use to account for the endogenous uncertainty measure, we see that future real and financial variables retain their significance and sign in response to rises in uncertainty, with most results remaining significant at the 1% and 5%.

Appendix Table A5 presents additional robustness checks for credit supply shocks, financial constraints, and 1st moment controls. First, we ask whether our results are robust to adjusting volatility shocks for financial leverage. Thus, in columns (1) and (1A) we regress all the real and financial outcomes on lagged leverage-adjusted volatility shocks, where volatility is adjusted by firm book leverage, i.e., $\sigma_{i,t} \cdot \frac{E_{i,t}}{E_{i,t}+D_{i,t}}$ where E is book equity (CEQ in Compustat) and D is total debt. Moreover, one concern could be that uncertainty reduces financial supply - for example, banks are unwilling to lend in periods of high uncertainty - which causes the results we observe. To address this we further include a variety of controls for external ratings given to firms from Standard & Poors (S&P) on their long-term obligations, an extensive set of firm-level controls for financial constraints used in the literature, and firm loadings on

the aggregate market price of risk (which further controls for aggregate 1st moment effects). Again our key results remain broadly similar.

Finally, given the importance for the instrumented investment results in guiding the target moments of the model in section 2, in Appendix Table A6 we re-examine our main investment Table 3 holding fixed the sample of firm-time observations used across all specifications (1) to (6). In particular, our sample is constrained by the availability of OptionMetrics data on firm-level implied volatility, which gives a total of 17,481 observations across all columns. Compared to the main Table 3 the point estimates on the coefficients are largely comparable in both magnitude and statistical significance (all at the 1%). Therefore, differences in point estimates across specifications (2SLS vs OLS, univariate vs multivariate, and realized vs implied volatility shocks) are not due to differences in sample but rather differences in the underlying specifications.

6 The finance uncertainty multiplier

This section examines the model's testable prediction that financial frictions amplify the negative real effects of uncertainty shocks. We do so using our instrumentation strategy to address endogeneity concerns in firm uncertainty. We take the "finance-uncertainty multiplier" prediction to the data by running a series of interactions of *uncertainty shocks* with *financial frictions*. As seen in Figure 2, in maximizing firm value firms find it optimal to cut investment upon an increase in uncertainty (Figure 2A), and when confronted with financial frictions (Figure 2B) find it optimal to further expand their investment cuts. We examine these testable predictions in Table 7. We analyze the multiplier effect in two dimensions.

First, we ask whether there is evidence in the data that investment rate of firms responds more intensively to uncertainty shocks during periods of heightened aggregate financial frictions relative to low frictions. We use Moody's aggregate BAA-AAA corporate credit spread from St. Louis Fed to account for movements in aggregate financial frictions affecting all firms. The annual series is standardized to ease interpretation of coefficients (see Appendix).

Therefore, we expect that firms cut investment, $\frac{I_{i,t}}{K_{i,t-1}}$, after increased uncertainty shocks, $\Delta\sigma_{i,t-1}$, and this cut is amplified further during periods of high aggregate financial frictions, $\Delta\sigma_{i,t-1} \cdot Credit_Spread_t$. Therefore:

$$\frac{I_{i,t}}{K_{i,t-1}} = \beta_1 \Delta\sigma_{i,t-1} + \beta_2 (\Delta\sigma_{i,t-1} \cdot Credit_Spread_t) + \beta_3 Credit_Spread_t + X_{i,t-1} \cdot \gamma + \varepsilon_{i,t} \quad (18)$$

Column 1 in Table 7 presents these results using our baseline 2SLS realized regression with full set of controls $X_{i,t-1}$ (i.e., columns (3) in Table 3). Indeed, firms significantly cut their investment rates in response to uncertainty shocks ($\beta_1 = -0.025$, significant at the 5%) and do so even further during high aggregate financial frictions ($\beta_2 = -0.042$, significant at the 1%). Therefore, data on public firms implies a total effect of uncertainty shocks in high financial friction years equal to a total drop in investment rates of $\beta_1 + \beta_2 = -0.067\%$ (significant at the 1%). This gives us an amplification measure for the multiplier effect when going from normal aggregate financial frictions to high frictions: $FUM = (-0.067 / -0.025) = 2.68$. These estimates provide support in the data for the amplification mechanism of the model in section 2.

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

previous interaction specification and run the following 2SLS triple interaction:

$$\begin{aligned}
\frac{I_{i,t}}{K_{i,t-1}} = & \beta_1 \Delta\sigma_{i,t-1} + \beta_2 (\Delta\sigma_{i,t-1} \cdot Credit_Spread_t) + \beta_3 Credit_Spread_t \\
& + \beta_4 (\Delta\sigma_{i,t-1} \cdot D_{i,t-5}^{fin.constraint}) + \beta_5 D_{i,t-5}^{fin.constraint} + \beta_6 (D_{i,t-5}^{fin.constraint} \cdot Credit_Spread_t) \\
& + \beta_7 (\Delta\sigma_{i,t-1} \cdot D_{i,t-5}^{fin.constraint} \cdot Credit_Spread_t) \\
& + X_{i,t-1} \cdot \gamma + (X_{i,t-1} \cdot D_{i,t-5}^{fin.constraint}) \cdot \gamma^{fin.constraint} + \varepsilon_{i,t}
\end{aligned} \tag{19}$$

where $D_{i,t-5}^{fin.constraint}$ is a dummy that takes value one for firms classified as ex-ante financially constrained using information in fiscal year $t - 5$, zero otherwise. Using a lag of 5 full years to classify firms helps us address potential concerns about endogeneity that might exist in commonly used proxies for financial constraints - which we borrow from the literature and describe below. Moreover, the 4 coefficients involving firm uncertainty shocks allow us to examine and formally test the stronger version of the multiplier effect. In particular, the total effect of uncertainty shocks for ex-ante *unconstrained* firms during high aggregate frictions is captured by coefficients $\beta_1 + \beta_2$, while the total effect for ex-ante *constrained* firms is $\beta_1 + \beta_2 + \beta_4 + \beta_7$. Therefore, the difference in these total effects, $\beta_4 + \beta_7$, captures the incremental response of constrained firms in years when their financial constraints likely bind the most. Formally, the null $H_0 : \beta_4 + \beta_7 \geq 0$ states that the *total negative effects* on investment are at least as large for ex-ante unconstrained firms, against the alternative $H_a : \beta_4 + \beta_7 < 0$ that the total negative effects of uncertainty shocks are, indeed, larger for constrained firms. Moreover, it's also useful to decompose this differential total effect and see whether its mostly driven by the increased response during times of high aggregate frictions, β_7 , or due to the incremental response in normal times alone, β_4 .

To classify firms we employ three widely used measures in the finance literature that proxy for firm-level financial constraints (e.g., [Panousi and Papanikolaou \(2012\)](#)). Using each firm's proxy built from information in fiscal year $t - 5$, we classify firms every year. In particular, we consider a firm in year t as ex-ante financially constrained if at year $t - 5$ its individual

financial constraint measure is equal to or above the cross-sectional median constrained firm that year. Firms below the median firm are then considered ex-ante unconstrained in year t .

The financial constraint proxies are: first, an index based on external credit ratings given to firms by Standard and Poor’s (S&P) in column (2), here we follow [Duchin, Ozbas, and Sensoy \(2010\)](#) and consider a firm constrained if it has positive debt and no bond rating and unconstrained otherwise (which includes firms with zero debt and no debt rating).³⁷; second, the Size and Age index (SA) of [Hadlock and Pierce \(2010\)](#) in column (3); third, the [Whited and Wu \(2006\)](#) in column (4).

Starting with the classification of firms based on the S&P credit ratings in column (2), we see that ex-ante unconstrained firms significantly drop their investment in response to uncertainty shocks ($\beta_1 = -0.028$, significant at the 5%), particularly during years of high financial frictions ($\beta_2 = -0.026$, significant at the 5%), for a total significant effect of $\beta_1 + \beta_2 = -0.054\%$, and a *within-group FUM* = $(-0.054 / -0.028) = 1.928$. In addition to the within-group FUMs, the point estimates also allow us to compare the size of the effects across the two groups: the *cross-group total effect FUM* = $(\beta_1 + \beta_2 + \beta_4 + \beta_7) / (\beta_1 + \beta_2) = (-0.079 / -0.054) = 1.46$.³⁸

We see similar inferences using other measures of firm-level financial constraints when classifying firms ex-ante. Using the SA index of [Hadlock and Pierce \(2010\)](#) in column (3), we find that unconstrained firms significantly respond to uncertainty shocks and more so in high financial friction years ($\beta_1 = -0.025$ and $\beta_2 = -0.031$, respectively and both significant at the 5%), for a total effect in high financial friction years of -0.056% , and an even larger *within-unconstrained-group FUM* = $-0.056 / -0.025 = 2.24$. The SA index also confirms that the total negative effects on investment are, indeed, larger for the ex-ante constrained firms during high frictions with a *cross-group total effect FUM* = $-0.078 / -0.056 = 1.39$ (p-

³⁷For 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).

³⁸Testing whether this *cross-group total effect FUM* = 1.46 > 1 is significant is simply another way of rewriting our formal alternative hypothesis $H_a : \beta_4 + \beta_7 < 0$ presented at the bottom of column (2), which has a p-value of 0.029, and thus we reject the null that ex-ante unconstrained firms see at least equal negative effects on investment

value 0.038). Using the Whited-Wu constraint measures in column (4) also gives comparable multipliers as those implied by the S&P ratings and SA indexes.

Finally, Figure 7 shows the average impact of uncertainty in our sample of firms given our key results in column (2) of Table 7. In particular, it uses the time variation in both the credit spread and the mix of financially constrained firms using the S&P rating to generate the employment size weighted marginal impact of uncertainty on investment. We see that in normal times (e.g. 2005) the mean impact of uncertainty is around -0.02 (so a 2 SD shock would reduce investment by about 1.2%). But, during the 2008-2009 crisis, because of both the rise in the credit spread and the drop in S&P rating for many firms, the mean impact of uncertainty approximately tripled to -0.06. Thus, on aggregate for our sample of firms, we see a substantial increase of the impact of uncertainty during the financial crisis highlighting the interaction of financial conditions and rising uncertainty.

In summary, Table 7 and Figure 7 provides strong support for the testable prediction that financial frictions amplify the negative effects of uncertainty shocks on real investment activity of firms. Our instrumented estimates are likely a lower bound of the effects applicable to the average firm in the economy since our sample contains only publicly listed firms.

Other real outcomes. The finance-uncertainty multiplier prediction is not only restricted to real capital investment, but also applies to the other real variables explored in this paper. Thus, Table 8 examines the causal multiplier effect for the growth in intangible capital investment in columns (1) and (2), cost of goods sold (3) and (4), and sales (5) and (6). As before, by running 18, we start off by asking whether the FUM effect holds on average for all firms in columns (1), (3), (5), and then use the S&P rating classifications to examine the *within-* and *cross-group* FUM in columns (2), (4), (6). As with capital investment, we see strong evidence that firms respond to uncertainty shocks, β_1 , and more so in high financial friction years, β_2 , with both coefficients significant at either the 1% or 5% for the 3 real variables. For instance, in column (1) upon an uncertainty shock firms drop their intangible capital investment, $\beta_1 = -0.036$, and further drop its rate in high friction years,

$\beta_2 = -0.069$, for a total effect of uncertainty shocks of $\beta_1 + \beta_2 = -0.105\%$, and a sizable average $FUM = -0.105 / -0.036 = 2.91$. Thus, the FUM effect is not restricted to real capital investment but also seen in intangibles. Moreover, we see strong multipliers for COGS and sales, with sizable average $FUM = 2.885$ and $FUM = 2.4$, respectively.

