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THE FINANCE UNCERTAINTY MULTIPLIER

Iván Alfaro
Nicholas Bloom
Xiaoji Lin

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ABSTRACT

We show how real and financial frictions amplify, prolong and propagate the negative impact of uncertainty shocks. We first use a novel instrumentation strategy to address endogeneity in estimating the impact of uncertainty by exploiting differential firm exposure to exchange rate, policy, and energy price volatility in a panel of US firms. Using common proxies for financial constraints we show that ex-ante financially constrained firms cut their investment even more than unconstrained firms following an uncertainty shock. We then build a general equilibrium heterogeneous firms model with real and financial frictions, finding financial frictions: i) amplify uncertainty shocks by doubling their impact on output; ii) increase persistence by extending the duration of the drop by 50%; and iii) propagate uncertainty shocks by spreading their impact onto financial variables. These results highlight why in periods of greater financial frictions uncertainty can be particularly damaging.

Iván Alfaro
Department of Finance
BI Norwegian Business School
Nydalsveien 37
N-0484 Oslo
Norway
ivan.alfaro@bi.no

Nicholas Bloom
Stanford University
Department of Economics
579 Jane Stanford Way
Stanford, CA 94305-6072
and NBER
nbloom@stanford.edu

Xiaoji Lin
University of Minnesota
Carlson School of Management
321 19th Ave S.
Minneapolis, MN 55445
xlin6@umn.edu

1 Introduction

This paper studies the interactions between uncertainty shocks and financial frictions both empirically and theoretically. Uncertainty shocks have been argued to play a significant role in explaining the sharp drops in output during the recent financial and COVID-19 crises. However, on the empirical front, identification of the causal effects of 2nd moment uncertainty shocks is challenging because of correlated 1st moment effects during economic downturns. Moreover, on the theoretical front, a significant challenge to a class of models on uncertainty is the difficulty in generating large and persistent responses resembling the slow recovery after the Great Recession. We show that adding financial frictions goes a long way in amplifying the impact of uncertainty shocks, in particular producing a larger recession and a slower recovery. Furthermore, adding financial frictions is also crucial in generating a propagation of the detrimental effects of uncertainty from real-only variables onto financial outcomes.

We start off by examining the causal response to uncertainty of real and financial outcomes of US publicly-listed firms, including tangible and intangible investment, employment, sales, cash, and equity payouts. In particular, taking endogeneity concerns seriously when estimating the effects of uncertainty,[1] we propose a novel instrumentation strategy for uncertainty that exploits differential industry-level exposure to exchange rate, factor price, and policy uncertainty. The strategy permits controlling for, say, exposure to oil prices suddenly crashing while separately identifying exogenous variation in firm volatility from increases in exposure to oil price volatility. This key separation between first and second moment effects is crucial given that when commodity prices see *upward or downward* movements, uncertainty in commodity prices observe *upward* simultaneous shifts. Hence, our strategy allows us to tease out second moment uncertainty effects while controlling explicitly for correlated first moment effects.

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

Our identification strategy works well in delivering strong first-stage F-statistics and satisfying the exclusion restriction in Hansen-Sargan over-identification tests. The instrumentation strategy suggests uncertainty *causally* reduces investment (in tangible and intangible capital), hiring and sales growth, while also leading firms to more cautiously manage their financial policies by increasing cash holdings and cutting debt and dividends. Moreover, if endogeneity is left untreated our results indicate that the effects of uncertainty can be largely underestimated by OLS regressions, by a factor of 1.7 to 2.4 depending on model specification and controls. Importantly, classifying firms into broad groups of *ex-ante* financially constrained and unconstrained firms, we find that investment of constrained firms responds more intensively to uncertainty shocks than unconstrained firms. In the aggregate, we find that the average impact of uncertainty shocks is increased up to three fold during periods of increased financial frictions (e.g. 2008-09) compared to periods of normal financial conditions. As firm-specific financial constraints bind and market-wide financial conditions worsen (e.g., spikes in the Aaa-Baa corporate credit spread), the detrimental effects of uncertainty are larger. This explains how in recessions - when financial conditions typically deteriorate - uncertainty shocks can be so damaging for growth.

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

First, an *amplification* effect. Adding financial frictions to the classical model of

[2]Models with a central role for adjustment costs include Bertola and Caballero (1990), Davis and Haltiwanger (1992), Dixit and Pindyck (1994), Caballero, Engel, and Haltiwanger (1995), Abel and Eberly (1996) and Cooper and Haltiwanger (2006).

[3]Models with costs of raising external finance include Hennessy and Whited (2007) and Bolton, Chen, and Wang (2011).

[4]Models with firms holding cash include Froot, Scharfstein, and Stein (1993), Bolton, Chen, and Wang (2013) and Eisfeldt and Muir (2016).

stochastic-volatility shocks - as in Dixit and Pindyck (1994), Abel and Eberly (1996) or Bloom (2009) - roughly doubles the negative impact of uncertainty shocks on investment. In our simulation, an uncertainty shock with real *and* financial frictions leads to a peak drop in output of 3.9%, but with *only* real frictions a drop of 1.8%. This happens despite these financial frictions - which we estimate empirically - being small in magnitude. Hence, modest financial adjustment costs generate large amplification effects. The intuition is that introducing financial frictions prevents firms costlessly buffering uncertainty shocks via financial channels.

Impact of uncertainty shocks on output in simulation

	Drop in output
Real frictions	−1.8%
Real+financial frictions	−3.9%

Notes: Results from the average of 500 simulations of the calibrated model (see section 5.3).

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

Our third key result is a *propagation* effect. Financial frictions spread the impact of uncertainty shocks onto financial variables, an important result that the classical model with only real frictions fails to generate. In particular, we show that alongside the negative impact of uncertainty shocks on investment, the model also predicts this shock 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.

The additional complexity required to model: (a) real and financial frictions, (b) uncertainty and financial shocks, and c) general equilibrium with heterogeneous firms, required us to make some simplifying assumptions. In particular, we ignore labor - including labor and labor adjustment costs would likely increase the impact of uncertainty shocks, since a drop in labor would lead to a larger drop in output in our model.

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.[5] This emphasizes the "real option" 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 strategy of exposure to energy, currency, and policy uncertainty to identify causal effects. We show how the effects of uncertainty can largely be underestimated

[5] Classic papers on uncertainty and growth include Romer (1990), Ramey and Ramey (1995), Leahy and Whited (1996), Guiso and Parigi (1999), Bloom (2009), Bachmann and Bayer (2013), Fernandez-Villaverde et al. (2011), and Fernandez-Villaverde et al. (2015). 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 aggregate consumption and financial implications of uncertainty, Eberly (1994) examines household durable purchases, while more recently Alfaro and Park (2019) are the first to look at the effects of employer-level uncertainty on employee spending and precautionary savings behavior, including daily purchases of nondurable and durable goods and services. 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. 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)). Additionally, He and Krishnamurthy (2013), Brunnermeier and Sannikov (2014), and Tella (2017) explore the relations between uncertainty and the aggregate outcomes through the financial intermediary channel.

if endogeneity is left untreated. We provide the literature with a set of instruments that can be useful for a wide-range of models on the causal impact of uncertainty on firm behavior.

Second, the finance literature on firms' financial management of liquidity. The notion of liquidity management goes back at least to Keynes' General Theory which argues that precautionary cash saving and financing constraints are closely linked if financial markets are imperfect.[6] 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 amplify the impact of uncertainty shocks on firms real (investment and hiring) and financial (cash and external financing) behavior.[7]

Finally, our paper is also closely related to the recent literature on financial frictions and business cycles.[8] We build on this literature to argue it is not a choice *between* uncertainty shocks and financial shocks as to which drives recessions, but instead these shocks *amplify* each other. So they should not be considered individually, rather jointly. Related work that links uncertainty and financial frictions includes: Gilchrist, Sim, and Zakrajsek (2014) who study the relationships between uncertainty, investment and credit spreads, and show that financial frictions magnify the effects of uncertainty through changes in credit spreads; Christiano, Motto, and Rostagno (2014) who imbed agency problems

[6]The recent development in the finance literature on liquidity managemnet and financial constraints include the theoretical work by 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), etc.

[7]There is a large literature, for example, Gomes (2001), Rampini and Viswanathan (2013), etc., which study the impact of various frictions on firms' financing policies.

[8]For example, 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.

associated with financial intermediation as in Bernanke, Gertler, and Gilchrist (1999) into a monetary dynamic general equilibrium model finding volatility shocks are important in driving the business cycle; Arellano, Bai, and Kehoe (2019) who build a DSGE model with frictions in labor and financial markets showing that uncertainty shocks lead to higher default risk and credit spreads, which cause firms to further cut employees; and Ottonello and Winberry (2016) who investigate the relationship between financial frictions and firm heterogeneity and the impact of monetary policy on firms' investment. Although we share with Gilchrist, Sim, and Zakrajsek (2014), Christiano, Motto, and Rostagno (2014) and Arellano, Bai, and Kehoe (2019) the idea that financial frictions amplify the impact of uncertainty shocks, our work differs in three important ways. First, we develop a micro data identification strategy to estimate the *causal* impact of uncertainty and financial shocks on firms. The set of variables examined in our paper that causally respond to uncertainty shocks covers both real and financial variables. Addressing endogeneity is important given potential bias and inconsistency in estimating the effects of uncertainty when using metrics based on financial measures like stock-returns.[9] Second, we use common proxies for financial constraints proposed in the finance literature to provide empirical evidence for the amplification prediction of the model, finding that *ex-ante* financially constrained firms cut investment substantially more than unconstrained firms in response to uncertainty shocks. Third, we include cash in our model, allowing firms an additional cash balance dimension to respond to uncertainty. Modeling cash is important given that cash holdings have increased in the US and Europe, with rising uncertainty one suggested reason.[10]

The rest of the paper is laid out as follows. Section 2 describes the instrumentation strategy and data. Section 3 presents the empirical findings on the effects of uncertainty shocks on both real and financial activity of firms. In section 4 we write down the model.

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

[10] See, e.g., Pinkowitz, Stulz, and Williamson (2016) and Chen, Karabarbounis, and Neiman (2017).

Section 5 presents the main quantitative results of the model. Section 6 concludes.

2 Data, instruments, and addressing endogeneity

This section discusses the instrumentation strategy, construction of instruments, and data sources used in the empirical analysis.[11]

2.1 Data

Stock returns are from CRSP and annual accounting variables from Compustat. The sample period is from January 1965 to December 2019 for OLS regressions and from December 1993 to December 2019 for the main 2SLS sample that uses the instrumentation strategy detailed below. Financial, utilities and public sector firms are excluded from the main sample (i.e., SIC between 6000 and 6999, 4950 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.[12] Moreover, our main tests include both firm and time (calendar year) fixed effects.

In measuring firm-level uncertainty we employ both *realized* annual volatility from CRSP stock returns and *option-implied* volatility from OptionMetrics. Annual realized volatility is the 12-month standard deviation of firms' cum-dividend daily stock returns from CRSP, and annualized by multiplying by $\sqrt{252}$ (a year typically spans 252 trading days).[13] Annual implied volatility is the 12-month average of firms' daily option-implied volatility from

[11] Replication code and data for regressions available on https://nbloom.people.stanford.edu/research.

[12] We lag the firm uncertainty measure by one year to make sure the daily stock return data over the year used to proxy uncertainty precedes the investment decision. If both were dated in the current year then on average half of the stock-return data (the data from the second half of the year) would follow after half of the investment data (the spending in the first half of the year), creating obvious yet unnecessary reverse causality issues. Moreover, firms report updating their capital investment decisions bi-annually on average Altig et al. (2021) and capital decisions often have long lags from decision to implementation, so that a one year lag also appears economically appropriate.

[13] For accuracy in measuring volatility, we drop firm-year observations with less than 200 daily CRSP returns (variable RET) in a given 12-month window. As is standard, 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).

OptionMetrics, where the daily observations are the simple average of forward 365-day-horizon at-the-money (ATM) call and put options.[14] Data from OptionMetrics is available starting January 1996.

Changes in variables x_t are measured in annual growth rates $\Delta x_t = \frac{x_t - x_{t-1}}{\frac{1}{2}(x_{t-1}+x_t)}$, which for positive values of x_t and x_{t-1} yields growth rates bounded between -2 and 2 (i.e., $\leq |200\%|$). 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 at year t follows Belo, Lin, and Bazdresch (2014) and is defined as $\frac{I_t}{\frac{1}{2}(K_{t-1}+K_t)}$, where $I_{i,t}$ is the flow of capital expenditures ($CAPX$ from Compustat) over the course of fiscal year t and $\frac{1}{2}(K_{t-1}+K_t)$ is the average of current and lagged year net property plant and equipment ($PPENT$). For ease in notation below we refer to investment rate as I/K_t. Details for variable construction, filters, and data sources are in the Online Appendix A. To reduce influence of outliers investment rate is bounded [-0.5,0.5], while other variables are winsorized at the 0.5 and 99.5 percentiles. Online Appendix section A.6 presents a battery of robustness tests on data and variable construction choices (e.g., variable definitions, filters, instrumental variables used, subsample analyses, winsorization, etc.,)

Table 1 reports summary statistics for the main sample of firm-year observations in 2SLS regressions.[15]

2.2 Identification strategy

Our identification strategy exploits firms' differential exposure to aggregate volatility shocks in energy, currency, and policy to identify exogenous variation in firm-level volatility that is orthogonal to the endogenous components driving firm-level volatility shocks. For example, to identify exogenous variation using oil price movements, the idea is that some firms are positively sensitive to oil price movements (e.g. mining and oil exploration firms),

[14] As with the construction of the aggregate VIX, using a 2-sided mix of call and put options is preferable (e.g., unlike a call or a put it is not a 1-sided uncertainty measure, while it also reduces the influence of smirks or other assymetries in implied volatiltiy). Moreover, the use of ATM options has the benefit of having the highest Black-Scholes Vega (the sensitivity of options prices to implied volatility).

[15] Additional variables and summary statistics are presented in Appendix Table A.1.

some are negatively sensitive (e.g. airlines and energy-intensive manufacturing firms), while others are neutral (e.g. business service firms). As such, firms have a different *directional exposure* to the *first moment* (oil price levels) – which in the example is positive, negative and zero respectively – while at the same time *non-directionally exposed* to the *second moment* (oil price uncertainty), which is positive, positive and zero respectively. Therefore, the strategy permits controlling for oil price level exposure while separately identifying exogenous variation in firm volatility from oil price uncertainty exposure. This key separation between first and second moment effects is crucial given that when commodity prices see *upward or downward* movements, uncertainty in commodity prices observe *upward* simultaneous shifts. Our strategy allows us to tease out second moment uncertainty effects while controlling explicitly for correlated first moment effects, e.g., control for economic downturns while isolating effects of heightened uncertainty. We extend the oil example to 9 sources of uncertainty - oil, 7 widely traded currencies, and policy - to generate 9 instruments to identify exogenous variation in firm uncertainty shocks. In exchange rates, our setup allows us to control for, say, effects associated with the US Dollar suddenly depreciating vis-a-vis the Euro while identification comes from uncertainty suddenly increasing in the bilateral exchange rate.[16]

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

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

[16]Related to our approach, Baker, Bloom, and Davis (2016) and Gulen and Ion (2016) construct firm-level uncertainty measures as the product of time-varying common uncertainty and firm-specific loadings. Our strategy uses the resulting uncertainty measures as instruments instead of regressors to identify exogenous variation in firm realized and forward-looking option-implied volatility shocks. Moreover, our identification comes from several different sources of aggregate uncertainty in policy and energy and exchange rate markets. We show that firms have highly significant differential exposure to those distinct sources of uncertainty, and interact with financial frictions in driving financial and real firm activity.

where $r_{i,t}^{risk\_adj}$ is the daily risk-adjusted return on firm i, r_t^c is the change in the price of commodity c, and α_j is industry j's intercept. The sensitivities are estimated at the industry level using daily returns of firms that share the same 2-digit Standard Industrial Classification (SIC) code. Estimating the main coefficients of interest, β_j^c, at the industry level (instead of at the firm-level) reduces the role of idiosyncratic noise in firm-level returns, increasing the precision of the estimates, and captures the idea that firms in the same industry have systematically similar exposure to the aggregate variables. Moreover, we allow the industry-level sensitivities to be time-varying by estimating them in 5-year rolling windows of daily data, $\beta_{j,\tau}^c$ where τ is the timing of the 5-year rolling window.

The risk-adjusted returns $r_{i,t}^{risk\_adj}$ in (1) are the residuals from running firm-level time-series regressions of daily CRSP stock returns on the classical Carhart (1997) four-factor asset pricing model (details in Appendix section A.3). Adjusting firm-level returns for aggregate risk addresses concerns over whether the sensitivities to energy, currencies, and policy are capturing exposures to common risk factors, although in practice this makes almost no difference.

The daily independent variables in (1) are the growth in crude-oil prices (which proxies for energy shocks), growth in the exchange rates of 7 widely traded currencies defined as "major" currencies by the Federal Board,[17] and the growth in economic policy uncertainty from Baker, Bloom, and Davis (2016).

Construction of instruments For the 9 aggregate price shocks (oil, 7 currencies, and policy) we multiply the absolute value of the time-varying sensitivities $\mid \beta_{j,\tau}^c \mid$ by shocks to the realized volatilities of the aggregate variables $\Delta\sigma_t^c$. This provides 9 instruments for lagged firm-level uncertainty shocks, $\Delta\sigma_{i,t-1}$, as follows:

$$z_{i,t-1}^c = \mid \beta_{j,\tau}^c \mid \cdot \Delta\sigma_{t-1}^c \tag{2}$$

[17]See http://www.federalreserve.gov/pubs/bulletin/2005/winter05_index.pdf . These include: the Euro, Canadian Dollar, Japanese Yen, British Pound, Swiss Franc, Australian Dollar, and Swedish Krona. Each 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.

For the volatilities, σ^c_{t-1}, of oil and the 7 currencies we use the 252-day standard deviation of daily returns on crude oil prices (West Texas Intermediate (WTI) oil price data from Thomson Reuters Eikon) and 252-day standard deviation of daily changes in bilateral exchange rates against the US Dollar (foreign currency units per 1USD data from the Federal Reserve Board (FRB) and downloaded from CRSP). For economic policy uncertainty we use the 252-day average of trading-day US economic policy uncertainty (EPU) from Baker, Bloom, and Davis (2016).[18]

We refine the timing of the instruments in (2) such that the sensitivities are predetermined in all key regression specifications (detailed below). Specifically, the sensitivities are lagged by three years, $\beta^c_{j,t-3}$, such that they pre-date both the outcome and control variables. The timing avoids using data for the sensitivities that overlaps in time with information entering the annual investment rate of firms $I/K_{i,t}$ at time t and controls $X_{i,t-1}$ at time $t-1$.

Hence, the final 9 uncertainty instruments for firm-level lagged uncertainty shocks, $\Delta\sigma_{i,t-1}$, are $z^c_{i,t-1} = \mid \beta^c_{j,t-3} \mid \cdot \Delta\sigma^c_{t-1}$. In words, this is the 3-year lagged cross-industry *non-directional* exposure times the lagged change in volatility for oil prices, 7 leading currencies, and policy uncertainty.[19] We show in Appendix section A.6 that the results are robust to doing a further refinement on the instruments where the exposures are adjusted for their statistical significance, a step that helps address potential concerns of noisy estimates and multicollinearity in (1).[20]

The baseline multivariate specifications include four important and extensive sets of

[18]Trading days for EPU are defined as calendar days in which FRB exchange rate daily data are available from WRDS records. We use realized volatility of the instruments instead of implied volatility due to their longer daily price sample that extends into the 1980s, whereas implied volatility data for some instruments only start after year 2000. However, the Online Appendix presents robustness tests using implied volatilities of the instruments instead of realized volatilities.

[19]For accuracy in matching the timing of firm accouting reports and volatility with the instruments, the rolling window sensitivities and the aggregate volatility shocks entering the instruments are timed to exactly match firm accounting report dates (i.e., year-month of *datadate* variable in Compustat). See section A.2 in Appendix for details on timing and measurment.

[20]In particular, each sensitivity, β^c_j, is adjusted by its statistical significance within each industry, $\beta^{c,weighted}_j = \omega^c_j \cdot \beta^c_j$. The sensitivity weight $\omega^c_j = \mid t^c_j \mid / \sum^c \mid t^c_k \mid$ is the ratio of the absolute value of the t-statistic of each instrument's sensitivity to the sum of all t-statistics in absolute value of instruments within the industry, with insignificant sensitivities at the 10% set to zero.

controls. First, controls for the first moment effects of each of the 9 instruments. These are the annual exposure of firms to aggregate price movements (i.e., returns rather than volatility) of each instrument. These are constructed as $\beta^c_{j,t-3} \cdot r^c_{t-1}$, which are both *directional* ($\beta^c_{j,t-3}$ can be positive or negative) and use the aggregate first-moment r^c_{t-1} price returns (rather than second moment movements $\Delta\sigma^c_{t-1}$).[21] These aggregate first moment controls help disentangle the second moment effects from correlated first moment effects. Second, we control for firm-level measures of first moment effects, i.e., Tobin's $Q_{i,t-1}$ and the stock return of the firm $r_{i,t-1}$ (measured as firms' 12-month compounded return from CRSP). These first moment firm-level controls further help tease out second moment effects of shocks to firm level volatility, $\Delta\sigma_{i,t-1}$. Third, we include a set of standard financial controls following Leary and Roberts (2014), which include $\text{Tangibility}_{i,t-1}$, Book $\text{Leverage}_{i,t-1}$, Return on $\text{Assets}_{i,t-1}$, and Firm $\text{Size}_{i,t-1}$. Fourth, to account for potential autocorrelation in the 8 outcome variables explored in the paper, we further include the 1-year lags for each outcome variable, Investment $\text{Rate}_{i,t-1}$, $\Delta\text{Employment}_{i,t-1}$, ΔIntangible $\text{Investment}_{i,t-1}$, $\Delta\text{COGS}_{i,t-1}$, $\Delta\text{Sales}_{i,t-1}$, ΔCorporate $\text{Payout}_{i,t-1}$, $\Delta\text{Debt}_{i,t-1}$, and ΔCash $\text{holdings}_{i,t-1}$. Therefore, in addition to the full set of firm and time fixed effects, the baseline specification includes a total of 23 controls $X_{i,t-1}$ (9 aggregate first-moment, 2 firm-level first-moment, 4 standard controls in finance, and 8 controls for potential autocorrelation). As shown below, results without controls are, in general, substantially stronger in magnitude and significance. In all, the empirical identification strategy along with the large set of controls allow the next section to examine the plausibly causal effects of uncertainty – as instrumented by 2SLS firm-level uncertainty shocks $\widehat{\Delta\sigma_{i,t-1}}^{2SLS}$ – on real and financial activity of firms.

[21] For oil and currencies, annual returns r^c_t are the annual growth rates in the 252-day average of daily oil spot prices and exchange rates. For economic policy uncertainty we measure r^c_t as the growth from one year to the next in the 4-quarter average of government expenditures as a share of GDP (see variable A822RE1Q156NBEA from St. Louis Fed, shares of gross domestic product: government consumption expenditures and gross investment). This share is counter cyclical and controls for 1st moment economic effects (e.g., downturns when policy uncertainty is high).

3 Empirical findings

We start by examining the plausibly causal effects of uncertainty shocks on firm-level capital investment rates, followed by other real outcomes – intangible capital investment, employment, cost of goods sold, and sales – and by financial variables – debt, payout, and cash holdings.

3.1 Investment results

Table 2 examines the effect of uncertainty shocks on capital investment rates. Column 1 presents the univariate OLS regression results of investment rate on the *realized* annual growth in stock return volatility. The specification includes firm and time fixed effects and standard errors are clustered at the 2-digit SIC industry, the same level at which factor exposures are estimated. The sample includes Compustat firms with CRSP data from 1965 to 2019. The point estimate in column 1 of -0.023 is highly significant (t-stat of 12.10), and indicates that the annual investment of firms as a fraction of the capital stock declines by 2.3 percentage points following a doubling in firm-level volatility (equivalent to a 3.25 standard deviation volatility shock). Relative to the unconditional mean annual investment rate of 22.9% (see descriptive statistics in Table 1), this is a decline of 10.04% per year. In standard deviation units, firm investment drops by 0.29 standard deviations in response to a doubling in firm volatility. Column 2 runs an analogue OLS regression but restricted to the 2SLS sample that is used in the baseline instrumentation strategy used throughout the rest of the paper, from 1993 to 2019. We see an almost identical point estimate (coefficient -0.024) with similar significance in the 27 year span covered by the 2SLS sample. These results indicate that uncertainty shocks correlate negatively with real firm investment decisions. However, as explained in section A.5, inferences from OLS results are likely to suffer from endogeneity bias. Therefore, columns 3 and 4 instrument firm realized volatility shocks using the instrumentation strategy discussed in section 2.2, with sample years 1993 to 2019. Column 3 is the 2SLS analogue of column 2 that includes the full set of 1st moment aggregate controls to identify and disentangle the 2nd moment uncertainty shock effects of interest. Column 4 further adds the full set of firm-level controls discussed above. We find that uncertainty shocks lead to significant drops (at the 1%) in firm-level investment rates that are larger than that of OLS regressions, with a drop of 5.7 and 4.1 points in the rate of investment in columns 3 and 4, respectively. As shown, if endogeneity is left untreated we find that uncertainty effects can be largely underestimated in OLS regressions, by a factor of 1.7 to 2.4 depending on model specification and controls included. Column 5 runs an analogue to column 4 but instrumenting firm-level *implied* volatility shocks,[22] with sample period 1998 to 2019. We find similar yet larger negative effects of uncertainty when proxied by forward-looking implied volatility shocks, indicating a drop of 5.8 points in investment following a doubling in firm-level volatility.[23]

Importantly, the instrumentation strategy across all 2SLS specifications in Table 2 seems to work well, as seen by the large first-stage $F-$tests with values ranging from 69.91 to 87.22, and a Hansen-Sargan over-identification $J-$test that does not reject the validity of the instruments with p values ranging from 0.462 to 0.665. The full 2SLS first stage results are discussed and presented in Appendix section A.4).