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

Financial outcomes. Finally, in Appendix Table A7 we show the causal multiplier effects for the financial variables explored in the paper. We see substantial FUM effects for debt, moderate ones for equity issuance, and nothing for cash holdings. Since these are constrained variables (financially constrained firms by definition will struggle to adjust their financial position) this result is not surprising, and thus the key test of the model is the FUM on real variables.

7 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 (FUM). 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. First, we take endogeneity concerns in measuring the effects of uncertainty seriously by employing a novel instrumentation strategy that exploits cross-sectional non-directional exposures to different aggregate sources of uncertainty. Using 2SLS estimations we document strong negative and causal effects of uncertainty shocks on both real activity and financial variables of firms. Consistent with the testable implications of the model, uncertainty shocks reduce firm investment (tangible and intangible), cost of good sold (input), and sales (output), while increasing cash holdings and reducing corporate dividend payout and debt.

Second, we document a strong and causal multiplier effect of uncertainty in years of heightened financial frictions. We find that the response to uncertainty shocks for firms is amplified with spikes in the aggregate US corporate credit spread BAA-AAA, indicating that the total response during high friction years is 2.68 as high as normal times (i.e., $FUM = 2.68$). Moreover, splitting firms into ex-ante financially constrained and unconstrained groups (where the classification takes place 5 years prior to the observed investment decisions), we find that the FUM is strong within each of the two groups, yet constrained firms respond almost 50% more intensively than unconstrained firms. We also find strong multiplier effects for intangible investment, cost of goods sold, and sales, while also documenting an amplified effect for debt obligations of firms. Moreover, our instrumented estimates are likely a lower bound of the effects average firms in the economy would observe in response to uncertainty shocks - e.g., the average US firm is much smaller and prone to binding financial constraints than the publicly traded firms explored in this paper.

Taken together we believe that rather than trying to evaluate whether uncertainty shocks *or* financial constraints are responsible for the drop in investment, hiring and output growth

during events like the 2008-2009 crisis, we should recognize and estimate their interactive multiplier effects.

References

- ABEL, A., AND J. EBERLY (1996): “Optimal Investment With Costly Reversibility,” *Review of Economic Studies*, 63, 581–593.
- ALESSANDRI, P., AND H. MUMTAZ (2018): “Financial regimes and uncertainty shocks,” *Journal of Monetary Economics*.
- ALMEIDA, H., M. CAMPELLO, I. CUNHA, AND M. S. WEISBACH (2014): “Corporate Liquidity Management: A Conceptual Framework and Survey,” *Annual Review of Financial Economics*, 6, 135–162.
- ALMEIDA, H., M. CAMPELLO, AND M. S. WEISBACH (2005): “The Cash Flow Sensitivity of Cash,” *Journal of Finance*, 59(4), 1777–1804.
- ALTINKILIC, O., AND R. S. HANSEN (2000): “Are There Economies of Scale in Underwriting Fees? Evidence of Rising External Financing Costs,” *Review of Financial Studies*, 13, 191–218.
- ARELLANO, C., Y. BAI, AND P. J. KEHOE (2016): “Financial Frictions and Fluctuations in Volatility,” *Working Paper*.
- ASQUITH, P., AND D. MULLINS (1986): “Equity issues and offering dilution,” *Journal of Financial Economics*, 15, 61–89.
- BACHMANN, R., AND C. BAYER (2013): “Wait-and-See Business Cycles?,” *Journal of Monetary Economics*, 60(6), 704–719.
- BACHMANN, R., AND G. MOSCARINI (2012): “Business Cycles and Endogenous Uncertainty,” *Working Paper, University of Notre Dame and Yale University*.
- BAKER, S., N. BLOOM, AND S. DAVIS (2016): “Measuring Economic Policy Uncertainty,” *Forthcoming Quarterly Journal of Economics*.
- BANSAL, R., AND A. YARON (2004): “Risks for the long run: A potential resolution of asset pricing puzzles,” *Journal of Finance*, 59, 1481–1509.
- BARRO, R. (2006): “Rare disasters and asset markets in the twentieth century,” *Quarterly Journal of Economics*, 121(3), 823–866.
- BASU, S., AND B. BUNDICK (2017): “Uncertainty Shocks in a Model of Effective Demand,” *NBER Working Paper No. 18420*.
- BATES, T. W., K. M. KAHLE, AND R. M. STULZ (2009): “Why Do U.S. Firms Hold So Much More Cash than They Used To?,” *Journal of Finance*, 64(5), 1985–2021.
- BAUMOL, W. (1970): “Earnings retention, new capital and the growth of the firm,” *Review of Economics and Statistics*, 52, 345–355.
- BERGER, D., I. DEW-BECKER, AND S. GIGLIO (2016): “Contractionary volatility or volatile contractions?,” *Working paper, Northwestern University*.
- BERNANKE, B., AND M. GERTLER (1989): “Agency costs, net worth, and business fluctuations,” *American Economic Review*, 79(1), 14–31.
- BERNANKE, B. S. (1983): “Irreversibility, Uncertainty, and Cyclical Investment,” *Quarterly Journal of Economics*, 98(1), 85–106.
- BERNANKE, B. S., M. GERTLER, AND S. GILCHRIST (1999): “The financial accelerator in a quantitative business cycle framework,” *Handbook of Macroeconomics*, 1, 1341–1393.
- BERTOLA, G., AND R. J. CABALLERO (1990): “Kinked Adjustment Costs and Aggregate Dynamics,” *NBER Macroeconomics Annual*, 5, 237–296.
- BIGIO, S. (2015): “Endogenous liquidity and the business cycle,” *American Economic Review*,

- 105(6), 1883–1927.
- BLOOM, N. (2009): “The Impact of Uncertainty Shocks,” *Econometrica*, 77, 623–685.
- BLOOM, N., S. BOND, AND J. V. REENEN (2007): “Uncertainty and investment dynamics,” *Review of Economic Studies*, 74(2), 391–415.
- BLOOM, N., M. FLOETOTTO, N. JAIMOVICH, I. SAPORTA-EKSTEN, AND S. TERRY (2016): “Really uncertain business cycles,” *National Bureau of Economic Research, Stanford University*.
- BOLTON, P., H. CHEN, AND N. WANG (2011): “A unified theory of Tobin’s q, corporate investment, financing, and risk management,” *Journal of Finance*, 66, 1545–1578.
- BOLTON, P., H. CHEN, AND N. WANG (2013): “Market timing, investment and risk management,” *Journal of Financial Economics*, 109, 40–62.
- BOLTON, P., N. WANG, AND J. YANG (Forthcoming): “Liquidity and Risk Management: Coordinating Investment and Compensation Policies,” *Journal of Finance*.
- CABALLERO, R., E. ENGEL, AND J. HALTIWANGER (1995): “Plant-level adjustment and aggregate investment dynamics,” *Brookings Papers on Economic Activity*, 2, 1–54.
- CAGGIANO, G., E. CASTELNUOVO, AND J. M. FIGUERES (2017): “Economic policy uncertainty and unemployment in the United States: A nonlinear approach,” *Economics Letters*, 151, 31–34.
- CALDARA, D., C. FUENTES-ALBERO, S. GILCHRIST, AND E. ZAKRAJSEK (2016): “The macroeconomic impact of financial and uncertainty shocks,” *European Economic Review*, 88, 185–207.
- CARHART, M. (1997): “On Persistence in Mutual Fund Performance,” *Journal of Finance*, 52,1, 57–82.
- CARLSTROM, C. T., AND T. S. FUERST (1997): “Agency costs, net worth, and business fluctuations: A computable general equilibrium analysis,” *American Economic Review*, 87(5), 893–910.
- CHEN, G. (2016): “Corporate Savings, Financing and Investment with Aggregate Uncertainty Shocks,” *Working Paper, Nanyang Technological University*.
- CHEN, H., H. WANG, AND H. ZHOU (2014): “Stock Return Volatility and Capital Structure Decisions,” *PBCSF-NIFR, Tsinghua University*, 13,04.
- CHEN, P., L. KARABARBOUNIS, AND B. NEIMAN (2017): “The global rise of corporate saving,” *Journal of Monetary Economics*, 89, 1–19.
- CHOE, H., R. MASULIS, AND V. NANDA (1993): “Common Stock Offerings across the Business Cycle: Theory and Evidence,” *Journal of Empirical Finance*, 1, 3–31.
- CHRISTIANO, L. J., R. MOTTO, AND M. ROSTAGNO (2014): “Risk Shocks,” *American Economic Review*, 104, 27–65.
- COOLEY, T. F., AND V. QUADRINI (2001): “Financial markets and firm dynamics,” *American Economic Review*, 91, 1286–1310.
- COOPER, R. W., AND J. C. HALTIWANGER (2006): “On the Nature of Capital Adjustment Costs,” *Review of Economic Studies*, 73(3), 611–633.
- DAVIS, S. J., AND J. HALTIWANGER (1992): “Gross Job Creation, Gross Job Destruction, and Employment Reallocation,” *The Quarterly Journal of Economics, MIT Press*, 107,3, 819–863.
- DEANGELO, H., L. DEANGELO, AND T. M. WHITED (2011): “Capital structure dynamics and transitory debt,” *Journal of Financial Economics*, 99, 235–261.

- DIXIT, A. K., AND R. S. PINDYCK (1994): *Investment under Uncertainty*. Princeton: Princeton University Press, Princeton, N.J.
- DUCHIN, R., O. OZBAS, AND B. SENSOY (2010): “Costly external finance, corporate investment and the subprime mortgage credit crisis,” *Journal of Financial Economics*, 97, 418–435.
- EISFELDT, A. (2004): “Endogenous liquidity in asset markets,” *Journal of Finance*, 59(1), 1–30.
- EISFELDT, A., AND T. MUIR (2016): “Aggregate External Financing and Savings Waves,” *Journal of Monetary Economics*, 84, 116–133.
- EISFELDT, A., AND D. PAPANIKOLAOU (2013): “Organization Capital and the Cross-Section of Expected Returns,” *Journal of Finance*, 68(4), 1365–1406.
- EREL, I., B. JULIO, W. KIM, AND M. WEISBACH (2012): “Macroeconomic Conditions and Capital Raising,” *Review of Financial Studies*, 25, 341–376.
- FALGELBAUM, P., E. SCHAAL, AND M. TASCHEREAU-DUMOUCHEL (2016): “Uncertainty Traps,” *Forthcoming, Quarterly Journal of Economics*.
- FERNANDEZ-VILLAVERDE, J., P. GUERRON-QUINTANA, K. KUESTER, AND J. RUBIO-RAMIREZ (2015): “Fiscal Volatility Shocks and Economic Activity,” *American Economic Review*, 105(11), 3352–3384.
- FERNANDEZ-VILLAVERDE, J., P. G. QUINTANA, J. F. RUBIO-RAMIREZ, AND M. URIBE (2011): “Risk Matters: The Real Effects of Volatility Shocks,” *American Economic Review*, 101,6, 2530–61.
- FROOT, K., D. SCHARFSTEIN, AND J. STEIN (1993): “Risk Management: Coordinating Corporate Investment and Financing Policies,” *Journal of Finance*, 48(5), 1629–1658.
- GILCHRIST, S., J. SIM, AND E. ZAKRAJSEK (2014): “Uncertainty, Financial Frictions and Investment Dynamics,” *Boston University mimeo*.
- GILCHRIST, S., AND E. ZAKRAJSEK (2012): “Credit spreads and business cycle fluctuations,” *American Economic Review*, 102(4), 1692–1720.
- GIROUD, X., AND H. M. MUELLER (2017): “Firm Leverage, Consumer Demand, and Employment Losses During the Great Recession,” *Quarterly Journal of Economics*, 132(1), 271–316.
- GOMES, J. (2001): “Financing investment,” *American Economic Review*, 65(2), 467–494.
- GOURIO, F. (2012): “Disaster Risk and Business Cycles,” *American Economic Review*, 102(6), 2734–2766.
- GOURIO, F., AND A. K. KASHYAP (2007): “Investment spikes: New facts and a general equilibrium exploration,” *Journal of Monetary Economics*, 54(1), 1–22.
- GRAHAM, J. (2000): “How big are the tax benefits of debt?,” *Journal of Finance*, 55(5), 1901–1941.
- GUIO, L., AND G. PARIGI (1999): “Investment and Demand Uncertainty,” *Quarterly Journal of Economics*, 114, 185–227.
- HADLOCK, C. J., AND J. R. PIERCE (2010): “New Evidence on Measuring Financial Constraints: Moving Beyond the KZ Index,” *The Review of Financial Studies*, 23(5), 1909–1940.
- HALL, R. E. (1988): “The Relation between Price and Marginal Cost in U.S. Industry,” *Journal of Political Economy*, 96(5), 921–947.
- HANDLEY, K., AND N. LIMA (2012): “Trade and Investment under Policy Uncertainty:

- Theory and Firm Evidence,” *NBER Working Paper 17790*.
- HENNESSY, C. A., A. LEVY, AND T. M. WHITED (2007): “Testing Q theory with financing frictions,” *Journal of Financial Economics*, 83(3), 691–717.
- HENNESSY, C. A., AND T. M. WHITED (2005): “Debt Dynamics,” *Journal of Finance*, 60, 1129–1165.
- (2007): “How costly is external financing? Evidence from a structural estimation,” *Journal of Finance*, 62, 1705–1745.
- HOLMSTROM, B., AND J. TIROLE (1998): “Private and public supply of liquidity,” *Journal of Political Economy*, 106, 1–40.
- ILUT, C., AND M. SCHNEIDER (2014): “Ambiguous Business Cycles,” *American Economic Review*, 104(8), 2368–99.
- JEFFREY M WOOLDRIDGE (2015): *Introductory econometrics: A modern approach*. Cengage Learning.
- JENSEN, M. C., AND W. H. MECKLING (1976): “Theory of the Firm: Managerial Behavior, Agency Costs and Ownership Structure,” *Journal of Financial Economics*, 3(4), 305–360.
- JEREMY J. SIEGEL (1998): *Stocks for the Long Run : The Definitive Guide to Financial Market Returns and Long-Term Investment Strategies*. McGraw-Hill, New York.
- JERMANN, U., AND V. QUADRINI (2012): “Macroeconomic Effects of Financial Shocks,” *American Economic Review*, 102(1), 238–71.
- JOHN MAYNARD KEYNES (1936): *The general theory of employment, interest and money*. New York, Harcourt, Brace, New York.
- KAHLE, K., AND R. STULZ (2013): “Access to Capital, Investment, and the Financial Crisis,” *Journal of Financial Economics*, 110(2), 280–299.
- KHAN, A., AND J. THOMAS (2008): “Idiosyncratic Shocks and the Role of Nonconvexities in Plant and Aggregate Investment Dynamics,” *Econometrica*, 76,2, 395–436.
- KING, R., AND S. REBELO (1999): *Handbook of Macroeconomics*. North-Holland, Amsterdam, Netherlands, Resuscitating real business cycles.
- KRUSELL, P., AND A. A. SMITH (1998): “Income and Wealth Heterogeneity in the Macroeconomy,” *Journal of Political Economy*, 106(5), 867–896.
- KURLAT, P. (2013): “Lemons markets and the transmission of aggregate shocks,” *American Economic Review*, 103(4), 1463–1489.
- LEAHY, J. V., AND T. WHITED (1996): “The Effect of Uncertainty on Investment: Some Stylized Facts,” *Journal of Money, Credit and Banking*, 28, 64–83.
- LEARY, M. T., AND M. R. ROBERTS (2014): “Do Peer Firms Affect Corporate Financial Policy?,” *Journal of Finance*, 69(1), 139–178.
- LEE, G., AND R. W. MASULIS (2009): “Seasoned equity offerings: Quality of accounting information and expected flotation costs,” *Journal of Financial Economics*, 92(3), 443–469.
- LHUISSIER, S., AND F. TRIPIER (2016): “Do uncertainty shocks always matter for business cycles?,” *CEPII working paper*.
- MELTZER, A. H. (1963): “The demand for money: a cross-section study of business firms,” *Quarterly Journal of Economics*, 77, 405–422.
- MILLER, M., AND D. ORR (1966): “A model of the demand for money by firms,” *Quarterly Journal of Economics*, 80, 413–435.
- MOYEN, N. (2004): “Investment-cash flow sensitivities: Constrained versus unconstrained firms,” *Journal of Finance*, 59, 2061–2092.

- MYERS, S. C., AND N. S. MAJLUF (1984): “Corporate financing and investment decisions when firms have information that investors do not have,” *Journal of Financial Economics*, 13(2), 187–221.
- NIEUWERBURGH, S. V., AND L. VELDKAMP (2006): “Learning Asymmetries in Real Business Cycles,” *Journal of Monetary Economics*, 53, 753–772.
- ORLIK, A., AND L. VELDKAMP (2015): “Understanding Uncertainty Shocks and the Role of the Black Swan,” *Working paper, NYU*.
- PANOUSI, V., AND D. PAPANIKOLAOU (2012): “Investment, Idiosyncratic Risk, and Ownership,” *Journal of Finance*, 67(3), 1113–1148.
- PASTOR, L., AND R. STAMBAUGH (2003): “Liquidity Risk and Expected Stock Returns,” *Journal of Political Economy*, 111, 642–685.
- PASTOR, L., AND P. VERONESI (2012): “Uncertainty about Government Policy and Stock Prices,” *Journal of Finance*, 67, 1219–1264.
- PINKOWITZ, L., R. M. STULZ, AND R. WILLIAMSON (2013): “Is there a U.S. High Cash Holdings Puzzle after the Financial Crisis?,” *Working Paper*.
- (2016): “Do U.S. Firms Hold More Cash than Foreign Firms Do?,” *The Review of Financial Studies*, 29(2), 309–348.
- RAJAN, R. G., AND L. ZINGALES (1995): “What do we know about capital structure? Some evidence from international data,” *Journal of Finance*, 50, 1421–1460.
- RAMEY, V., AND G. RAMEY (1995): “Cross-country evidence on the link between volatility and growth,” *American Economic Review*, 85,5, 1138–51.
- RAMPINI, A., AND S. VISWANATHAN (2013): “Collateral and capital structure,” *Journal of Financial Economics*, 109, 466–492.
- RIDDICK, L. A., AND T. M. WHITED (2009): “The corporate propensity to save,” *Journal of Finance*, 64, 1729–1766.
- RIETZ, T. (1988): “The equity premium: a solution,” *Journal of Monetary Economics*, 22(1), 117–131.
- ROMER, C. (1990): “The Great Crash and the Onset of the Great Depression,” *Quarterly Journal of Economics*, 105(3), 597–624.
- SEGAL, G., I. SHALIASTOVICH, AND A. YARON (2015): “Good and Bad Uncertainty: Macroeconomic and Financial Market Implications,” *Journal of Financial Economics*, 117, 369–397.
- SHARPE, S. A. (1994): “Financial Market Imperfections, Firm Leverage, and the Cyclicity of Employment,” *American Economic Review*, 84(4), 1060–1074.
- STEIN, L., AND E. STONE (2013): “The effect of uncertainty on investment, hiring and RD: causal evidence from equity options,” *Arizona State University mimeo*.
- STOCK, J., AND M. WATSON (2012): “Disentangling the channels of the 2007-09 recession,” *Brookings Papers on Economic Activity*, 1, 81–135.
- WELCH, I. (2004): “Capital Structure and Stock Returns,” *Journal of Political Economy*, 112, 106–131.
- WHITED, T., AND G. WU (2006): “Financial Constraints Risk,” *Review of Financial Studies*, 19, 531–559.

Table 1
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	85% of the risk-free rate (matches cash to asset ratio for cash holding firms)
Share on capital	α	0.33	Capital share in output is one-third, labor share is two-thirds
Markup	ε	4	33% markup. With constant returns to scale yields $a + b = 0.75$
Wage	\bar{w}	1	Wage rate normalized to 1
Rate of depreciation for capital	δ	0.03	Capital depreciation rate assumed 3% per quarter
Fixed cost of investment	c_k	0.01	1% of quarterly revenue (Also tried 2% & 4%)
Fixed operating cost	f	0.2	Firms' average SG&A to sales ratio
Uncertainty shock (2 state Markov)			
Persistence of logged idiosyncratic productivity	ρ_z	0.95	Quarterly persistence of idiosyncratic productivity (Khan & Thomas 2008)
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	$\pi_{L,H}^L$	2.60%	Uncertainty shocks expected every 9.6 years (Bloom et al 2016)
Transition probability remaining in high uncertainty	$\pi_{H,H}^H$	94%	Quarterly probability of remaining in high uncertainty (Bloom et al 2016)
Stochastic financing cost (2 state Markov)			
Low external financing cost state	η_L	0.005	Low cost .5% of output (Altinkilic & Hansen 2000)
High external financing cost state	η_H	0.05	High cost 5% of output (Altinkilic & Hansen 2000). Robust 2.5%,10%
Transition probability low to high financing cost state	$\pi_{L,H}^L$	2.60%	Same as uncertainty shock (Also tried 5%)
Transition prob. remaining in high financing cost state	$\pi_{H,H}^H$	94%	Same as uncertainty shock (Also tried 50%)
Impact of uncertainty on financial cost	λ	0.04	Correlation between the Baa-Aaa spread and VIX

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

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

	Real		Financial			
	I/K	ΔEmp	ΔCash	Div/K	FUM-I	FUM-E
A: Data						
ΔVolatility	-0.089	-0.074	0.227	-0.019	na	na
B: Real frictions only						
ΔVolatility	-0.042	-0.014	na	-0.007	1.00	1.00
C: Real+Nonstochastic financial frictions						
ΔVolatility	-0.059	-0.020	0.063	0.008	1.39	1.45
D: Real+Stochastic financial frictions						
ΔVolatility	-0.073	-0.026	0.964	-0.029	1.73	1.89
E. Stochastic financial frictions only						
ΔVolatility	0.005	0.007	0.226	-0.032	-0.13	-0.53
F: No frictions						
ΔVolatility	0.003	0.006	na	-0.024	-0.08	-0.45

Notes: Row (A) Data reports the results for investment rate, employment growth, cash growth, and equity payout to assets ratio from columns (2) of tables (3), (5), (6), respectively. Rows (B) to (F) reports the model counterparts from regressions using simulation data on volatility ($\sigma_{i,t}$) growth. The reported statistics in the model are from simulated data with 3000 firms and 200 quarterly observations. I/K is the investment rate, ΔEmp is the employment growth, ΔCash is the cash growth rate, and Div/K the dividend scaled by capital in the model and cash dividend plus repurchase scaled by total assets in the data. FUM-I stands for the finance uncertainty multiplier for investment and FUM-E stands for the finance uncertainty multiplier for employment. The are the slopes of I/K and ΔEmp of the benchmark model (row D) scaled by those from the model with real frictions only (row B). For comparability all the regressions (in the data and model) include firm and time fixed effects and all are significant at the 1% level with firm-clustered standard errors. The only difference is employment is annual in the real data (since no quarterly real employment data is available).