In summary, Table 2 provides *causal* support that increases in uncertainty lead to reductions in capital investment rates of US publicly listed firms, which can be largely underestimated if endogeneity is left untreated. In terms of magnitudes columns 4 and 5 imply that a *two-standard* deviation increase in realized and implied volatility shocks reduces the rate of investment by 2.5 to 3.6 percentage points, respectively. These may be modest compared to the unconditional mean of firm-level investment of 22.9% (see Table 1), but large in comparison to the 3.3 percentage point total drop in aggregate investment

[22]For presentational purposes and to ease comparison across realized and implied volatility effects, the growth in implied volatility in column 5 is standardized to have the same standard deviation as growth in realized volatility in column 4.

[23]The raw coefficient on the growth in implied volatility in column 5 (i.e., run on the raw sample of growth in implied volatility that has not first being re-scaled to have the same standard deviation of growth in realized volatility in column 4) is -0.093 with same significance at the 5% .

during recessions.[24] Although implied volatility has the nice feature of being forward-looking in nature, our preferred specification is in column 4 with realized volatility due to the substantially larger firm-year sample size (56,172 vs 26,977 observations in columns 4 and 5, respectively).

3.2 Other real and financial outcomes

Table 3 examines the effects of uncertainty shocks on the growth of other *real* and *financial* outcomes. Panel A examines the responses in the growth rates of intangible investment, $R\&D$ $+(0.3 \cdot XSGA)$,[25] Employment EMP, cost of goods sold $COGS$, sales $SALE$, corporate payout measured as the sum in common and preferred dividends plus share repurchase $(DVC + DVP + PRSTKC)$, total firm debt measured as the sum of of short- and long-term debt, $DLC + DLTT$, and corporate cash holdings measured as cash and short-term investments, CHE.

Column 1 repeats the investment rate results from the preferred 2SLS specification discussed above and presented in column 4 of Table 2. Using the same preferred 2SLS specification, columns 2 through 5 present the responses of the other real variables while 6 to 8 the responses of the financial variables. All specifications include the full set of aggregate and firm-level controls and firm and time fixed effects. The data requirements on non-missing outcomes and controls guarantee that all columns in Table 3 have the same firm-year sample, and thus the same 1st stage regression that shows a large 1st-stage $F-$ statistic of 79.68.

As shown, the real activity of firms is causally negatively impacted by uncertainty shocks, with intangibles, employment, COGS and sales all dropping. The drop in intangibles (coefficient -0.052) implies that, on average, firms not only cut investment in physical assets but also reduce their investment in intangible assets (e.g., R&D, intellectual property, brand

[24] The average total drop in NIPA gross private domestic investment/GDP ratios in all 11 recessions during period 1947Q1-2019Q4, measured as the difference in the minimum ratio during NBER-defined recessions and the maximum ratio in the four quarters prior to the onset of a recession.

[25] Measured following Peters and Taylor (2017) as $R\&D$ $+(0.3 \cdot XSGA)$, where $R\&D$ is research and development in Compustat and 30% of $XSGA$ –which is sales, general and administration expenses– is intangible investment (see section A for details)

equity, etc.,). Employment and firm output (as proxied by sales) are also negatively affected by uncertainty.

As for financial variables, firms take more cautious financial decisions by cutting equity payouts and debt while increasing cash holdings in response to uncertainty shocks. The latter response is consistent with a precautionary savings channel, where firms build up cash that they do not use the next period (e.g., hiring and investment in physical and/or intangibles is not realized). Moreover, the payout results are consistent with firms building up additional precautionary savings by cutting their outflows of cash spent on paying dividends and buying back previously-issued equity stock, while the debt result indicates that firms borrow less as part of this more cautious financial stance. The model in section 4 reconciles and provides intuition into these dynamics in firm real and financial activity, and highlights that the detrimental and causal effects of uncertainty extend beyond real outcomes and *propagate* onto financial variables in the presence of financial frictions.

Panel B in Table 3 compares the magnitudes of the economic effects of uncertainty shocks on all the different outcomes, showing sizeable magnitudes of responses, with for example a 2 standard deviation volatility shock leading to changes in real and financial activity typically between 0.1 to 0.3 standard-deviations.

Overall, Table 3 provides support that uncertainty matters in a *causal* way for real and financial activity of firms, and that the effects go beyond the response of physical investment. We conduct numerous robustness checks to our instrumentation strategy and variable construction, which are presented in section A.6 in the Online Appendix. The next section builds on the casual and negative response to uncertainty of firm investment and documents how the response is amplified by the presence of financial frictions.

3.3 Financing frictions and uncertainty shocks

We examine whether financial frictions amplify the negative real effects of uncertainty shocks by running a series of interactions of *uncertainty shocks* with *financial frictions*. We analyze the amplification effect in two dimensions - across time (periods of lower and higher aggregate financial frictions) and across firms (firms with lower and higher financial constraints).

First, we ask whether there is evidence that the investment rate of firms responds more intensively to uncertainty shocks during periods of heightened aggregate financial frictions. As our primary measure of financial frictions we use Moody's aggregate Baa-Aaa corporate credit spread, which tends to increase when credit conditions worsen in the economy. The aggregate spread is standardized over time to ease interpretation and comparison of coefficients across regression specifications, see Appendix A for data details. We expect that firms cut investment, $I/K_{i,t}$, after increased uncertainty shocks, $\Delta\sigma_{i,t-1}$, and this cut is amplified further during periods of high aggregate financial frictions, Fin_Index_t.

Table 4 presents the interaction results using our baseline 2SLS regression with full set of controls, firm and time fixed effects. For comparison, column 1 repeats the non-interacted baseline regression discussed above and presented in column 1 in Table 3. Column 2 presents the interaction of firm uncertainty and aggregate financial frictions.[26] The interaction reveals firms significantly cut their investment rate in response to uncertainty shocks (coefficient of -0.022), particularly during periods of high aggregate financial frictions (coefficient of -0.023). These two coefficients imply that when the Moody's credit spread increases by 1 standard deviation in years of high financial frictions, the rate of corporate investment drops by -0.045 percentage points, which represents a doubling of impact compared to years of normal aggregate financial frictions (i.e., a multiplier of $-0.045/-0.022 = 2.05$).

Second, we investigate if the response to uncertainty shocks is amplified in the cross-section for firms facing larger financial constraints. To test this we generate a measure of firm-level financial constraints, $D_{i,t-5}^{fin.constrained} = \{0,1\}$, which is a dummy that takes the value one for firms classified as ex-ante financially constrained using information in fiscal year $t-5$,

[26] The yearly Fin_Index_t is collinear with the year fixed effects, so neither included nor reported. The specification has 2 endogenous terms a) volatility shock and b) its interaction with Fin_Index_t, which are both instrumented with 2 analogue sets of instruments, a) the IVs and b) their interaction with Fin_Index_t. Controls, including 1st moment, are similarly interacted.

and zero otherwise. We use a lag of 5 years to capture ex-ante financial situations of firms and address potential endogeneity concerns that might exist in contemporaneous measures of financial constraints. This financial constraint measure $D_{i,t-5}^{Fin.Constrained}$ is the mode (e.g., consensus) of the three leading firm-level proxies for financial constraints: the S&P credit ratings where a firm at year t is ex-ante constrained if it lacks a credit rating in year $t-5$,[27] the Whited and Wu (2006) index where constrained firms are those equal to or above the median value, and the size and age measure of Hadlock and Pierce (2010) where constrained firms are those equal to or above the median value.[28] In column (3) we see that, indeed, financially constrained show a significantly larger response to uncertainty (coefficient of -0.020), which is about 60% higher than non-constrained firms, $(-0.020 - 0.034)/-0.034 = 1.59$.[29]

Next in column (4) we look at an even tougher test, which is whether uncertainty has a more negative impact on investment during periods of greater financial frictions for more financially constrained firms. This involves testing a triple interaction of uncertainty, $\Delta\sigma_{i,t-1}$, financial frictions, Fin_Index_t, and firm financial constraints, $D_{i,t-5}^{Fin.Constrained}$ (noting we also include all lower-level pairwise interactions and the financial constraint indicator but only report those coefficients involving uncertainty in the table for brevity).[30] As shown, the triple interaction is negative and significant (coefficient of -0.014), and implies an estimated impact of uncertainty on constrained firms in years of high aggregate financial frictions of

[27] See, for example Duchin, Ozbas, and Sensoy (2010) and Panousi and Papanikolaou (2012) for credit ratings and financial frictions. Ratings are from Compustat-Capital IQ rating data downloaded from Wharton Research Data Services (WRDS), using variable SPLTICRM (S&P Domestic Long-Term Issuer Credit Ratings).

[28] The use of cutoffs to classify firms into broad groups instead of using the continuous firm-level financial constraint measures is also standard (e.g., Duchin, Ozbas, and Sensoy (2010) and Panousi and Papanikolaou (2012)) because firm-level measures are imperfect proxies for financial constraints, yet they can largely succeed at broadly capturing differences across constrained and unconstrained groups. We follow Duchin, Ozbas, and Sensoy (2010) in using the median firm each year as cutoff to classify firms.

[29] The indicator $D_{i,t-5}^{Fin.Constrained}$ is included but not reported for brevity. Moreover, the 2 endogenous terms involving firm volatility shocks are instrumented with 2 analogue sets of instruments, a) the IVs and b) their interaction with the indicator $D_{i,t-5}^{Fin.Constrained}$. Controls are similarly interacted.

[30] The specification includes 4 endogenous terms involving firm uncertainty shocks, which are instrumented with 4 sets of IVs with similar functional forms, a) IVs, b) the IVs interacted with Fin_Index_t, c) IVs interacted with firm indicator $D_{i,t-5}^{Fin.Constrained}$, d) the IVs in a triple interaction. Indicator $D_{i,t-5}^{Fin.Constrained}$ and its interaction with Fin_Index_t are also included but not reported for brevity. The specification in column 4 therefore fully nests the models in columns 3, 2, and 1.

-0.054 ($= -0.023-0.019+0.002-0.014$), which is 2.35 times the baseline impact of -0.023. This result highlights how financial frictions at the aggregate- and firm-level can substantially amplify the detrimental impact of uncertainty shocks.

Figure 2 shows the average impact over time of uncertainty on firm investment implied by the results in column 4 of Table 4. The figure uses the observed time variation in both the Moody's credit spread and the financial constraint classification of firms to generate the marginal impact of uncertainty on investment (weighted by firm capital stock sizes). We see that on average the mean impact of firm uncertainty on investment as a fraction of the capital stock is around -1.5 percentage points. Strikingly, however, during the 2008-2009 crisis, because of both the worsening in the market-wide credit conditions and binding of the firm-specific financial constraints, the mean impact of uncertainty is roughly tripled to -5.0. Thus, in the aggregate during the financial crisis firms observed a tripling of the average negative impact of uncertainty. This result highlights the importance of analyzing the joint interacted effects of uncertainty and financial conditions rather than each component in isolation or in competition with each other in driving economic activity.

One concern when testing the interacted effects is whether Moody's credit spread is a good measure of aggregate financial frictions, thus columns 5 and 6 present the amplification effects on investment using other leading proxies for aggregate financial conditions. These proxies are the US financial distress measure by Romer and Romer (2017) in column 5 – a series that assesses "the health of the US financial system"– and the Chicago Fed Adjusted National Financial Conditions Index (ANFCI) in 6 – a series that "has been historically associated with tighter-than-average financial conditions" and is an index "that isolates a component of financial conditions that is uncorrelated with economic conditions, the state of the business cycle, and level of inflation". As with the Moody's spread the 2 series are standardized to ease interpretation of coefficients and make the points estimates comparable across columns. We find similar results using the alternative measures of aggregate financial conditions. Importantly, the formal test on the triple interaction term is highly significant, and indicates that in years when aggregate financial and credit conditions worsen firms with binding financial constraints drop their investment by 1.4 to 1.6 percentage points more than otherwise similar albeit less constrained firms.

In all, columns 4,5,6 indicate that the causal effects of uncertainty on investment differs between constrained and unconstrained firms *particularly* in years of heightened financial frictions. Another way of confirming the idea that financial frictions amplify the negative effects of uncertainty is by shifting the timing of the tightening of the aggregate credit conditions. We do so in columns 7 and 8 by running a placebo, where instead of measuring the Moody's credit spread at year t we shift the Moody's credit spread by $t-3$ years. This is a placebo falsification test for the role of heightened credit conditions amplifying the effect of uncertainty. The idea is that if we shift the spike in the market-wide credit frictions of, say, the 2008-2009 financial crisis to instead be measured in 2005-2006 placebo years, we should not find any amplification effect on the role of uncertainty. Indeed, column 7 shows that the negative effect of uncertainty on investment remains significant for years of average credit frictions (coefficient -0.039 significant at the 1%) yet there is no amplification effect coming from heightened placebo credit friction years (coefficient 0.008 insignificant), which is in sharp contrast to the amplifications effects seen in column 2. In fact, the placebo results in column 7 are very similar to those of the non-interacted results in column 1 where there is no role for amplification effects from financial conditions. Similarly, column 8 presents the placebo equivalent of column 4 and shows that the aggregate placebo financial variable does not matter for investment (i.e., coefficients involving the placebo Fin_Index_t are zero). In fact, the placebo results in column 8 are very similar to those in column 3 that have no role for the aggregate credit conditions.