Table 3
Investment rate

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

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

Table 4
Investment rate - 2SLS 1st stage results

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

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

Table 5
Additional real quantities

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

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

Table 6
Financial outcomes

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

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

Table 7
Impact of realized volatility shocks on investment for *ex-ante* financially constrained and unconstrained firms during heightened credit frictions

Investment Rate _t	(1)	(2)	(3)	(4)
Financial Constraint measure		S&P Rating	Size&Age	WhitedWu
$\Delta\sigma_{i,t-1}$	-0.025** (0.011)	-0.028** (0.011)	-0.025** (0.011)	-0.030*** (0.011)
$\Delta\sigma_{i,t-1} \cdot D_{i,t-5}^{Fin.Const}$		-0.002 (0.012)	-0.003 (0.013)	-0.001 (0.013)
$\Delta\sigma_{i,t-1} \cdot Cred_Spread_t$	-0.042*** (0.015)	-0.026** (0.012)	-0.031** (0.013)	-0.029** (0.013)
$\Delta\sigma_{i,t-1} \cdot D_{i,t-5}^{Fin.Const} \cdot Cred_Spread_t$		-0.023** (0.010)	-0.019** (0.009)	-0.015 (0.012)
Observations	28,320	25,898	25,897	24,679
F-test 1st Stage Cragg-D	61.37	28.42	26.31	25.77
F-test 1st Stage Kleib.-P.	10.13	8.001	9.071	7.450
p-value Sargan-H J	0.799	0.992	0.672	0.768
p-value $(\beta_{\Delta\sigma}^{FC} + \beta_{CS.\Delta\sigma}^{FC}) \geq 0$		0.029	0.038	0.139

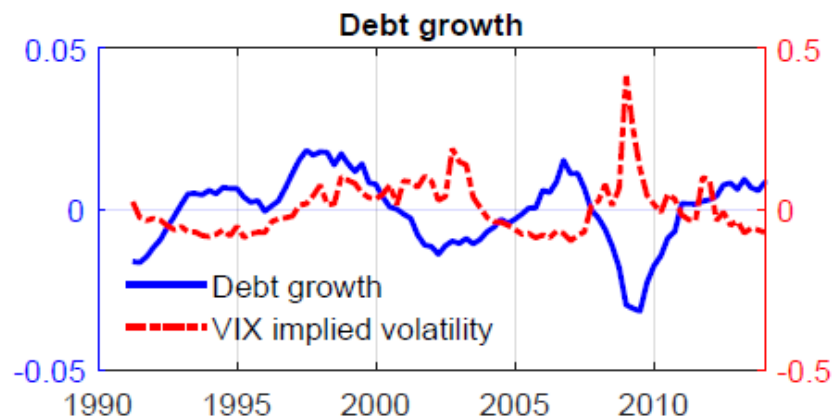
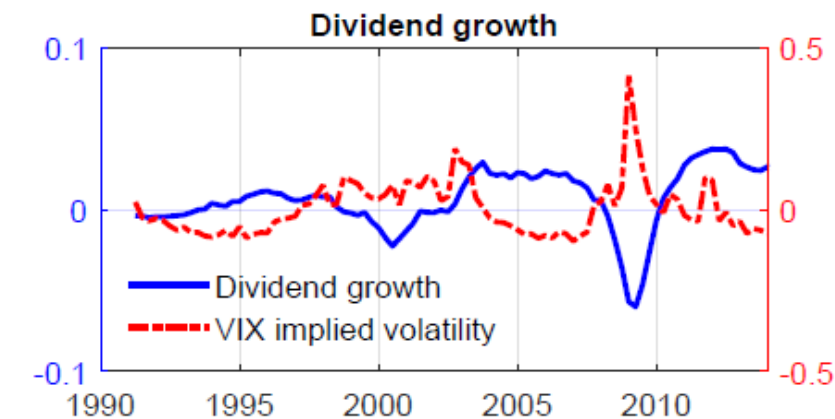
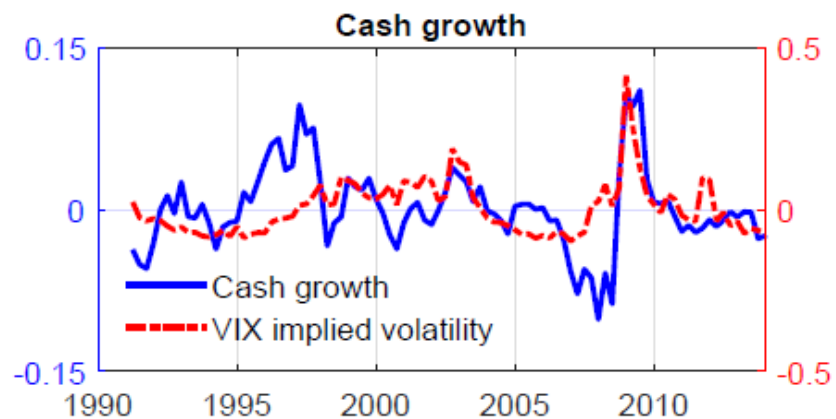
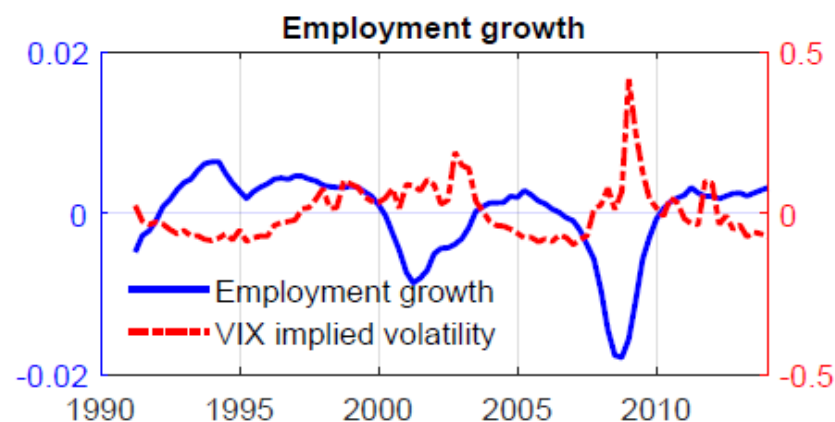
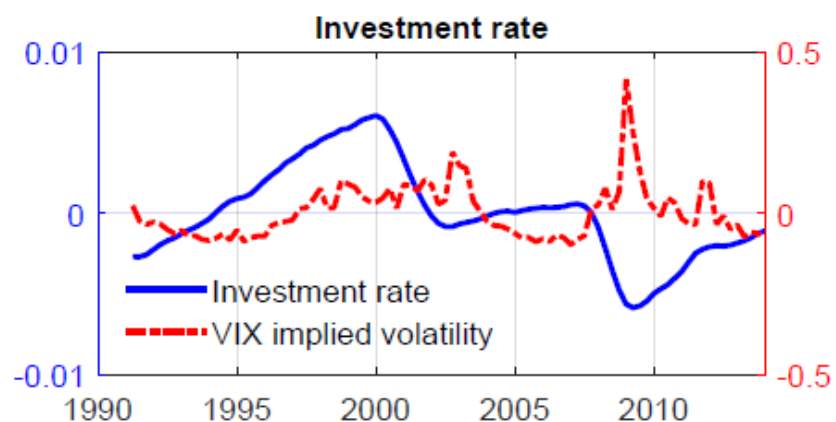
Notes: Table presents 2SLS annual regression results of firm-level investment rate on 1-year lagged changes in firm-level annual realized volatility of daily CRSP returns, $\Delta\sigma_{i,t-1}$, and its interaction with the year t aggregate Moody's corporate credit spread BAA-AAA, $Credit_Spread_t$, and a dummy, $D_{i,t-5}^{Fin.Constrained}$, that takes value one for firms classified as ex-ante financially constrained using information in fiscal year $t - 5$, zero otherwise. A full set of firm-level controls, 1st moment aggregate return shock controls, and both firm and year fixed effects are included (e.g., as in baseline specification (3) in Table 3). Standard errors in parenthesis are clustered at the 3digit SIC industry. The credit spread is standardized to ease interpretation of coefficients. Investment rate at fiscal year t is defined as I_t/K_{t-1} (capx/lagged net property plant & equipment from Compustat). We address endogeneity concerns on firm-level volatility by instrumenting with industry-level (3SIC) non-directional exposure to 10 aggregate sources of uncertainty shocks, which include the lagged exposure to annual changes in expected volatility of energy, currencies, and 10-year treasuries (as proxied by option-implied volatilities of oil, 7 widely traded currencies, and TYVIX), and economic policy uncertainty from Baker, Bloom, and Davis (2016). Firms are either ex-ante financially constrained or unconstrained based on their constraint status in year $t - 5$, as classified by: S&P credit ratings (column 2), which follows Duchin, Ozbas, and Sensoy (2010) and consider a firm constrained if it has positive debt and no bond rating and unconstrained otherwise (which includes firms with zero debt and no debt rating), Size and Age index (SA) of Hadlock and Pierce (2010) (3), and the Whited-Wu index (4). A firm in year t is ex-ante financially constrained if at year $t - 5$ is equal to or above the median constrained firm that year, unconstrained otherwise. We test the null $H_0 : (\beta_{\Delta\sigma}^{FC} + \beta_{CS.\Delta\sigma}^{FC}) \geq 0$ that the total negative effects on investment are at least as large for unconstrained firms, against the alternative $H_a : (\beta_{\Delta\sigma}^{FC} + \beta_{CS.\Delta\sigma}^{FC}) < 0$ that the total negative effects of uncertainty shocks are larger for ex-ante constrained firms. Data sample is from fiscal year 2005 to December 2016. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1, † p<0.15.

Table 8
Real impact of volatility shocks for *ex-ante* financially constrained and unconstrained firms during heightened credit frictions

Financial Constraint measure	(1)	(2)	(3)	(4)	(5)	(6)
	S&P Credit Ratings (1-6)					
	Δ Intang. Invest _{<i>i,t</i>}		Δ COGS _{<i>i,t</i>}		Δ Sales _{<i>i,t</i>}	
$\Delta\sigma_{i,t-1}$	-0.036** (0.018)	-0.005 (0.023)	-0.148*** (0.035)	-0.132*** (0.039)	-0.170*** (0.064)	-0.129** (0.058)
$\Delta\sigma_{i,t-1} \cdot D_{i,t-5}^{Fin.Const}$		-0.052** (0.023)		-0.022 (0.029)		-0.071** (0.034)
$\Delta\sigma_{i,t-1} \cdot Cred_Spread_t$	-0.069** (0.028)	-0.056** (0.026)	-0.279*** (0.069)	-0.255*** (0.068)	-0.238*** (0.048)	-0.211*** (0.048)
$\Delta\sigma_{i,t-1} \cdot D_{i,t-5}^{Fin.Const} \cdot Cred_Spread_t$		-0.009 (0.022)		-0.034† (0.024)		-0.039† (0.024)
Observations	15,777	15,777	25,931	25,931	25,931	25,931
F-test 1st Stage Cragg-D	29.80	14.74	59.63	28.47	59.63	28.47
F-test 1st Stage Kleib.-P.	7.044	5.572	8.201	7.901	8.201	7.901
p-value Sargan-H J	0.080	0.115	0.031	0.050	0.034	0.024
p-value ($\beta_{\Delta\sigma}^{FC} + \beta_{CS \cdot \Delta\sigma}^{FC} \geq 0$)		0.007		0.031		0.003

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

Figure 1: Uncertainty, real outcomes and financial flows



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

Figure 2: Investment Policy Functions

Figure 2A: Real fixed costs only

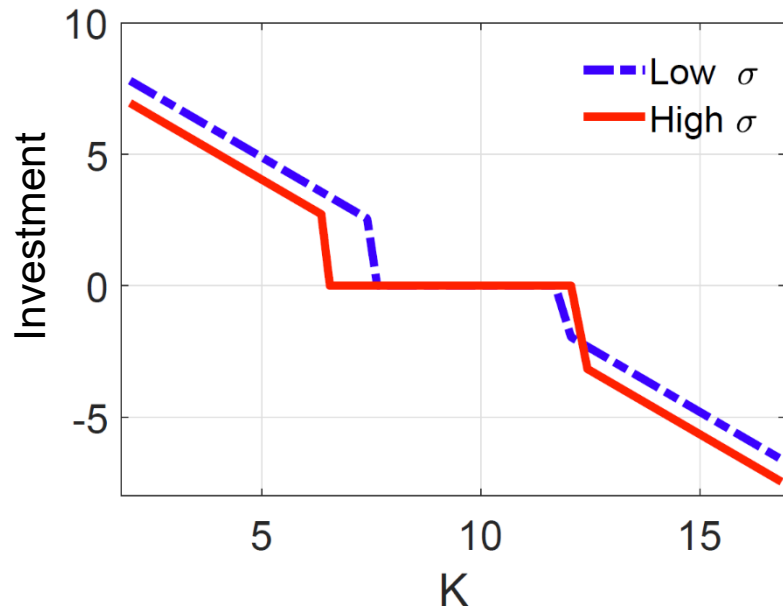
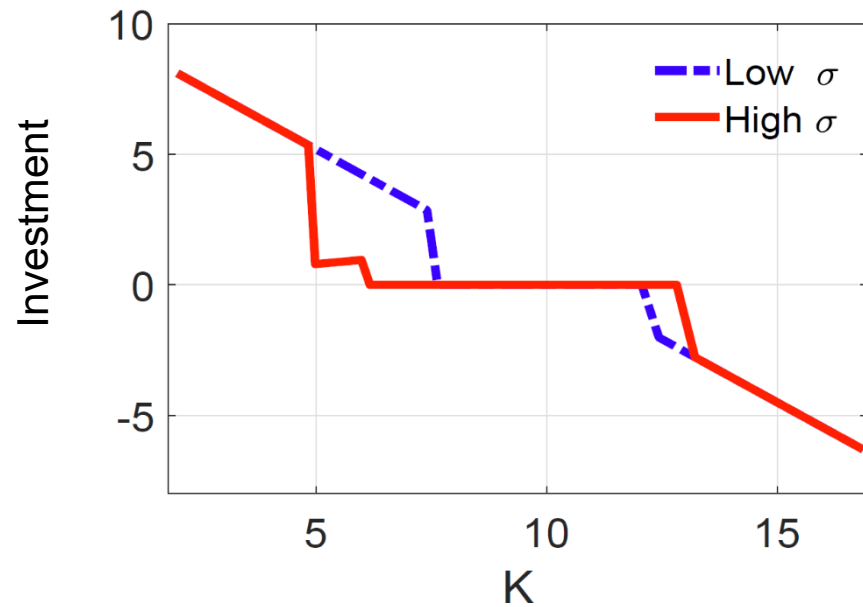
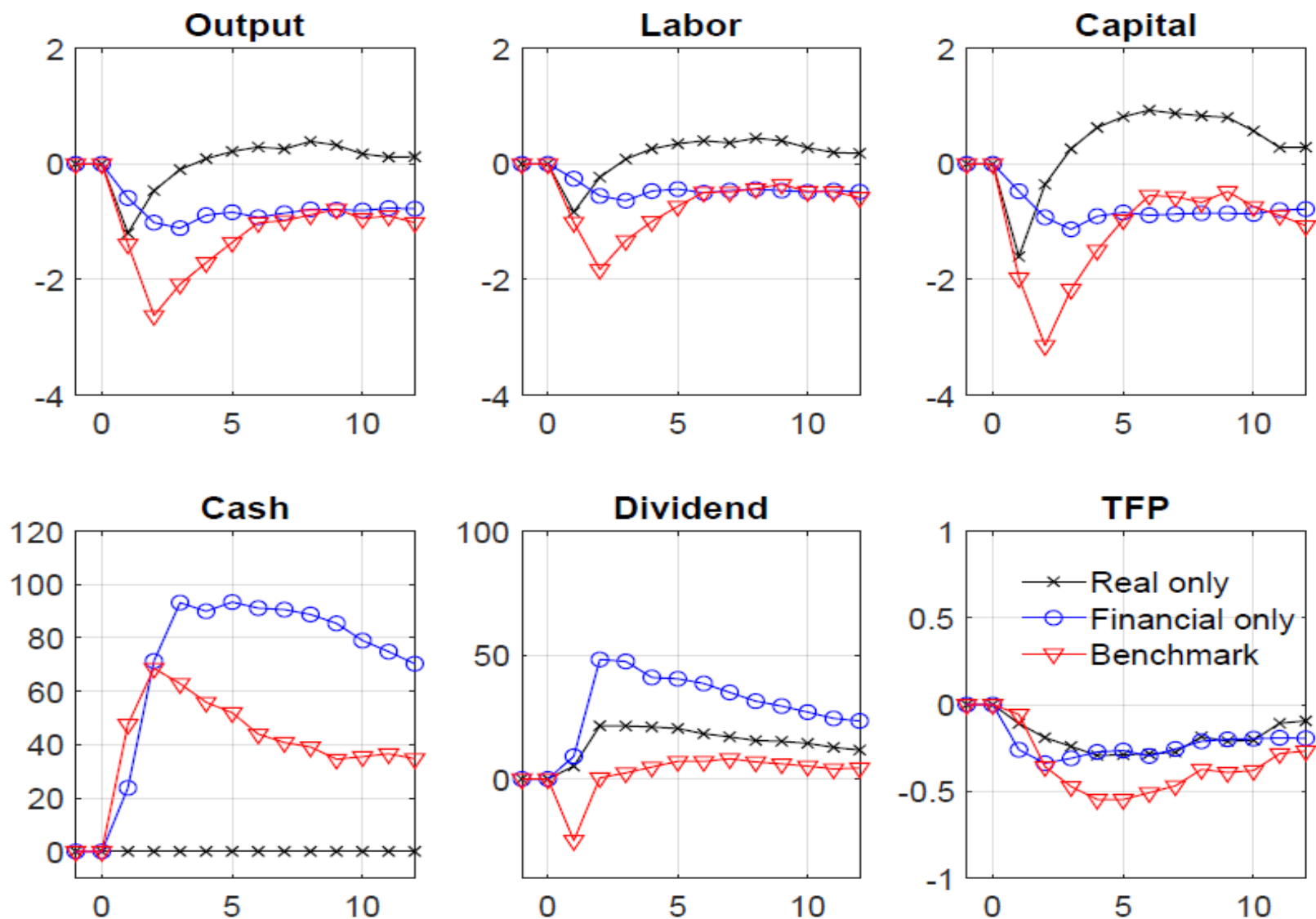


Figure 2B: Benchmark: real and financial fixed costs



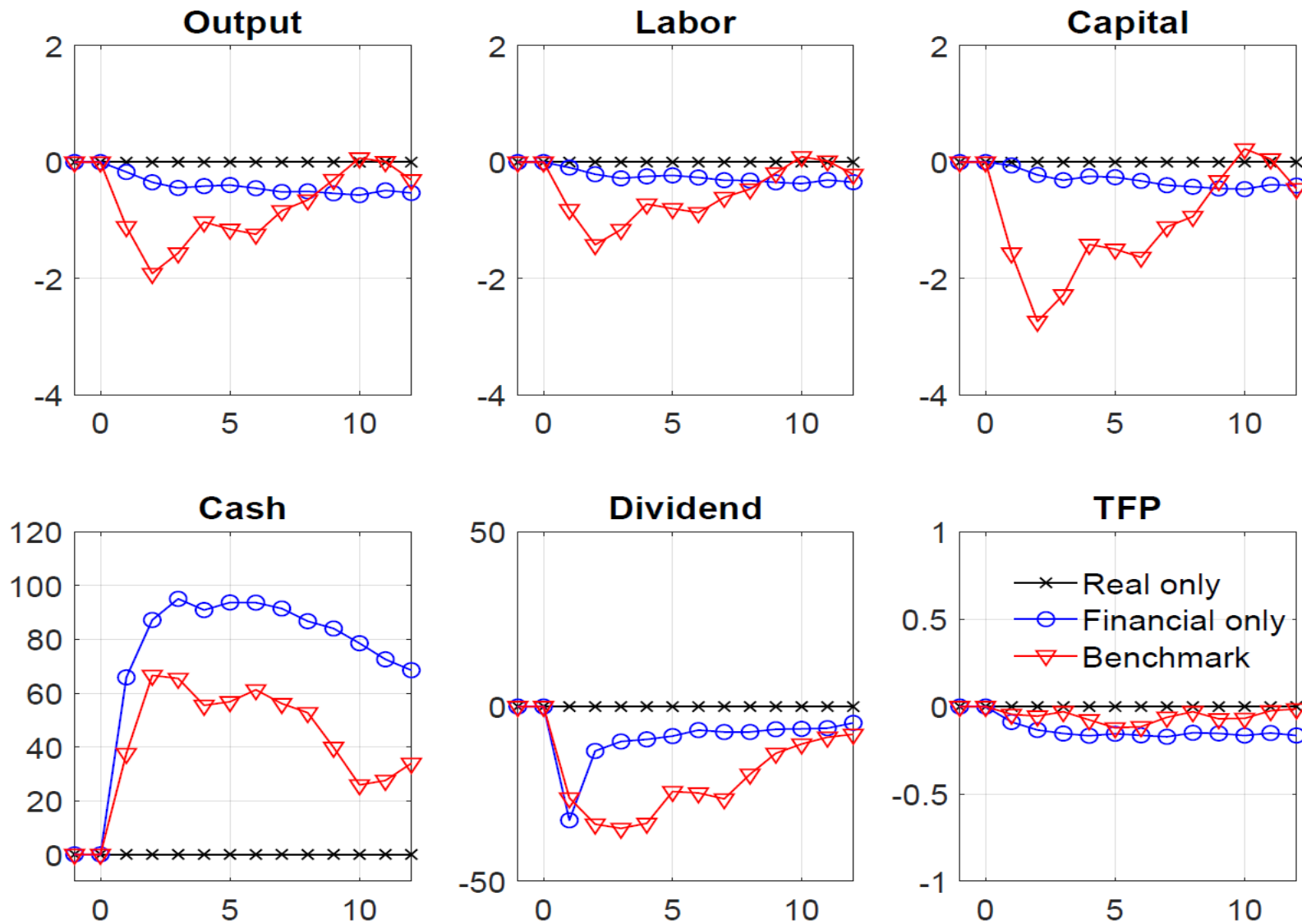
Notes: Figures 2A and 2B plot the optimal investment policies associated with low and high uncertainty shock states of the model with real investment costs only (top left) and the benchmark model (top right), respectively. In both figures, we fix the idiosyncratic productivity and cash at their median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