In summary, Table 4 and Figure 2 suggest that financial frictions amplify the negative effects of uncertainty shocks on real investment activity of firms. The next section presents the model that discusses the mechanism for the *amplification* effect for uncertainty, and as discussed in section 3.2 does so using a rich framework that highlights the *propagation* of detrimental uncertainty effects onto other real and financial variables shown to also causally respond to uncertainty shocks in Table 3.

4 Model

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

4.1 Technology

Firms use physical capital ($k_{j,t}$) to produce a single final good ($y_{j,t}$). The production function is decreasing returns to scale given by

$$y_{j,t} = X_t z_{j,t} k_{j,t}^{\alpha}, \tag{3}$$

in which X_t and $z_{j,t}$ are aggregate and firm-specific productivities and α is a constant with $0 < \alpha < 1$.

Both aggregate and firm-specific productivities (in log terms) following an AR(1) process

$$\log(X_{t+1}) = \log(\bar{X})(1-\rho^X) + \rho^X \log(X_{t+1}) + \sigma_t^X \varepsilon_{t+1}^X, \tag{4}$$

$$\log(z_{j,t+1}) = \rho^z \log(z_{j,t}) + \sigma_{j,t}^z \varepsilon_{j,t+1}^z, \tag{5}$$

in which ε_{t+1}^X is an i.i.d. standard normal aggregate productivity shock and $\varepsilon_{j,t+1}^z$ are an i.i.d. standard normal shock (drawn independently across firms), $\bar{X}$ is the long-run average of aggregate productivity, ρ^X and ρ^z are autocorrelations of aggregate and firm-specific productivities, and σ_t^X and $\sigma_{j,t}^z$ are the macro and micro uncertainty (time-varying conditional volatilities) of the productivity processes.

We assume that the evolutions of macro and micro volatility σ_t^X and $\sigma_{j,t}^z$ follow two-state Markov processes, where the transition matrix for σ_t^X and $\sigma_{j,t}^z$ are governed by

$$\sigma^X \in \left\{\sigma_L^X, \sigma_H^X\right\}, \text{where } \Pr\left(\sigma_{t+1}^X = \sigma_l^X | \sigma_t^X = \sigma_k^X\right) = \pi_{k,l}^{\sigma^X} \tag{6}$$

$$\sigma_{j,t}^z \in \left\{\sigma_L^z, \sigma_H^z\right\}, \text{where } \Pr\left(\sigma_{j,t+1}^z = \sigma_l^z | \sigma_{j,t}^z = \sigma_k^z\right) = \pi_{k,l}^{\sigma^z}. \tag{7}$$

Physical capital accumulation is given by

$$k_{j,t+1} = (1-\delta)k_{j,t} + i_{j,t}, \tag{8}$$

where δ is the depreciation rate for capital and $i_{j,t}$ is investment.

Nonconvex adjustment costs, denoted as $g_{j,t}$, are given by:

$$g_{j,t} = c_k y_{j,t} 1_{\{i_{j,t} \neq 0\}}, \tag{9}$$

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 $c_k y_{j,t} 1_{\{i_{j,t} \neq 0\}}$ capture the costs of adjusting capital that are independent of the size of the investment. They are scaled by firms' output so that firms do not outgrow adjustment costs in the model.

4.2 Cash holding

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

$$n_{j,t+1} = R_n n_{j,t} + h_{j,t}, \tag{10}$$

where $h_{j,t}$ is the investment in cash and $R_n > 0$ is the return on holding cash. Following Cooley and Quadrini (2001), we assume that return on cash is strictly less than the subjective discount rate $R = 1/\beta$, i.e., $R_n = \kappa R$ with $0 < \kappa < 1$, and cash can be freely adjusted.

We assume the aggregate net supply of the liquid asset excluding the firm's demand is an exogenous process as a function of the spot interest rate $R_{f,t}$. Specifically we assume the net supply of liquid asset N_{t+1}^S follows a constant elasticity of supply function,

$$N_{t+1}^S = \vartheta {R_{f,t}}^{\zeta}, \tag{11}$$

where ζ determines the elasticity and $\vartheta > 0$ is a constant.

4.3 External financing costs

The final part of the firm's problem concerns the external financing costs. We do not model financial intermediation costs endogenously associated with asymmetric information or agency frictions. Instead we choose to summarize the costs of external financing in a reduced form way as in Gomes (2001), Hennessy and Whited (2005) and Bolton, Chen, and Wang (2011). Specifically, when the sum of investment in capital, investment adjustment cost and investment in cash exceeds the output, 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.[31]

Because external financing costs will be paid only if payouts are negative, we define the firm's payout before financing cost ($e_{j,t}$) as output minus investment in capital and cash accumulation, less investment adjustment costs

$$e_{j,t} = y_{j,t} - i_{j,t} - h_{j,t} - g_{j,t}. \tag{12}$$

Furthermore, external financing costs vary over time and across firms, consistent with Erel et al. (2012) who show that firms' access to external finance markets also changes with macroeconomic conditions.[32] The micro-foundations of time-varying financing conditions include endogenous time-varying adverse selection problems in Eisfeldt (2004) and Kurlat (2013) who show that uncertainty increases the adverse selection cost from external financing,

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

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

agency frictions varying over time as in Bernanke and Gertler (1989) and Carlstrom and Fuerst (1997), and time-varying liquidity as in Pastor and Stambaugh (2003). Furthermore, empirically, Choe, Masulis, and Nanda (1993) find that the adverse selection costs measured as negative price reaction to 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.[33]

As such, we use η_t to capture the time-varying aggregate financing conditions that also vary over time, which is assumed for simplicity to follow a two-point Markov chain

$$\eta_t \in \{\eta_L, \eta_H\}, \text{where } \Pr\left(\eta_{t+1} = \eta_l | \eta_t = \eta_k\right) = \pi^{\eta}_{k,l}. \tag{13}$$

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, assuming costs for raising external finance when payouts are negative. Specifically, the external financing costs $\psi_{j,t}$ are assumed to be proportional to the proceeds raised:[34]

$$\psi_{j,t} = \eta_t \left| e_{j,t} \right| \mathbf{1}_{\{e_{j,t}<0\}}. \tag{14}$$

Firms do not incur costs when paying dividends or repurchasing shares. So η_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.

4.4 Firm's problem

We denote the firm's value function by $v\left(k_{j,t}, n_{j,t}, z_{j,t}, \sigma^z_{j,t}; X_t, \sigma^X_t, \eta_t, \mu_t\right)$. The state variables are given by (1) a firm's capital stock, $k_{j,t}$, (2) a firm's cash holding $n_{j,t}$, (3) the firm's idiosyncratic productivity, $z_{j,t}$, (4) the current value of micro uncertainty, $\sigma^z_{j,t}$, (5)

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

[34] We have also solved the model with fixed financing costs which does not depend on the external funds raised. We use proportional financing costs because it is more likely to be the primary form of costs that firms face when raising external funds. However, the amplification effect of financial frictions remains robust. The intuition is that both fixed and proportional external financing costs enlarge the Ss band of investment relative to the model with only fixed investment costs, thus amplifying the negative impact of uncertainty shocks on investment.

aggregate productivity, X_t, (6) the current value of macro uncertainty, σ_t^X, (7) the current value of financing wedge, η_t, and, (8) the joint distribution of idiosyncratic productivity, micro uncertainty and firm-level capital stocks and cash holding, μ_t, which is defined for the space S=R$_+$×R$_+$× R$_+$ × {0∪R$_+$}

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

$$v_{j,t} = \max_{i_{j,t}, n_{j,t+1}} \left[e_{j,t} - \psi_{j,t} + \mathbb{E}_t M_{t,t+1} v_{j,t+1} \right], \tag{15}$$

subject to firms' capital accumulation equation (Eq. 8) and cash accumulation equation (Eq. 10), where $e_{j,t} - \psi_{j,t}$ captures the net payout distributed to shareholders given a law of motion for the joint distribution of idiosyncratic productivity, volatility, capital and cash

$$\mu_{t+1} = \Gamma\left(X_t, \sigma_t^X, \eta_t, \mu_t\right) \tag{16}$$

M_{t+1} is the stochastic discount factor from the household problem in Section (4.5).

4.5 Households

There is a continuum of identical households of measure unity. Households choose consumption and investment in firm shares to maximize the lifetime utility. Let $\phi_{j,t}$ denote the shares households invest in firms. The household problem is given by

$$U_t = \underset{C_t, \phi_{j,t+1}}{max} \left\{ log(C_t) + \beta \mathbb{E}_t U_{t+1} \right\} \tag{17}$$

The household budget constraint is

$$C_t + \int p_{j,t} d\phi_{j,t+1} = \int q_{j,t} d\mu_t, \tag{18}$$

where $q_{j,t}$ is the the sum of dividends and the resale value of their investments and $p_{j,t}$ is the price of the new shares that households buy.

Competitive equilibrium A competitive equilibrium is defined as a set of quantities $\{C_t, k_{j,t+1}, n_{j,t+1}, \phi_{j,t+1}\}$, pricing functions $\{M_{t,t+1}, q_{j,t}, p_{j,t}\}$ and life utility and value functions $\{U_t, v_{j,t}\}$ such that they solve the firms' and households' optimizations and the market clearing conditions hold.

- Goods market clears

$$C_t = \int (y_{j,t} - i_{j,t} - g_{j,t} - \psi_{j,t}) d\mu_t. \tag{19}$$

- Equity market clears

$$\mu_{t+1} = \int \int \phi_{j,t+1} Q\left(z_{j,t+1}|z_{j,t}\right) Q\left(\sigma^z_{j,t+1}|\sigma^z_{j,t}\right) dz_{j,t} d\sigma^z_{j,t}. \tag{20}$$

- Liquid asset market clears

$$N^S_{t+1} = \int n_{j,t+1} d\mu_t. \tag{21}$$

5 Main results

This section presents the model solution and the main results.[35] We first calibrate the model parameters, then we simulate the model and study the quantitative implications of the model for the relationship between uncertainty shocks, financial shocks, and firms' real activity and financial flows.

5.1 Calibration

Below we briefly discuss how we calibrate the parameters of the baseline model. Appendix Section B.4 provides a detailed discussion of the calibration for some of the key parameters.

*Household preferences and firm's technology***.** The subjective discount factor β is set at $\beta = 0.988$ quarterly, implying a subject net discount rate $R - 1 = 5\%$ annually. We set the returns-to-scale parameter α at 0.7, close to the value estimated by Cooper and Ejarque (2001) and Hennessy and Whited (2007). We set the capital depreciation rate δ at 0.05, consistent with Caballero and Engel (1999). Return-on-cash saving R_n is assumed to be less than the subjective discount rate due to the tax disadvantage of carrying cash for firms or agency frictions associated with cash holding. Given that there is no readily available estimates for R_n and the adjustment costs parameters c_k ,η_L, and η_H, we set $\kappa = 0.97$ so that $R_n = 97\% R$, $c_k = 0.03, \eta_L = 0.03$, and $\eta_H = 0.06$ to match the investment slope in the

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

multi-variate IV regression and the cash-to-revenue ratio in the data. The model implied moments are -0.125 and 27%, respectively, close to the data counterparts at -0.09 and 0.29. We also check robustness of these parameters in Section 5.3. For the real-only model, we set $c_k = 0.2$ so that the model implied investment slope is -0.119 close to the data moment.

Stochastic processes. We set the persistence of aggregate and firm-specific productivities as $\rho^X = 0.95$ and $\rho^Z = 0.95$ following Khan and Thomas (2008). Following Bloom et al. (2018), we set the baseline aggregate and firm-specific volatilities as $\sigma_L^X = 0.0067$ and $\sigma_L^Z = 0.051$, respectively, the high uncertainty state $\sigma_H^X = 1.6 * \sigma_L^X$ and $\sigma_H^Z = 4.1 * \sigma_L^Z$, and the transition probabilities of $\pi_{L,H}^{\sigma^X} = 0.026$, $\pi_{L,H}^{\sigma^Z} = 0.026$ and $\pi_{H,H}^{\sigma^X} = 0.943$, and $\pi_{H,H}^{\sigma^Z} = 0.943$. Because there is no readily available estimate for the transition probabilities of financial shock in the data, we set $\pi_{L,H}^{\eta} = 0.05$ and $\pi_{H,H}^{\eta} = 0.50$ so that the high financial adjustment costs state is expected to happen every 20 quarters and the expected length of the high financial costs state is 2 quarters.[36]

Net supply of liquid cash. For tractability, we assume $\zeta \to \infty$ such that the net supply of cash is infinitely elastic. This assumption implies that the market for cash always clears so that one does not need to solve the spot rate that equates the supply and the aggregate demand for cash.[37]

5.2 Policy functions

To illustrate the intuition of the model mechanism we analyze the policy functions implied by the model with real and financial adjustment costs. Figures 3A, 3B and 3C plot the optimal investment policies associated with low and high financial adjustment costs states (3A), low and high uncertainty states (3B), and low-low financial and uncertainty states and high-high financial costs and uncertainty states.[38] In all figures, we fix the aggregate and idiosyncratic productivities, aggregate capital, and firm cash at their median grid points.

[36]We also solved a model with the transition matrix of financial shocks the same as the uncertainty shocks. The quantitative result is similar to the baseline calibration as shown in Figure 5.