Figure 3: The Impact of a pure Uncertainty Shock



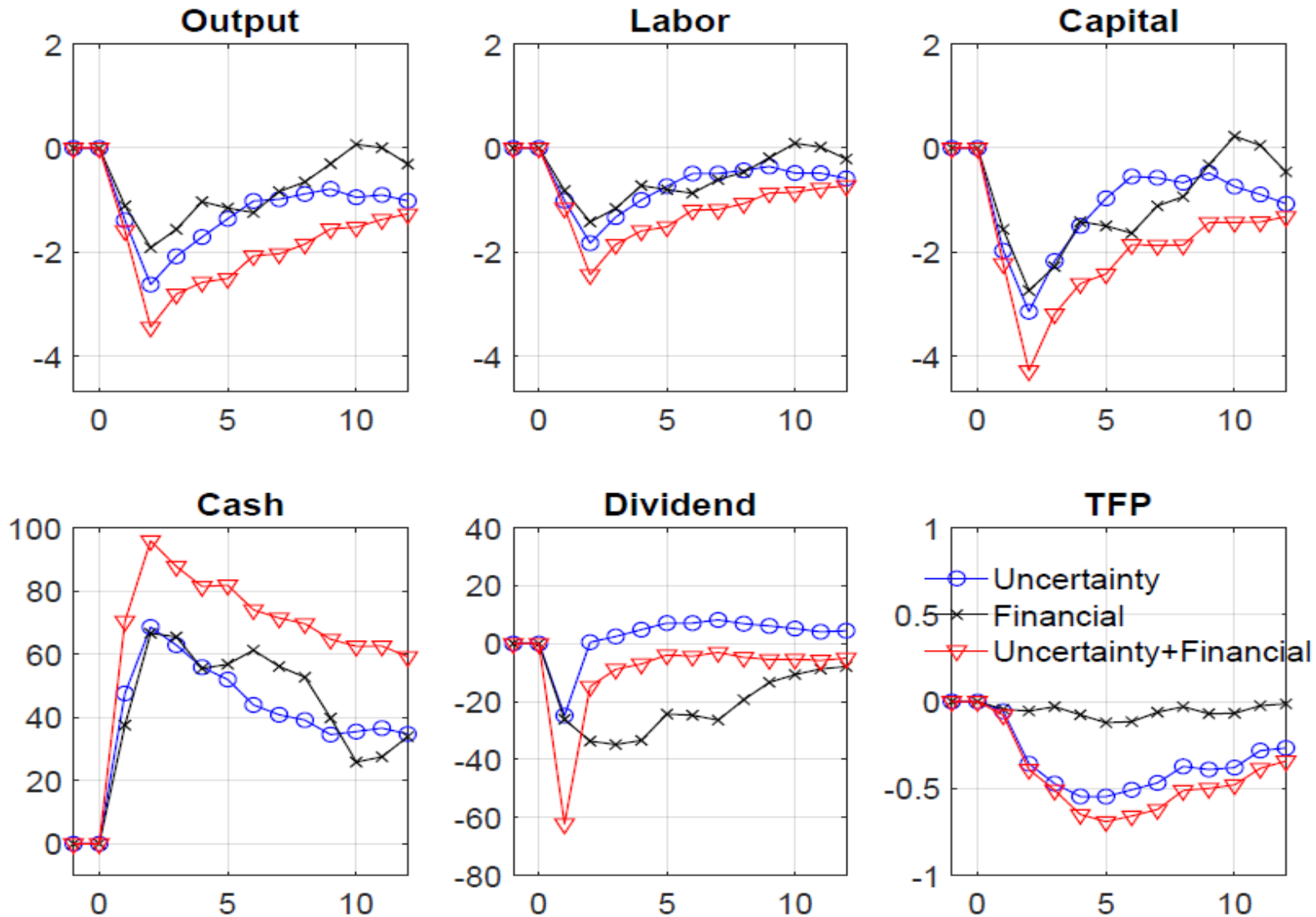
Notes: We plot the percent deviations of average output, labor, capital, cash, dividend and aggregate TFP from their values in quarter 0 of three model specifications: i) the model with real cost only (black x-mark); ii) the model with financial cost only (blue circle), and iii) the benchmark with both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

Figure 4: The Impact of a pure Financial Shock



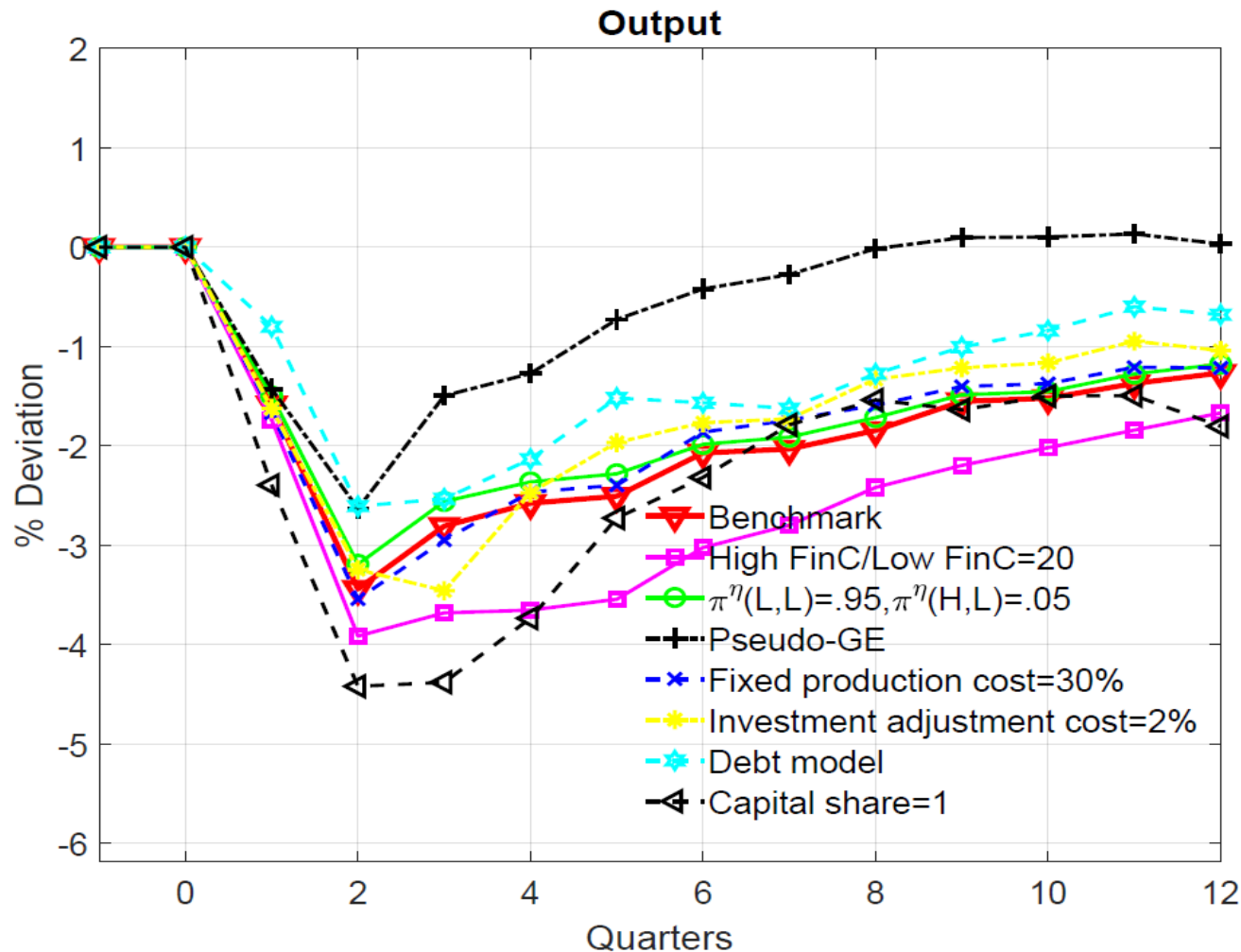
Notes: We plot the percent deviations of average output, labor, capital, cash, dividend and aggregate TFP from their values in quarter 0 of three model specifications: i) the model with real cost only (black x-mark); ii) the model with financial cost only (blue circle), and iii) the benchmark with both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