[37]Moreover, we do not need to include the aggregate cash as an aggregate state variable to approximate the cross-sectional distribution when apply the Krusell-Smith method to solve the model.

[38]We set both macro and micro uncertainty to either low and high state together in this analysis.

In Figure 3A, 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 a disinvestment region when the firm is large. Furthermore, the Ss band expands with higher financial adjustment due to the amplification to the real-option effects inducing greater caution in firms investment behavior. However, optimal investment in the baseline model displays a second flat region in the high financing cost state, which arises when the firm is investing but only financed by internal funds. Turning to Figure 3B we see that the Ss band associated with high uncertainty states (both macro and micro uncertainty) is bigger than the low uncertainty state. Lastly in Figure 3C, we see that the Ss band associated with high uncertainty states and high financing adjustment cost is bigger than the low uncertainty and low financial adjustment cost states. Similar to Figure 3A, optimal investment also displays a second flat region. This happens because firms are facing binding financial constraints ($E_t = 0$), and are not prepared to pay the financing costs of raising external equity.

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

5.3 Inspecting the mechanism

We inspect the model mechanism by investigating the impulse responses of the model and the magnitude of the financial adjustment costs.

5.3.1 Impulse responses

We simulate the impulse responses of the baseline model and the model with real frictions only. We run our model for 500 simulations each with 230 periods and then kick both macro and micro uncertainties and/or financing costs up to its high level in period 201 and then let the model to continue to run as before. Hence, we are simulating the response to a one period impulse and its gradual decay. Overall, we show that real frictions alone cannot generate a persistent impact of uncertainty shocks, whereas combining real and financial frictions can generate large drops in quantities and also persistent responses and slow recoveries.

Figure 4 plots the impulse responses of the real and financial variables of the benchmark model to pure uncertainty shocks (both macro and micro uncertainties rise). Starting with the classic "real adjustment cost" only model (black line, x symbols) we see a peak drop in output of 1.8% and an overshoot above the trend. This is driven by drops and recoveries in capital. Investment drops and recovers due to real-option effects leading firms to pause investing, while depreciation continues to erode capital stocks. Consumption rises because output falls less than investment (and adjustment costs). TFP falls and recovers due to the increased misallocation of capital after uncertainty shocks - higher uncertainty leads to more rapid reshuffling of productivity across firms, which with reduced investment leads to more input misallocation. Firms pay out higher dividends when uncertainty rises because firms do not invest and pay profits out to shareholders. It is worth noting that the real-only model cannot generate persistent drop in output and investment. 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, and a longer-run overshoot from the Oi-Hartman-Abel effect.[39]

Turning to the baseline model (red line, triangle symbols) with "real and financial adjustment costs" we see a much larger peak drop in output of 3.9%, alongside larger drops in investment. Hence, in line with the empirical results, we see that adding financial costs to the classic model roughly doubles the impact of uncertainty shocks. Furthermore, the interaction of financial costs with uncertainty generates a desire by the firms to increase cash holdings when uncertainty is high, leading to more persistent drops in output and capital.

[39]The Oi-Hartman-Abel effects describes how output can expand with a mean-preserving increase in cross-sectional variance of productivity. The reason is productive firms expand to exploit the shock and unproductive firms contract to reduce the impact of the shock (see Bloom et al. (2018) for details).

The duration of impact roughly triples compared to the baseline - output and investment fall for 3 periods rather than 1, while output remains below steady state for 5 periods rather than 2.

Robustness We consider changes in parameter values in the baseline model (details in section B.5). These include i) a model with the transition matrix of financial shocks the same as the uncertainty shocks, ii) a model without cash, iii) a model with constant financial adjustment costs, iv) a model with nonconvex financial adjustment costs, v) model with the financial adjustment costs as 90% of the baseline, vi) a model with the financial adjustment costs as 110% of the baseline, vii) model with the real adjustment costs as 90% of the baseline, and viii) a model with the real adjustment costs as 110% of the baseline. These models implied impulse responses are plotted in Figure 5. The broad summary is that while the quantitative results vary somewhat across different models, the qualitative results are robust - uncertainty shocks lead to drops and rebounds in output, investment (alongside rises in cash and drops in equity payouts), and adding in financial adjustment costs make the impact larger and more persistent.

5.3.2 Magnitude of adjustment costs

Notably, despite the large amplification effect and the persistent responses generated by adding financial frictions, the magnitude of financial costs is reasonably small. In particular, in the baseline model the aggregate financial adjustment cost is only 3% of the aggregate annual output. This implies that the strong amplification of financial frictions does not rely on large total adjustment costs. The intuition is that introducing financial frictions prevents firms costlessly buffering uncertainty shocks via financial channels.[40]

[40] Even small levels of financial frictions can have large impacts as Ss bands are extremely sensitive to adjustment costs around zero. Dixit (1993) Dixit (1989) and Abel and Eberly (1996) all show that (in continous time models) the derivative of distance between the Ss bands with respect to adjustment costs is infinite around zero transactions costs.

6 Conclusion

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

Second, we document a larger negative impact of uncertainty on investment in years of heightened financial frictions, particularly for financially constrained firms. In the aggregate, we find that the average impact of uncertainty shocks is increased up to three fold during periods of increased financial frictions (e.g. 2008-09) compared to periods of normal financial conditions. As firm-specific financial constraints bind and market-wide financial conditions worsen (e.g., spikes in the Aaa-Baa corporate credit spread), the detrimental effects of uncertainty are larger. This explains how in recessions - when financial conditions typically deteriorate - uncertainty shocks can be so damaging for growth.

We then build a DSGE model with heterogeneous firms which includes two key components: first, real and financial frictions, and second, uncertainty and financial shocks. This delivers three key insights. First, *amplification* - combining real and financial frictions roughly doubles the impact of uncertainty shocks on output. Furthermore, combining an uncertainty shock with a financial shock in this model increases the impact by about another two thirds, since these shocks have an almost additive effect. Since uncertainty and financial shocks are highly collinear (e.g. Stock and Watson 2012) this is important for modelling their impacts. Second, *persistence* - adding financial frictions roughly extends by half the duration of drops after an uncertainty shock. This is because financial frictions lead firms to become more financially conservative after an uncertainty shock, reducing investment rates during the rebound. Finally, *propagation* - financial frictions spread the impact of uncertainty shocks to financial outcomes as well as real outcomes. In this model uncertainty shocks not only reduce investment and hiring, but also raise firms cash holding, while cutting equity payouts. Collectively, these predictions of a large, persistent and widespread impact of uncertainty shocks on real and financial variables matches the evidence from the recent financial crisis.

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

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Table 1
Descriptive statistics

	Mean	St. Dev.	N Obs.
Dependent			
Investment Rate$_{i,t}$	0.229	0.142	56,172
ΔIntangible Investment$_{i,t}$	0.057	0.233	56,172
ΔEmployment$_{i,t}$	0.024	0.222	56,172
ΔCost of Goods Sold$_{i,t}$	0.057	0.277	56,172
ΔSales$_{i,t}$	0.058	0.263	56,172
ΔPayout$_{i,t}$	0.054	0.947	56,172
ΔDebt$_{i,t}$	0.035	0.688	56,172
ΔCash Holdings$_{i,t}$	0.045	0.686	56,172
Independent			
ΔRealized Volatility$_{i,t-1}$	-0.013	0.308	56,172
ΔImplied Volatility$_{i,t-1}$	-0.020	0.308	26,977

Notes: Table reports summary statistics for the main sample of firm-year observations in 2SLS regressions from 1993 to 2019. Investment rate at year t is defined as $\frac{I_t}{\frac{1}{2}(K_{t-1}+K_t)}$ (i.e., capx/average of current and lagged property plant & equipment from Compustat). Changes in variables, Δx, are annual growth rates defined as $\frac{x_t - x_{t-1}}{\frac{1}{2}(x_t + x_{t-1})}$. Annual realized volatility is the 12-month standard deviation of firms' cum-dividend daily stock returns from CRSP, and annualized by multiplying by $\sqrt{252}$. Annual implied volatility is the 12-month average of firms' daily option-implied volatility from OptionMetrics, where the daily observations are the average of 365-day-horizon at-the-money call and put options. To ease comparison across realized and implied volatility effects, the growth in option implied volatility, ΔImplied Volatility$_{i,t-1}$, is scaled to have the same standard deviation as the growth in realized volatility, ΔRealized Volatility$_{i,t-1}$, in their respective regression samples. Intangible investment follows Peters and Taylor (2017) and is defined as $R\&D$ $+(0.3 \cdot XSGA)$, where $R\&D$ is research and development (with missing values set to zero) and 30% of $XSGA$ which is sales, general and administration expenses is intangible investment. To avoid double counting of intangible flows, $R\&D$ is first subtracted from $XSGA$ to isolate the SG&A expenses that companies report. Employment is EMP, cost of goods sold $COGS$, sales $SALE$, corporate payout is the sum of non-missing values in common and preferred dividends + share repurchase, i.e., $DVC + DVP + PRSTKC$. Debt is the sum of non-missing values in short term + long term debt, $DLC + DLTT$. Corporate cash holdings is cash and short-term investments, CHE, from Compustat. Variables are winsorized at the 0.5 and 99.5 percentiles. St. Dev is standard deviation and N Obs. is number of observations. See sections 2 and Online Appendix A for additional summary statistics and data details.

Table 2
Firm Investment and uncertainty shocks

Investment rate$_{i,t}$	(1) OLS Realized	(2) OLS Realized	(3) IV Realized	(4) IV Realized	(5) IV Implied
ΔVolatility$_{i,t-1}$	-0.023***	-0.024***	-0.057***	-0.041***	-0.058**
	(0.002)	(0.002)	(0.014)	(0.014)	(0.022)
Firm-level controls$_{i,t-1}$	No	No	No	Yes	Yes
IV$_{i,t-1}$ 1st moment controls	No	No	Yes	Yes	Yes
Firm, time FEs	Yes	Yes	Yes	Yes	Yes
SE cluster industry	Yes	Yes	Yes	Yes	Yes
Sample start year	1965	1993	1993	1993	1998
Sample end year	2019	2019	2019	2019	2019
Observations	95,394	56,172	56,172	56,172	26,977
1st stage $F-$test			87.22	79.68	69.91
$p-$val Sargan–Hansen $J-$test			0.462	0.665	0.572

Notes: Table reports OLS and 2SLS firm panel regressions of firms' investment rate on 1-year lagged changes in firm-level annual volatility and controls (either firm-, aggregate-level, or both). Investment rate at year t is defined as $\frac{I_t}{\frac{1}{2}(K_{t-1}+K_t)}$ (i.e., capx/average of current and lagged property plant & equipment from Compustat). Sample period is indicated in rows, where the 2SLS sample from 1993 to 2019 is based on the availability of data required to construct all 9 instrumental variables (IVs). Column (5) sample using option-implied volatility is constrained by the availability of firm-level data from OptionMetrics. Endogeneity in volatility is addressed by instrumenting with industry-level (2SIC) non-directional exposure to 9 aggregate sources of uncertainty shocks. These include exposures to realized volatility shocks of energy and currencies (as proxied by oil and 7 widely traded currencies) and economic policy uncertainty from Baker, Bloom, and Davis (2016). Annual realized volatility is the 12-month standard deviation of firms' cum-dividend daily stock returns from CRSP, and annualized by multiplying by $\sqrt{252}$. Annual implied volatility is the 12-month average of firms' daily option-implied volatility from OptionMetrics, where the daily observations are the average of 365-day-horizon at-the-money call and put options. To ease comparison across realized and implied volatility effects, the growth in option implied volatility is scaled to have the same standard deviation as the growth in realized volatility in their respective regression samples. Firm and calendar-year fixed effects are included across all columns, with standard errors clustered at the 2-digit SIC industry (in parentheses). To tease out the impact of 2nd-moment uncertainty shocks from 1st-moment aggregate shocks, controls include the 2-digit SIC directional exposure to changes in the price of each of the 9 aggregate instruments (i.e., 1st moment returns) labeled "IV$_{i,t-1}$ 1st moment". 2SLS first-stage $F-$statistics are Kleibergen-Paap (KP) that cluster standard errors at the industry-level (2SIC). Overidentification test for the validity of instruments is the $p-$value for the Sargan-Hansen over-identification $J-$test. Full 2SLS first stage results are discussed in Appendix section A.4. Firm-level controls include Stock Return$_{i,t-1}$ (measured as firms' 12-month compounded return from CRSP), Tangibility$_{i,t-1}$, Book Leverage$_{i,t-1}$, Tobin's $Q_{i,t-1}$, Return on Assets$_{i,t-1}$, and Firm Size$_{i,t-1}$. Further, to account for potential autocorrelation in outcome variables, controls include the 1-year lag in Investment Rate$_{i,t-1}$, and lagged annual changes in ΔEmployment$_{i,t-1}$, ΔIntangible Investment$_{i,t-1}$, ΔCOGS$_{i,t-1}$, ΔSales$_{i,t-1}$, ΔCorporate Payout$_{i,t-1}$, ΔDebt$_{i,t-1}$, and ΔCash holdings$_{i,t-1}$. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1, † p<0.15. See section 2 and Online Appendix A for information on variable construction and data details.

Table 3
Real and Financial Outcomes

	(1) IV	(2) IV	(3) IV	(4) IV	(5) IV	(6) IV	(7) IV	(8) IV
A: Baseline regressions	Investment $\text{Rate}_{i,t}$	$\Delta\text{Intang Inv}_{i,t}$	$\Delta\text{Emp}_{i,t}$	$\Delta\text{COGS}_{i,t}$	$\Delta\text{Sales}_{i,t}$	$\Delta\text{Payout}_{i,t}$	$\Delta\text{Debt}_{i,t}$	$\Delta\text{Cash}_{i,t}$
$\Delta\text{Volatility}_{i,t-1}$	-0.041***	-0.052***	-0.032*	-0.151***	-0.217**	-0.423***	-0.137**	0.167**
	(0.014)	(0.016)	(0.016)	(0.019)	(0.082)	(0.085)	(0.053)	(0.067)
Firm-level $\text{controls}_{i,t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\text{IV}_{i,t-1}$ 1st moment controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm, time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE cluster industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	56,172	56,172	56,172	56,172	56,172	56,172	56,172	56,172
1st stage $F-$test	79.68	79.68	79.68	79.68	79.68	79.68	79.68	79.68
$p-$val Sargan–Hansen $J-$test	0.665	0.469	0.538	0.097	0.279	0.891	0.073	0.161
B: Effect of a 2 st.dev volatility shock (of size 0.616)								
Magnitude of effect	-0.025	-0.032	-0.020	-0.093	-0.134	-0.261	-0.084	0.103
Response of outcome in st.dev units	-0.178	-0.138	-0.089	-0.336	-0.509	-0.275	-0.123	0.150

Notes: Table reports 2SLS firm panel regression results for 8 different real and financial firm outcomes regressed on 1-year lagged changes in annual firm-level realized volatility of daily CRSP returns and a full set of controls (both firm- and aggregate-level). 2SLS sample is 1993 to 2019 and based on the availability of data required to construct all 9 instrumental variables (IVs). Column (1) reports results for the baseline 2SLS specification presented in column (4) of Table 2, where investment rate at year t is defined as $\frac{I_t}{\frac{1}{2}(K_{t-1}+K_t)}$ (i.e., capx/average of current and lagged property plant & equipment from Compustat). Columns (2) to (8) report results of annual growth rates in (2) intangible investment (which follows Peters and Taylor (2017) and defined as $R\&D$ $+(0.3 \cdot XSGA)$, where $R\&D$ is research and development (with missing values set to zero) and 30% of $XSGA$ sales, general and administration expense is intangible investment), employment EMP (3), cost of goods sold $COGS$ (4), sales $SALE$ (5), corporate payout (6) (measured as common and preferred dividends + share repurchase, i.e., $DVC + DVP + PRSTKC$), total debt (7) (short term + long term debt, $DLC + DLTT$) and corporate cash holdings (8) (cash and short-term investments, CHE, from Compustat). For any variable x, annual growth rates are defined as $\Delta x_t = \frac{x_t - x_{t-1}}{\frac{1}{2}(x_t + x_{t-1})}$. To make the effects comparable across columns, Panel B reports the response of outcomes in st.dev.units and in response to a 2 st.dev. volatility shock (refer to Table 1 for summary statistics). Endogeneity in volatility is addressed by instrumenting with industry-level (2SIC) non-directional exposure to 9 aggregate sources of uncertainty shocks. These include exposures to realized volatility shocks of energy and currencies (as proxied by oil and 7 widely traded currencies) and economic policy uncertainty from Baker, Bloom, and Davis (2016). Annual realized volatility is the 12-month standard deviation of firms' cum-dividend daily stock returns from CRSP, and annualized by multiplying by $\sqrt{252}$. Firm and calendar-year fixed effects are included across all columns, with SEs clustered at 2-digit SIC industry (in parentheses). To tease out the impact of 2nd-moment uncertainty shocks from 1st-moment aggregate shocks, controls include 2-digit SIC directional exposure to changes in the price of each of the 9 aggregate instruments (i.e., 1st moment returns) labeled "$\text{IV}_{i,t-1}$ 1st moment". 2SLS first-stage $F-$statistics are Kleibergen-Paap (KP) that cluster SEs at 2SIC level. Over-identification test is the $p-$value for the Sargan-Hansen $J-$test. Firm-level controls include Stock $\text{Return}_{i,t-1}$ (measured as firms' 12-month compounded return from CRSP), $\text{Tangibility}_{i,t-1}$, Book $\text{Leverage}_{i,t-1}$, Tobin's $Q_{i,t-1}$, Return on $\text{Assets}_{i,t-1}$, and Firm $\text{Size}_{i,t-1}$. Further, to account for potential autocorrelation in outcome variables, controls include the 1-year lag in Investment $\text{Rate}_{i,t-1}$, and lagged annual changes in $\Delta\text{Employment}_{i,t-1}$, ΔIntangible $\text{Investment}_{i,t-1}$, $\Delta\text{COGS}_{i,t-1}$, $\Delta\text{Sales}_{i,t-1}$, ΔCorporate $\text{Payout}_{i,t-1}$, $\Delta\text{Debt}_{i,t-1}$, and ΔCash $\text{holdings}_{i,t-1}$. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1, † p<0.15. See section 2 and Online Appendix A for information on variable construction and data details.

Table 4
Effect of uncertainty shocks amplified by financial frictions

Investment rate$_{i,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Aggregate Financial Conditions Index$_t$		Moody's Cred Spread		Moody's Cred Spread	Romer&Romer US Fin. Distress	Chicago Fed ANFCI Index	Moody's Placebo tests Fin_Index shifted $t-3$	
$\Delta\sigma_{i,t-1}$	-0.041***	-0.022**	-0.034***	-0.023**	-0.028**	-0.027**	-0.039***	-0.031***
	(0.014)	(0.010)	(0.012)	(0.010)	(0.012)	(0.012)	(0.013)	(0.011)
$\Delta\sigma_{i,t-1}\cdot Fin\_Index_t$		-0.023**		-0.019**	-0.006	-0.008	0.008	0.006
		(0.009)		(0.008)	(0.007)	(0.007)	(0.007)	(0.005)
$\Delta\sigma_{i,t-1}\cdot D^{Fin.Const}_{i,t-5}$			-0.020***	0.002	-0.001	-0.004		-0.019***
			(0.006)	(0.009)	(0.011)	(0.010)		(0.007)
$\Delta\sigma_{i,t-1}\cdot D^{Fin.Const}_{i,t-5}\cdot Fin\_Index_t$				-0.014***	-0.016**	-0.014***		0.004
				(0.005)	(0.006)	(0.005)		(0.006)
Observations	56,172	56,172	56,172	56,172	56,172	56,172	56,172	56,172
1st stage $F-$test	79.68	27.25	58.30	39.45	44.25	36.71	35.88	36.74
$p-$val Sargan-H	0.665	0.531	0.723	0.509	0.547	0.665	0.932	0.844

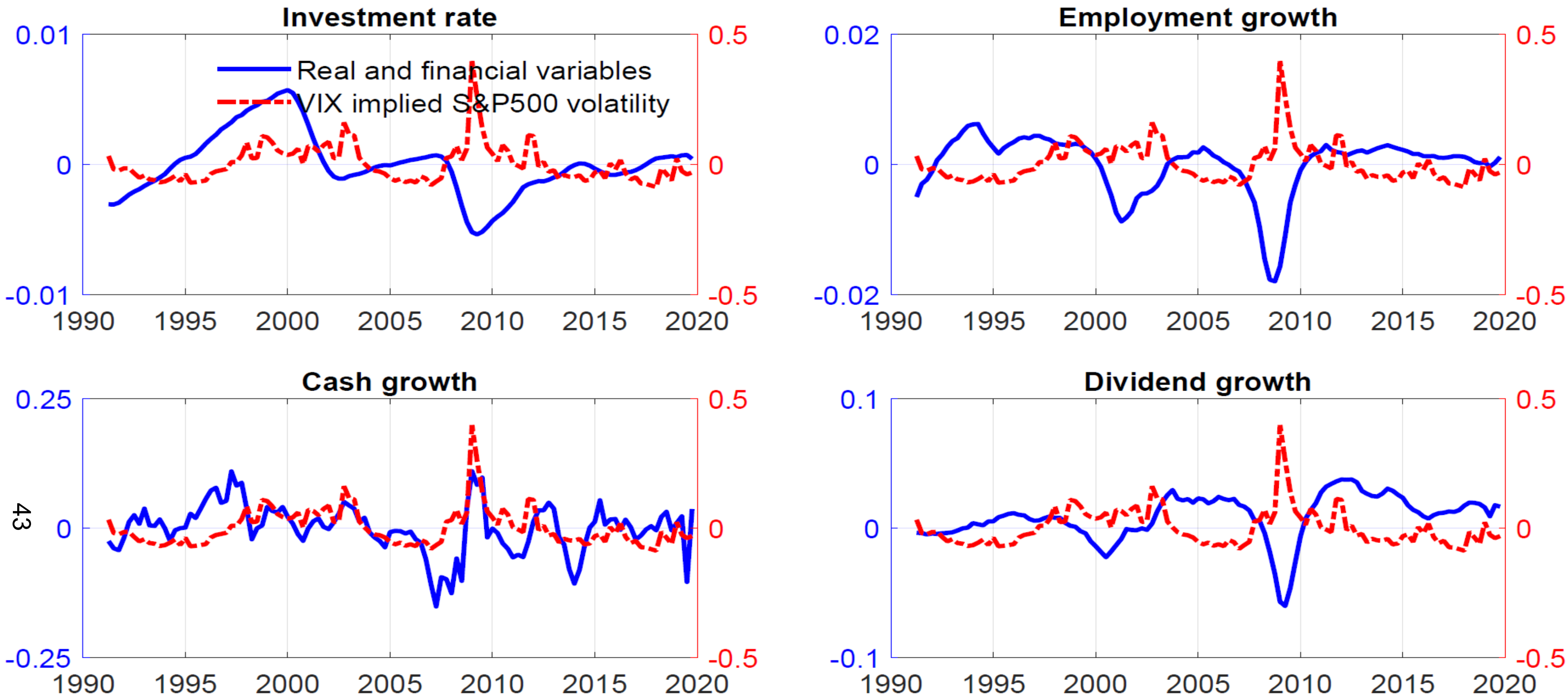
Notes: Table reports 2SLS firm panel regression results of firm-level investment rate on 1-year lagged changes in firm-level realized volatility of daily CRSP returns, $\Delta\sigma_{i,t-1}$, and its interaction with different aggregate financial frictions indexes Fin_Index_t measured each calendar year t that capture deterioration of market-wide financial conditions, and its interaction with a firm-level dummy, $D^{Fin.Constrained}_{i,t-5}$, that takes value one for firms classified as ex-ante financially constrained using information in year $t-5$, zero otherwise. Financial frictions indexes, Fin_Index_t, are proxied by the Moody's aggregate corporate credit spread BAA-AAA in cols. (2,4,7,8), the U.S financial distress measure by Romer and Romer (2017) in (5), and the Chicago Fed index for national financial conditions that is adjusted for 1st-moment economic effects (ANFCI) in (6). The aggregate indexes are standardized in the time series to ease interpretation and comparison of coefficients across columns. The 2SLS sample period is from 1993 to 2019 and based on the availability of data required to construct all 9 instrumental variables (IVs). All columns include a full set of firm-level controls, aggregate 1st moment controls, firm and year fixed effects, and SEs clustered at industry 2SIC level – i.e., identical controls as in the baseline specification (1) in Table 3. Column (1) repeats the non-interacted baseline results presented in column (1) of Table 3. Column (2) interacts $\Delta\sigma_{i,t-1}$ with Fin_Index_t proxied by Moody's credit spread, the regression does not include Fin_Index_t as it is collinear with the year fixed effects. Column (3) interacts $\Delta\sigma_{i,t-1}$ with dummy $D^{Fin.Constrained}_{i,t-5}$. Firms in year t are either ex-ante financially constrained (value 1) or unconstrained (0) based on their constrained status in year $t-5$. To classify firms we build a firm-level index $D^{Fin.Constrained}_{i,t-5}=\{0,1\}$ that uses the mode (e.g., consensus) of 3 leading firm-level proxies for financial constraints: $D^{Fin.Constrained}_{i,t-5}=\text{mode}(D^{S\&P-credit-ratings}_{i,t-5}, D^{Whited-Wu}_{i,t-5}, D^{Size-Age}_{i,t-5})$. For S&P credit ratings (e.g., Duchin, Ozbas, and Sensoy (2010) and Panousi and Papanikolaou (2012)), a firm at year t is ex-ante constrained if it lacks a credit rating in year $t-5$, unconstrained otherwise. For indexes by Whited and Wu (2006) (WW) and Hadlock and Pierce (2010) (SA), a firm in year t is ex-ante financially constrained if at year $t-5$ its index is equal to or greater than the median constrained firm that year, unconstrained otherwise. Cols. (4,5,6,8) run a triple interaction of $\Delta\sigma_{i,t-1}$ with Fin_Index_t and $D^{Fin.Constrained}_{i,t-5}$. In Columns (2,4,5,6,7,8) Fin_Index_t is collinear with the time fixed effects, thus not included and not reported. To preserve space estimates on $D^{Fin.Constrained}_{i,t-5}$ and $D^{Fin.Constrained}_{i,t-5}\cdot Fin\_Index_t$ appearing in any of the cols. (3 to 8) are not presented in the Table but included in the regressions. Cols. (7,8) perform placebo tests where Moody's credit spread is shifted to year $t-3$, such that the timing of true spikes in aggregate financial conditions is misaligned and thus interactions with Fin_Index_{t-3} are placebo. 2SLS first-stage $F-$statistics are Kleibergen-Paap (KP) that cluster SEs at 2SIC level. Over-identification is the $p-$value for the Sargan-Hansen $J-$test. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1, † p<0.15. See section 2 and Online Appendix A for information on variable construction and data details.