Figure 5: The Impact of Uncertainty and Financial Shocks



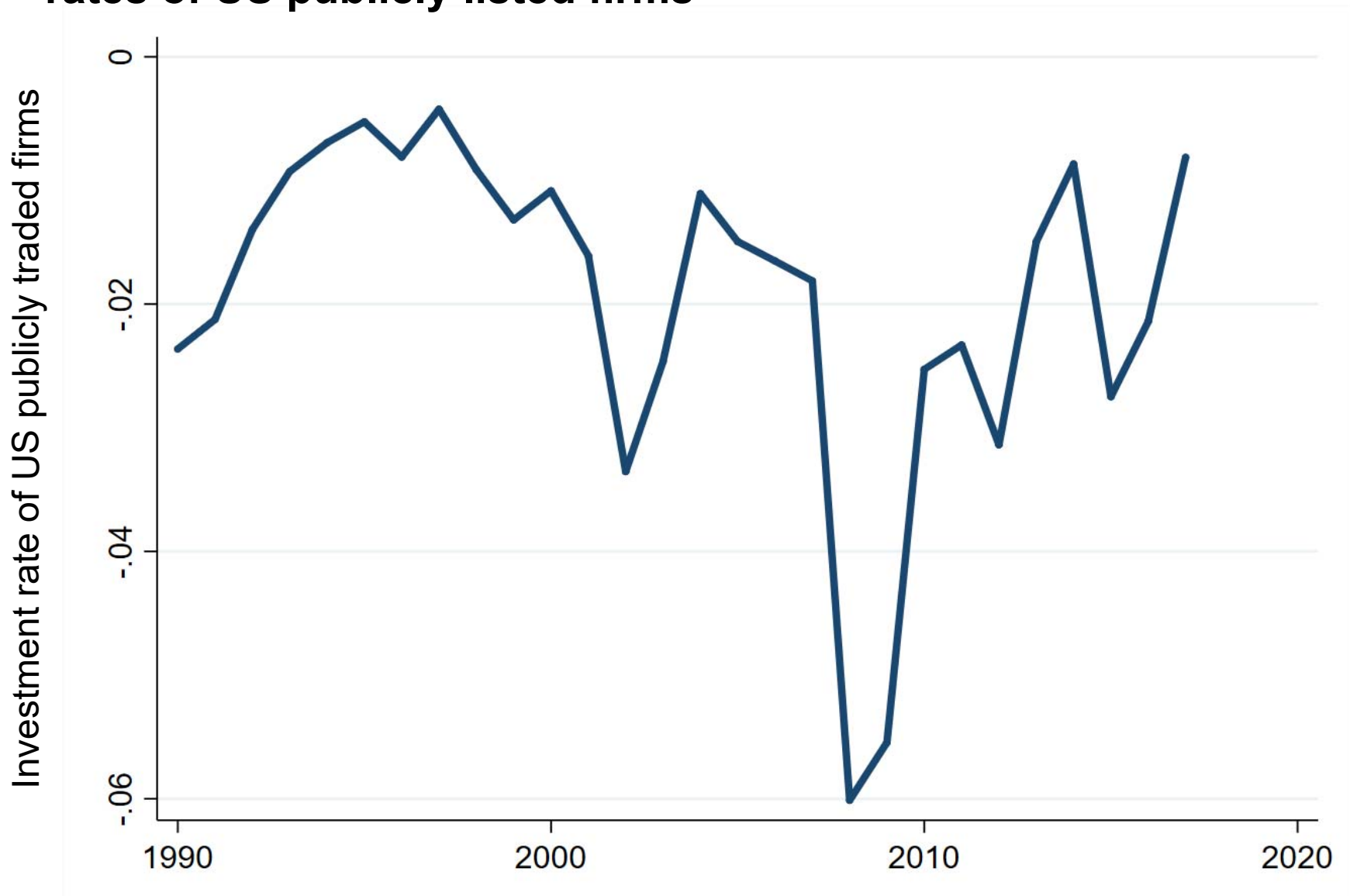
Notes: We plot the percent deviations of average output, labor, capital, cash, dividend and aggregate TFP from their values in quarter 0 of the benchmark model with both real and financial costs. All plots are based on simulations of 30,000 firms of 1000-quarter length. We impose an uncertainty shock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

Figure 6: Robustness check of the Impact of Uncertainty and Financial Shocks



Notes: We plot the percent deviations of average output from their values in quarter 0 of the benchmark model with both real and financial costs (red-triangle), the model with the high financing-cost-state-to-low-cost-state ratio at 20 (magenta-square), the model with a different transition matrix of financial shocks (green-circle), the pseudo-GE model (black-plus), the model with fixed production cost at 30% (blue-dashed-cross), the model with investment adjustment cost at 2% (yellow-star), the model with debt and equity (cyan-dashed star) and the model with the capital share at 1 (black-dashed-triangle). All plots are based on simulations of 30,000 firms of 1000-quarter length. We impose a combined uncertainty and financial shocks in the quarter labelled 1, allowing normal evolution of the economy afterwards.

Figure 7: Implied effect of uncertainty shocks on investment rates of US publicly listed firms



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

Appendix For Online Publication

A Numerical algorithm

We use the value function iteration procedure to solve the firm's maximization problem numerically. We specify the two grids of 82 points for capital and 312 points for cash, respectively, with upper bounds \bar{k} and \bar{n} that are large enough to be non-binding. The grid for capital is constructed recursively given the pre-specified lower and upper bounds \underline{k} and \bar{k} , following $k_i = k_{i-1}/(1 - \delta)$, where $i = 1, \dots, s$ 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 $i = 1, \dots, s$ 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 $i = 1, \dots, s$ 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 Calibration details

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

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

carrying cash for firms or agency frictions. Unfortunately, there is no readily available value for return on cash saving. In the model it determines firms' choice on cash saving, so we calibrate $r_n = 80\%r_f$ to match the average ratios of cash to total assets for firms that hold non-zero cash, which is 5% in Compustat firms.

- Markup ε : We calibrate $\varepsilon = 4$, which implies a markup of 33%, toward the upper end of the range estimates for price–cost markups in [Hall \(1988\)](#).
- Fixed cost of investment c_k : We set $c_k = 1\%$ of quarterly revenue. We have also solved the model with $c_k = 2\%$ and 4% and find the results are robust with these different values of c_k .
- Fixed operating cost F : We set F to be 20% of the lagged productivity in the model, consistent with the average SGA-to-sales ratio of 20% for the Compustat firms.
- Stochastic financing cost $\{\eta_L, \eta_H\}$: Because external financing costs include both direct costs, e.g., flotation costs and indirect costs due to asymmetric information, there are no empirical estimates for the total cost. We set the baseline external equity financing cost parameter $\eta_L = 0.005$ and the high financing cost state $\eta_H = 10\eta_L = 0.05$. The calibrated financial costs are 1.78% of the sales (conditional on firms taking on external financing), within the range the estimates in [Altinkilic and Hansen \(2000\)](#) and [Hennessy and Whited \(2005\)](#). We have also solved the model with $\eta_H/\eta_L = \{2, 5, 8, 16, 20\}$ and find the quantitative results remain robust.
- Impact of uncertainty on financial cost λ : The external financing costs in the model can be broadly interpreted as total financing costs incurred by the firm, including costs on all marginal sources of financing, e.g., on both equity and debt, and other marginal sources. We use several measures for firms' cost of external financing: 1) total financing cost index: the total external financing cost index constructed by [Eisfeldt and Muir \(2016\)](#); 2) lending standards: Net Percentage of Domestic Respondents Tightening Standards for Commercial and Industrial Loans Large and Medium Firms (DRTSCILM). 3) the Moody's Baa-Aaa spread. The first measure is on total external financing costs, while the rest two are more on debt financing costs. Then we compute the correlation between the VIX and these measures. The correlation between the total financing cost index and VIX is 0.42; the correlation between the lending standards and VIX is 0.72, while the correlation between VIX and the BAA-AAA spread ranges from 0.46 from 1960s to 2010s and 0.64 from 1990s to 2010s. As such, we set $\lambda = 4\%$ so that the implied correlation between the external financing cost and the uncertainty is 69%, toward the high end of the three correlation estimates.

C Data

Data used in the empirical analysis is described in detail in this section. Sources include Compustat, CRSP, OptionMetrics, Thomson Reuters Eikon, CBOE, St. Louis Fed, and [Baker, Bloom, and Davis \(2016\)](#). Table [A2](#) presents descriptive statistics of main variables

used in the firm-level panel regressions. Our annual sample period begins in 1963 and ends in 2016.³⁹

C.1 Company financial reports and realized stock return volatility

We draw financial information for US publicly held companies from Compustat. Sample is annual from 1963 to December 2016. We use Compustat fiscal-year annual company data from balance sheet, income statement, and cash flow statement. Financial, utilities, and public sector firms are excluded from the sample. In particular, we exclude firms with historical SIC codes in the range of 6000 to 6999, 4900 to 4999, and equal to or greater than 9000.⁴⁰ When Compustat reports more than one annual data for the same-company in a given fiscal year (e.g., when a company changes its fiscal-year end month) we drop the first chronologically dated observations and keep only the last data for that fiscal year, ensuring only one data point per firm-fiscal year. We drop any firm-year observations having zero or negative employment, total assets, and/or sales.

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

Our set of dependent variables starts with capital formation. We measure firm investment rate (implicitly the change in gross capital stock) as $\frac{CAPX_{i,t}}{K_{i,t-1}}$ where K is net property plant and equipment, and $CAPX$ is capital expenditures. We bound investment rate above at 0.5 and below at -0.10. For all other variables, we winsorize the levels, ratios, and growths every fiscal semester at the 1 and 99 percentiles. Aside from investment, we also explore additional real outcomes which include employment, EMP in Compustat, Intangible Capital, defined as $SG\&A + R\&D$ (sales, general and administration plus research and development), cost of goods sold, $COGS$, and sales ($SALE$). Our set of financial outcomes include corporate payout defined as $Payout = DV + PRSTKC$, where DV is cash dividends and $PRSTKC$ is purchase of common and preferred stock from Compustat. Cash holdings is the level of cash and short-term investments, CHE . Total debt is $Total\ Debt = DLC + DLTT$, where DLC and $DLTT$ are short-term and long-term debt from Compustat, respectively.

Our main set of firm-level controls includes the following variables (in levels). *Stock Return* is a firm’s compounded fiscal-year return, using CRSP daily returns (including dividends

³⁹OLS and 2SLS regressions are run in STATA v.15 using the package REGHDFE.

⁴⁰In 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 SIC 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 SIC code in the time-series. When none of the above are available we employ the firm’s current (header) SIC code for all years.

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

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

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

C.2 Implied volatility

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

OptionMetrics provides daily implied volatility from January 1996 onward for securities with exchange-traded equity options. Each security has a corresponding series of call and put options which differ in their expiration dates and strike prices. For each of these options, OptionMetrics imputes an implied volatility for each trading day using the average of the end-of-day best bid and offer price quotes. To be consistent with the annual Compustat data used throughout, our main tests focus only on 365-day implied volatility. We further restrict our analysis to call options. Note that a call option and a put option on a given underlying

asset with the same strike price and expiration date have the same implied volatilities; the difference in their prices comes from the fact that interest rates and dividends affect the value of call and put options in opposite directions. Therefore, our principal proxy for uncertainty is 365-day implied volatility of at-the-money-forward call options.

C.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 Currencies⁴¹. These include the Euro, Canadian Dollar, Japanese Yen, British Pound, Swiss Franc, Australian Dollar, and Swedish Krona. Each one of these trades widely in currency markets outside their respective home areas, and (along with the U.S. dollar) are referred to by the Board staff as major currencies. The returns to the daily currency spot prices are used in the daily regression described in equation 16 .

In addition to the daily currency returns, 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, downloaded from Thomson Reuters Eikon. We construct the annual industry-by-year volatilities by averaging the daily implied volatility data over the corresponding 252-day backward-looking window for each fiscal-year month-end data of a company.

C.4 10-Year US Treasury Note implied volatility

We use daily implied volatility from the Cboe/CBOT 10-year U.S. Treasury Note Volatility Index (ticker symbol: TYVIXSM), which uses Cboe’s VIX methodology to measure a constant 30-day expected volatility of 10-year Treasury Note futures prices, and is calculated based on transparent pricing from CBOT’s actively traded options on the T-Note futures. The TYVIX are the first exchange-traded contracts based on interest rate volatility that offer a standardized way of gaining exposure to forward implied interest rate volatility. TYVIX data are available from Q1 2003.⁴²

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

C.5 Energy prices and implied volatility

We employ shocks to oil price as a general proxy for energy prices. We collect oil price and implied volatility data also from Thomson Reuters Eikon. In particular, Eikon provides daily price and 30-day implied volatility data for one-month crude oil futures. The data are from the New York Mercantile Exchange Division’s light, sweet crude oil futures contract. This

⁴¹See: http://www.federalreserve.gov/pubs/bulletin/2005/winter05_index.pdf .

⁴²See: <http://www.cboe.com/products/vix-index-volatility/volatility-on-interest-rates/cboe-cbot-10-year-u-s-treasury-note-volatility-index-tyvix> .

contract is the world’s most liquid, largest-volume futures contract on a physical commodity. The contract size is 1,000 U.S. barrels and delivery occurs in Cushing, Oklahoma. Our data on oil futures implied volatility starts in Q3 2005. We extend this sample to match the start of the sample of the 10 treasuries implied volatility (TYVIX) to Q1 2003 by using the daily realized volatility (i.e., standard deviation) of oil price returns estimated over the past 252 day window. Results are robust to dropping oil instrument altogether or using realized volatility.

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.

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

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

Taking into account that daily data on implied volatility of treasuries (TYVIX The Cboe/CBOT) starts in 1Q 2003, our main 2SLS regression sample containing the full set of 10 instruments (oil, 7 exchange rates, 10-year treasuries, and policy) effectively starts for any firm in fiscal year 2005. Our sample ends in December 2016.⁴³

⁴³Oil 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.

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

	Real		Financial			
	I/K	Δ Emp	Δ Cash	Div/K	FUM-I	FUM-E
A: Benchmark						
Δ Volatility	-0.073	-0.026	0.964	-0.029	1.73	1.89
B: H/L = 20						
Δ Volatility	-0.068	-0.024	0.998	-0.033	1.61	1.76
C: Different transition matrix of η_t						
Δ Volatility	-0.066	-0.023	0.967	-0.032	1.56	1.68
D: Pseudo-GE						
Δ Volatility	-0.057	-0.022	0.806	-0.035	1.34	1.63
E: $f = 0.30$						
Δ Volatility	-0.081	-0.028	0.841	-0.024	1.90	2.08
F: $c_k = 0.02$						
Δ Volatility	-0.085	-0.029	0.584	-0.019	2.01	2.11
G: $\alpha = 1$						
Δ Volatility	-0.090	na	-0.022	-0.001	2.13	na
H: Model with debt and equity						
Δ Volatility	-0.059	-0.0218	0.458	-0.030	1.40	1.60

Notes: This table reports the model regression results of real and financial variables on volatility growth. The reported statistics in the model are from simulated data with 3000 firms and 200 quarterly observations. We report the cross-simulation averaged annual moments. I/K is the investment rate, Δ Emp is the employment growth, Δ Cash is the cash growth rate, and Div/K is the ratio of dividend to capital in the model and cash dividend plus repurchase to total assets in the data. FUM-I stands for the finance uncertainty multiplier for investment and FUM-E stands for the finance uncertainty multiplier for employment. The are the slopes of I/K and Δ Emp of the benchmark model (row A) scaled by those from the model with real frictions only (row B) from Table 2. Panel A is the benchmark calibration. Panels B lowers the high financing-cost-state-to-low-cost-state ratio (η_H/η_L) to 20 while keeping the low financial cost state $\eta_L = 0.005$. Panel C sets the transition probabilities of financial shocks of $\pi_{L,H}^\sigma = 0.05$ and $\pi_{H,H}^\sigma = 0.95$. Panel D is the pseudo-GE model with interest rates, prices and wages as functions of uncertainty shock. Panel E is the model with smaller fixed production cost $F = 0.20$. Panel F is the model with bigger investment adjustment cost $c_k = 0.02$. Panel G is the model with the share of capital $\alpha = 1$. Panel H extends the benchmark by including costly equity and 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
Descriptive statistics

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

Notes: This table presents summary statistics of all main variables used in the empirical regression analysis. Sample period is annual from 1963 to 2016. Notation Δx stands for growth rate of variable x , defined as $(x_t - x_{t-1}) / (0.5 * x_t + 0.5 * x_{t-1})$, standard deviation is S. Dev., while. P1, P10, P50, P90 and P99 stand for the 1, 10, 50, 90 and 99 percentiles, respectively. Data sources include CRSP, Compustat, OptionMetrics, Thomson Reuters Eikon, CBOE, St. Louis Fed, and [Baker, Bloom, and Davis \(2016\)](#). See sections 4 and 5 for the details on the construction of variables.

Table A3
2SLS Sensitivity to individual instruments

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

Notes: This table presents 2SLS robustness tests to our instrumentation strategy for main real and financial outcome results (with full set of controls) presented in column (3) of Tables 3, 5, and 6. In column (1) we present the baseline 2SLS multivariate results that instruments firm-realized volatility shocks using all 10 instruments but each one constructed using the *raw non-significance adjusted* industry 3SIC exposures estimated in regression (16). Columns (2 to 11) examine the results when we further drop individual instruments one at a time from the full set of 10 instruments. The statistics under "Investment Rate Stats" correspond to the 1st stage results of the multivariate 2SLS regression of investment rate. The 1st Stage statistics for other real and financial estimations are largely comparable to their benchmark specifications with the full set of instruments. Firm and calendar-year fixed effects are included. Standard errors clustered at the 3 digit SIC industry. To tease out the impact of 2nd moment uncertainty shocks from 1st moment aggregate shocks we also include as controls the lagged directional industry 3SIC exposure to changes in the price of each of the 10 aggregate instruments (i.e., 1st moment return shocks). These are labeled 1st moment 10IV $_{i,t-1}$. Firm-level Tobin's Q and stock return control for 1st moment effects at the firm-level. Data availability on implied volatility of treasuries and oil restrict the start of the 2SLS sample to fiscal year 2005. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1, † p<0.15. Standard errors are in parentheses. See section 4 for data details.

Table A4
Uncertainty effects: 2SLS robustness to different functional forms

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

Notes: This table presents 2SLS multivariate regression results of real and financial outcome variables on different functional forms of lagged firm-level volatility. Columns (1) and (1A) are the baseline 2SLS multivariate regressions, with full set of controls, presented in columns (3) and (6) of main Tables 3, 5, and 6, which measure volatility shocks using the annual growth in CRSP realized and OptionMetrics implied firm-level volatility, respectively. Columns (2) and (2A) use the annual growth in the square of volatility. Columns (3) and (3A) the level of volatility, (4) and (4A) the square of volatility, and (5) and (5A) the log of volatility. All specifications address endogeneity concerns on firm-level volatility by instrumenting with industry-level (3SIC) non-directional exposure to 10 aggregate sources of uncertainty shocks. The statistics under "Investment Rate Stats" correspond to the 2SLS 1st stage of firm-level investment rates on the different proxies for uncertainty. 1st Stage statistics for other real and financial estimations are largely comparable to their benchmark specifications. Firm and calendar-year fixed effects are included. Standard errors clustered at the 3 digit SIC industry. To tease out the impact of 2nd moment uncertainty shocks from 1st moment aggregate shocks we also include as controls the lagged directional industry 3SIC exposure to changes in the price of each of the 10 aggregate instruments (i.e., 1st moment return shocks). These are labeled 10IV $_{i,t-1}$. Firm-level Tobin's Q and stock return control for 1st moment effects at the firm-level. Data availability on implied volatility of treasuries and oil restrict the start of the 2SLS sample to fiscal year 2005 to 2016. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1, † p<0.15. See section 4 for data details.

Table A5
2SLS Robustness tests

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

Notes: This table presents 2SLS robustness results for main real and financial outcome specifications examined in columns (3 and 6) of Tables 3, 5, and 6. All specifications include full set of controls. In columns (1) and (1A) we investigate whether the results are robust to adjusting volatility by firm leverage, i.e., $\sigma_{i,t} \cdot \frac{E_{i,t}}{E_{i,t} + D_{i,t}}$ where E is book equity and D is total debt. Additional controls include: covariance w/ market, which adds firm lagged CAPM beta to control for firm loading on the market price of risk (e.g., control for 1st moment effects), financial constraint indexes, which add a set of 6 lagged firm-level controls for firm financial constraints. These include the lagged White-Wu index, lagged SA index of Hadlock and Pierce (2010), the Kaplan-Zingales index, reciprocal of total assets, reciprocal of age. The S&P credit ratings column further adds a full set of dummies based on every possible credit rating category given by S&P on long-term debt. Omitted dummy is for no credit ratings. To tease out the impact of 2nd moment uncertainty shocks from 1st moment aggregate shocks we also include as controls the lagged industry 3SIC exposure to changes in the price of each of the 10 aggregate instruments (i.e., 1st moment return shocks). These are labeled 10IV $_{i,t-1}$. Firm and calendar-year fixed effects are included. Standard errors clustered at the 3-digit SIC industry. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1, † p<0.15. Sample is from 2005 to December 2016. Standard errors are in parentheses. See section 4 for data details.

Table A6
Investment rate, using same panel across specifications

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

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

Table A7
Financial impact of volatility shocks for *ex-ante* financially constrained and unconstrained firms during heightened credit frictions

Financial Constraint measure	(1)	(2)	(3)	(4)	(5)	(6)
	S&P Credit Ratings (1-6)					
	$\Delta\text{Total Debt}_{i,t}$	$\Delta\text{Payout}_{i,t}$	$\Delta\text{Cash}_{i,t}$			
$\Delta\sigma_{i,t-1}$	-0.114† (0.070)	-0.082 (0.075)	-0.271** (0.123)	-0.242† (0.150)	0.061 (0.077)	0.106 (0.085)
$\Delta\sigma_{i,t-1} \cdot D_{i,t-5}^{Fin.Const}$		-0.075 (0.078)		-0.023 (0.134)		-0.133* (0.072)
$\Delta\sigma_{i,t-1} \cdot \text{Cred_Spread}_t$	-0.215** (0.095)	-0.233** (0.094)	-0.087 (0.194)	-0.042 (0.188)	0.207† (0.134)	0.157† (0.108)
$\Delta\sigma_{i,t-1} \cdot D_{i,t-5}^{Fin.Const} \cdot \text{Cred_Spread}_t$		0.018 (0.063)		-0.128 (0.110)		0.091 (0.087)
Observations	25,878	25,878	25,907	25,907	25,928	25,928
F-test 1st Stage Cragg-D	59.71	28.48	59.70	28.48	59.64	28.47
F-test 1st Stage Kleib.-P.	8.276	8.184	8.150	7.928	8.197	7.898
p-value Sargan-H J	0.756	0.796	0.209	0.282	0.199	0.449
p-value $(\beta_{\Delta\sigma}^{FC} + \beta_{CS \cdot \Delta\sigma}^{FC}) \geq 0$		0.230		0.126		0.693 \leq

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