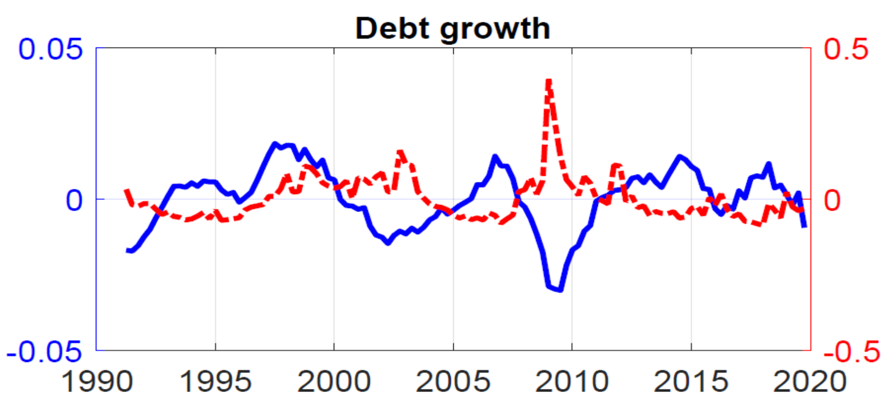
Table 5
Predetermined parameter values under baseline calibration

Description	Notation	Value	Justification
Technology			
Subjective discount factor	β	0.988	Long-run average of U.S. firm-level discount rate
Return on saving	κ	0.97	97% of the subjective discount rate & cash/revenue ratio
Share on capital	α	0.70	Cooper and Ejarque (2001) and Hennessy and Whited (2007)
Rate of depreciation for capital	δ	0.05	Capital deprec. rate assumed 5% per qtr (Caballero and Engel (1999))
Fixed real adjustment cost	c_k	0.03	Investment slope in the multivariate IV regression & cash/revenue ratio
Uncertainty shock (2 state Markov)			
Conditional macro volatility of productivity	σ_L^X	0.0067	Baseline macro uncertainty (Bloom et al 2018)
Conditional macro volatility in high uncertainty state	σ_H	0.0107	Macr uncertainty shocks 1.6*baseline uncertainty (Bloom et al 2018)
Transition probability low to high uncertainty	$\pi_{L,H}^{\sigma^X}$	2.60%	Uncertainty shocks expected every 9.6 years (Bloom et al 2018)
Transition probability remaining in high uncertainty	$\pi_{H,H}^{\sigma^X}$	94.3%	Quarterly probab. of remaining in high uncertainty (Bloom et al 2018)
Conditional micro volatility of productivity	σ_L^z	0.051	Baseline micro uncertainty (Bloom et al 2018)
Conditional micro volatility in high uncertainty state	σ_L^z	0.209	Micro uncertainty shocks 4.1*baseline uncertainty (Bloom et al 2018)
Transition probability low to high uncertainty	$\pi_{L,H}^{\sigma^z}$	2.60%	Uncertainty shocks expected every 9.6 years (Bloom et al 2018)
Transition probability remaining in high uncertainty	$\pi_{H,H}^{\sigma^z}$	94.3%	Quarterly probab. of remaining in high uncertainty (Bloom et al 2018)
Long-run average of aggregate productivity	$\log(\bar{X})$	-1	Long-run average of aggregate capital
Stochastic financing cost (2 state Markov)			
Low fixed financial adjustment cost	η_L	0.03	Investment slope in the multivariate IV regression & cash/revenue ratio
High fixed financial adjustment cost	η_H	0.06	Investment slope in the multivariate IV regression & cash/revenue ratio
Transition probability low to high financing cost state	$\pi_{L,H}^{\eta}$	5%	High financial cost state expected every 5 years (Also tried $\pi_{L,H}^{\sigma^X}$)
Transition prob. remaining in high financing cost state	$\pi_{H,H}^{\eta}$	50%	Expected length of high financial cost state for 2 quarters (Also tried $\pi_{H,H}^{\sigma^X}$)

Notes: This table presents the predetermined and the calibrated parameter values of the baseline model. Full details are in Appendix Section B.4.

Figure 1: Uncertainty, real outcomes and financial flows





Notes: Investment rate is from investment and capital data from BEA NIPS tables. Employment is seasonally adjusted total private employment from BLS. Short-term debt, long-term debt, and cash are from the NIPA Integrated Macroeconomic Accounts Table S.5.q nonfinancial corporate business, deflated by the CPI (NIPA table 1.1.4). Cash is the time and savings deposits. Debt is the sum of short-term debt, which includes open market paper and short-term loans, and long-term debt which includes bonds and mortgages. Aggregate real dividends is from Shiller's webpage http://www.econ.yale.edu/~shiller/data.htm. Growth rates of variables are moving averages with a window of 4 quarters ahead. VIX is the implied volatility of S&P 500. Sample period is 1991Q1–2019Q4.

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

Notes: Plots the average investment rate of all sample Compustat firms (weighted by tangible fixed assets) using the results from Table 4 column (4) where the response of firms to uncertainty depends on both the binding of firm financial constraints (as measured by an index based on the consensus between S&P credit ratings, Size & Age, and Whited-Wu indexes) and the worsening of credit and financial conditions (Moody's Aaa-Baa corporate credit spread). The response is more negative in 2008 and 2009 as firm financial constraints bind and market-wide financial conditions worsen (Aaa-Baa spread). Annual sample period is 1993-2019.

Figure 3: Investment policy functions

Figure 3A: Increasing Financial Frictions

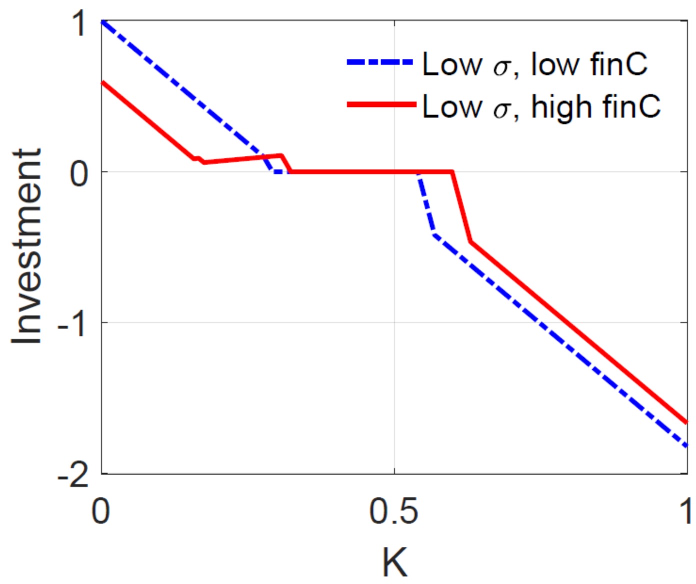


Figure 3B: Increasing Uncertainty

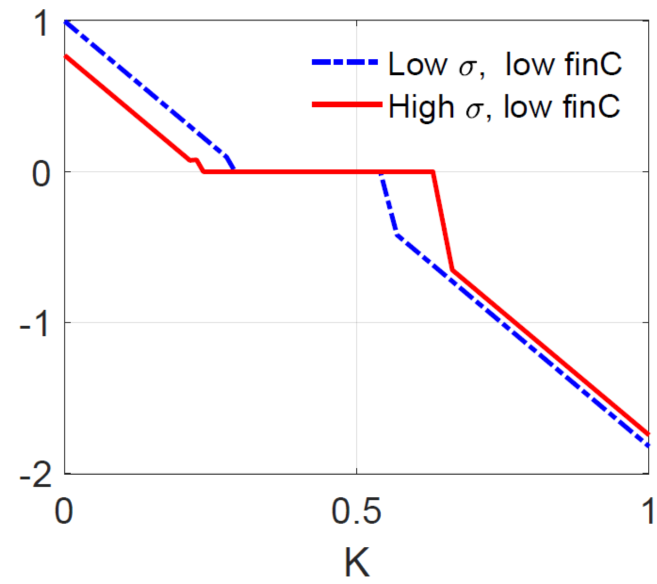
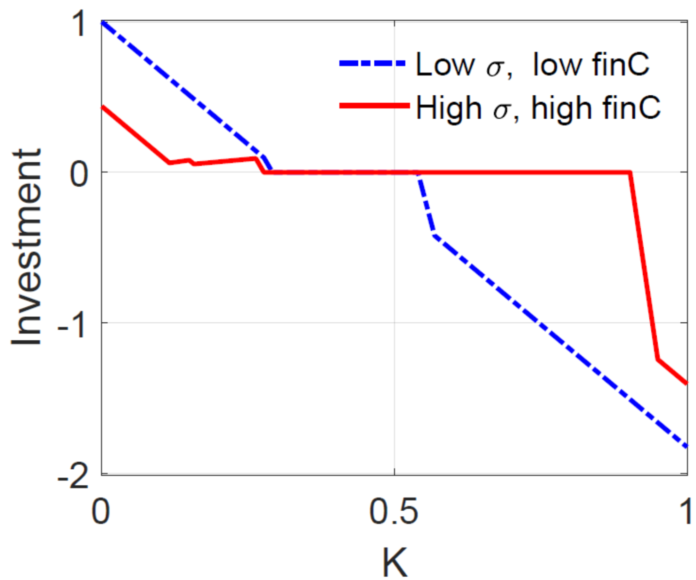
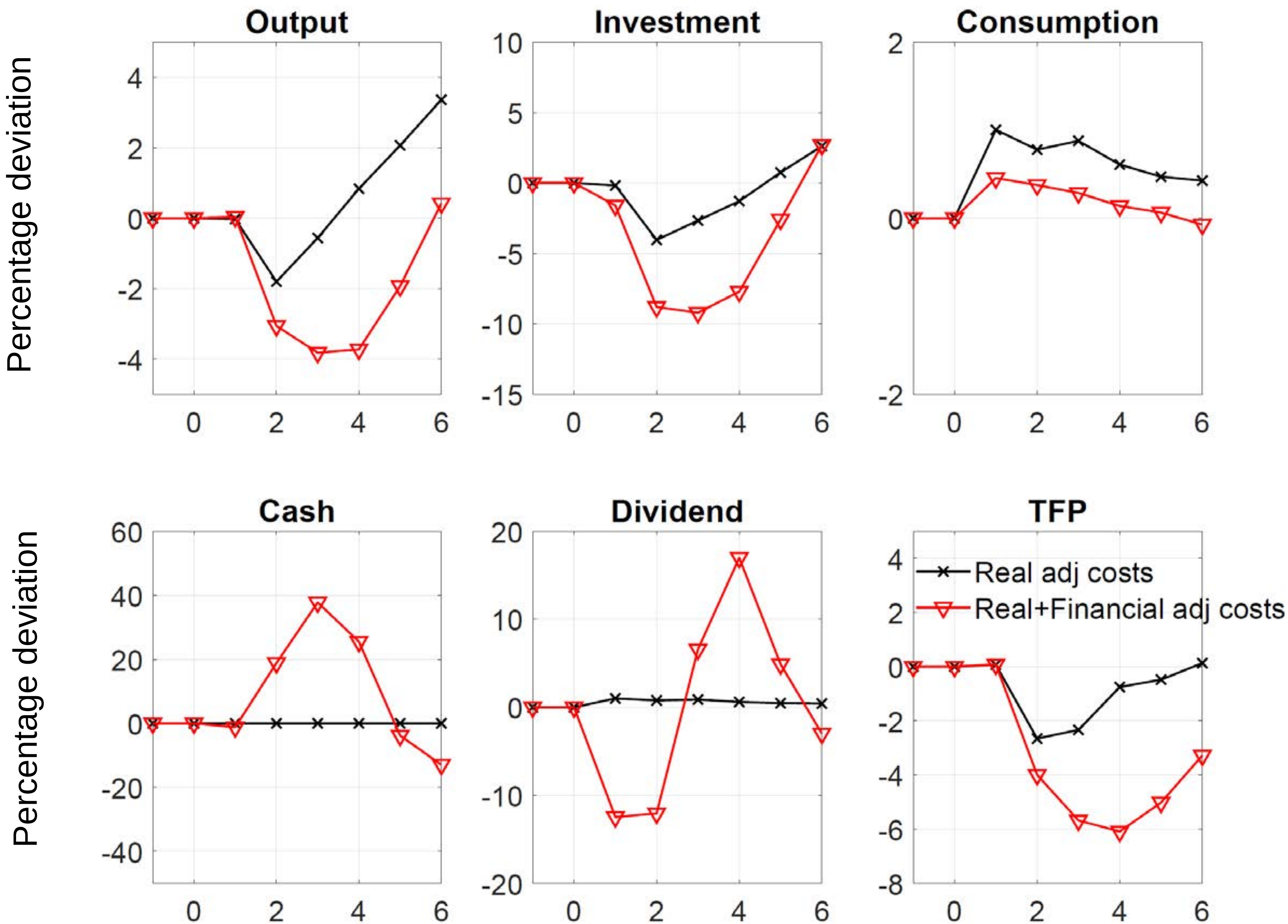


Figure 3C: Increasing Financial Frictions and Uncertainty



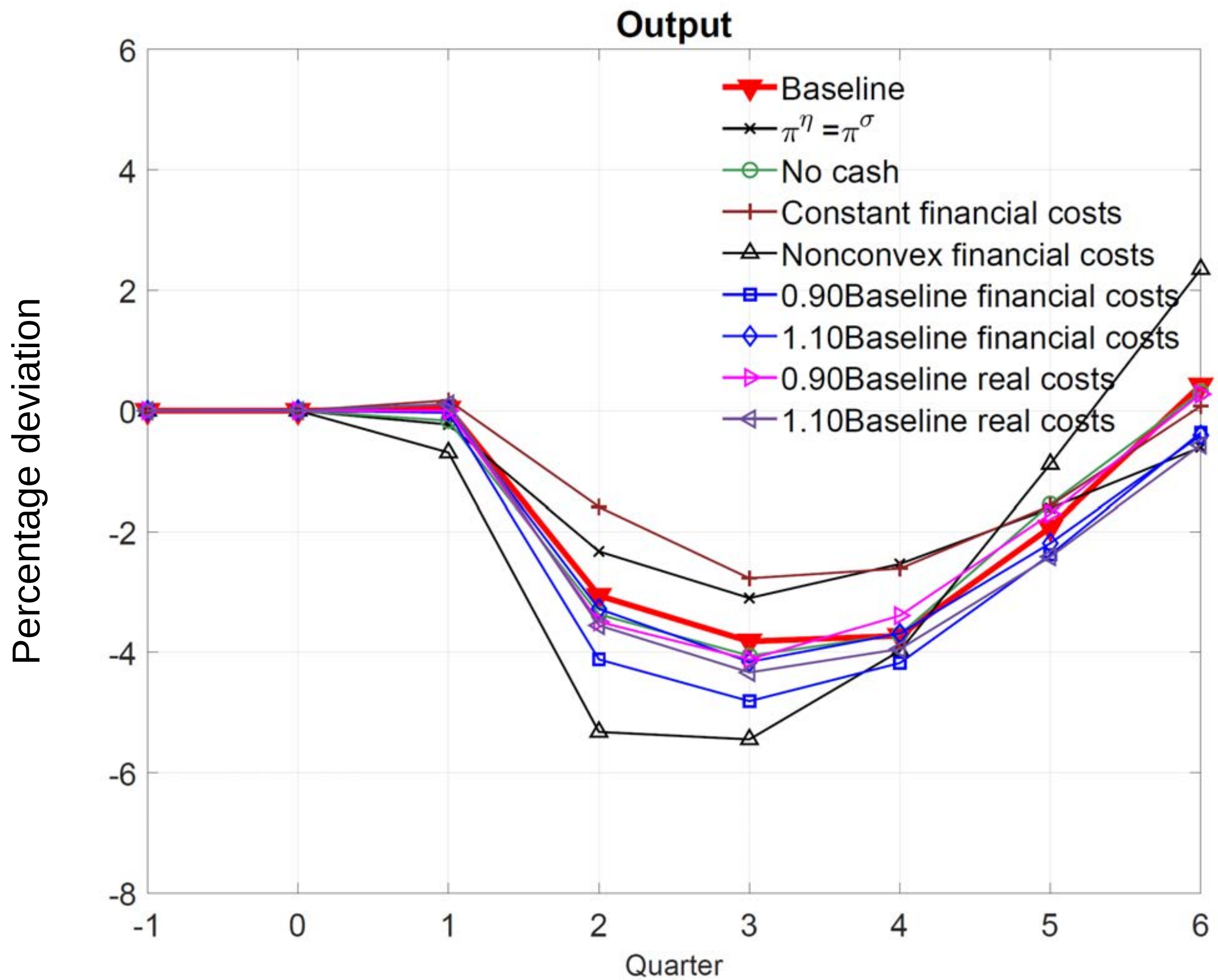
Notes: Figures 3A, 3B and 3C plot the optimal investment policies associated with low and high financial adjustment costs states (3A), low and high uncertainty states (3B), and low and high financial adjustment costs and low and high uncertainty states of the model with real adjustment costs and financial adjustment costs. In all figures, we fix the aggregate and idiosyncratic productivities and cash at their median grid points.

Figure 4: The impact of a pure uncertainty shock



Notes: We plot the percentage deviations of the average output, investment, consumption, cash, dividend and aggregate TFP from their values in quarter 0 of two model specifications: i) the model with real adjustment costs only (black x-mark), and ii) the benchmark model with both real and financial adjustment costs (red triangle). All plots are based on 500 simulations of 200-quarter length. We impose an uncertainty shock in the quarter labelled 1, allowing normal evolution of the economy afterwards.

Figure 5: Robustness check of the impact of uncertainty 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 (Baseline, red-triangle), the model with the transition matrix of financial shocks the same as the uncertainty shocks (black-cross), the model without cash (green-circle), the model with constant financial costs (brown-plus), and the model with nonconvex financial adjustment costs (black-triangle), the model with the financial adjustment costs as 90% of the baseline (blue-square), the model with the financial adjustment costs as 110% of the baseline (blue-rhombus), the model with the real adjustment costs as 90% of the baseline (magenta-triangle), and the model with the real adjustment costs as 110% of the baseline (purple-triangle). All plots are based on the average of 500 simulations of 200-quarter length. We impose an uncertainty shock in the quarter labelled 0, allowing normal evolution of the economy afterwards.

Appendix For Online Publication

A Data Appendix

Data used in the empirical analysis is described in this section. Sources include Compustat, CRSP, OptionMetrics, Thompson Reuters Eikon, St. Louis Fed, and Baker, Bloom, and Davis (2016). Table A.1 reports summary statistics for the main sample of firm-year observations in 2SLS regressions. Sample period for the 2SLS regressions begins in 1993 and ends in 2019.[41]

A.1 Company financial reports and stock return volatility

We draw financial information for US publicly held companies from Compustat. OLS sample is annual from January 1965 to December 2019 and from December 1993 to December 2019 for 2SLS. We use Compustat company data from balance sheet, income, and cash flow statements. Financial, utilities and public sector firms are excluded from the main sample (i.e., SIC between 6000 and 6999, 4950 and 4999, and equal to or greater than 9000).[42] We merge Compustat with CRSP using the CRSP/Compustat Merged (CCM) link table, and ensure that mapped firms from Compustat GVKEY to CRSP permno identifiers produce a standard 1-to-1 mapping with one firm (GVKEY) data point per calendar year. Our main empirical tests involve changes in firm variables from one year to the next. To ensure that these changes are indeed annual, we require a 12 month distance between fiscal-year end dates of accounting reports.

Changes in variables x_t are measured in annual growth rates $\Delta x_t = \frac{x_t - x_{t-1}}{\frac{1}{2}(x_{t-1}+x_t)}$, which for positive values of x_t and x_{t-1} yields growth rates bounded between -2 and 2 (i.e., $\leq |200\%|$).[43] 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 at year t follows Belo, Lin, and Bazdresch (2014) and defined as $\frac{I_t}{\frac{1}{2}(K_{t-1}+K_t)}$, where $I_{i,t}$ is the flow of capital expenditures ($CAPX$ from Compustat) over the course of fiscal year t and $\frac{1}{2}(K_{t-1}+K_t)$ is the average of current and lagged year net property plant and equipment ($PPENT$). For ease in notation we refer to investment rate as I/K_t. To reduce influence of outliers investment rate is bounded [-0.5,0.5], while other firm variables are winsorized at the 0.5 and 99.5 percentiles. Section A.6 relaxes the winsorization on investment rate to [-1,1], defines it in other ways, and presents many other robustness tests to data and variable choices (e.g., expands main sample to include financials, utilities, government firms, presents sub sample tests, etc.,)

[41] OLS and 2SLS regressions are run in STATA v.17 using the package IVREGHDFE, which in turn uses the standard IVREG2 package with multi-way fixed effects.

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

[43] If 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).

In measuring firm-level uncertainty we employ both *realized* annual volatility from CRSP stock returns and *option-implied* volatility from OptionMetrics. Annual realized volatility is the 12-month standard deviation of firms' cum-dividend daily stock returns from CRSP (variable RET), and annualized by multiplying by $\sqrt{252}$ (a year typically spans 252 trading days). For accuracy in measuring volatility, we drop firm-year observations with less than 200 daily CRSP returns in a given year. As is standard, 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).

Although our main measure of firm-level uncertainty is realized annual stock return volatility,[44] we further proxy for uncertainty by using OptionMetrics' forward 365-day *implied* volatility of a mix of at-the-money (ATM) forward call and put options. A mix of ATM forward 365-day call and puts is preferable because: (I) a 2-sided mix of puts and calls (as in the construction of the VIX) reduces any influences of smirks or other asymmetries, and (II) ATM options have the nice feature of the Black-Scholes Vega (the sensitivity of options prices to implied volatility) being the highest among other type of options (e.g., out-of-the-money (OTM) and in-the-money (ITM)). Moreover, regarding the data source 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. We use daily data from OptionMetrics' volatility surface which contain implied volatilities for a list of standardized options for constant maturities and deltas. A standardized option is available only if sufficient data exists of the underlying option price on that date to accurately compute interpolated values, with interpolations done every day and do not include look-ahead bias when computing the volatility surface. One advantage of using the volatility surface is that it avoids making arbitrary decisions on which strike prices to include when computing an implied call or put volatility of a given stock. Our empirical analyses uses call and put options' implied volatilities with a delta of $|+/-0.5|$ (i.e., ATM call and puts) and to be consistent with the annual panel data using forward expiration of 365 days. Therefore, our main measure of annual option-implied volatility is the 12-month average of firms' daily option-implied volatility from OptionMetrics, where the daily observations are the simple average of 365-day-horizon ATM call and put options.

Other outcome variables annual changes in: intangible investment that follows Peters and Taylor (2017) and is defined as $R\&D + (0.3 \cdot XSGA)$, where $R\&D$ is research and development from Compustat (with missing values set to zero) and 30% of $XSGA$ – which is sales, general and administration expenses– is intangible investment. To avoid double counting of intangible flows, $R\&D$ is first subtracted from $XSGA$ to isolate the SG&A expenses that companies report. Employment is EMP, cost of goods sold $COGS$, sales $SALE$, corporate payout is the sum of non-missing values in common and preferred dividends + share repurchase, i.e., $DVC + DVP + PRSTKC$. Debt is the sum of non-missing values in

[44] Due to the substantially larger firm-year sample size (56,172 vs 26,977 observations in columns 4 and 5, respectively, in Table 2). The larger sample is because implied volatility data from OptionMetrics is not available for all listed firms (e.g., smaller listed firms may lack options) and because options data is only available after 1996.

short term + long term debt, $DLC+DLTT$. Corporate cash holdings is cash and short-term investments, CHE, from Compustat.

Firm-level controls include the 1-year lags of all the following variables. $Stock\ Return_t$ is the 12-month compounded return from CRSP (including dividends and adjusted for delisting, RET), $Tangibility_t = PPEGT_t/AT_{t-1}$, where $PPEGT$ is gross property, plant, and equipment and AT is total assets from Compustat. $Book\ leverage_t = Debt_t/(Debt_t+CEQ_t)$, where CEQ is common book equity. Tobin's Q follows Duchin, Ozbas, and Sensoy (2010), $Q_t = (market\ value\ of\ assets_t)\ /(0.9 \cdot book\ assets_t + 0.1 \cdot market\ value\ of\ assets_t)$, where book assets= AT, market value of assets is $(AT + ME - CEQ - TXDB\ )$, ME is CRSP market value of equity (i.e. stock price times shares outstanding), $TXDB$ is deferred taxes from Compustat with missing values set to zero. Outliers in Tobin's Q are bounded above at value 10. Return on assets, $ROA_t = EBIT_t/AT_{t-1}$, where $EBIT$ is earnings before interest and tax. Firm size is log $SALE_t$.

To examine firms with economically-sensible accounting reports and operating activity (e.g., firms with non-zero operations), we apply some standard filters to the Compustat-CRSP merged sample. We drop firm-year observations having non-positive total assets, employment, and sales, and require non-negative values for cost-of-goods sold, payout, debt, cash, and intangible investment. These firm-year observations are likely associated with firms with zero operations and/or mistakes in accounting reports. Firms are required to have non-missing SIC codes (as defined above). These basic filters must be satisfied by firms every year up to a lag of 5 years so that firms have proper data when classifying firms into ex-ante financially constrained and unconstrained groups using year $t-5$ information. Moreover, the sample requires that firms have a full set of non-missing outcomes at year t (see Table 3), non-missing current and lagged shocks to firm-level realized volatilities, and non-missing values for any of the firm-level controls (current and lagged) discussed in the instrumentation strategy section 2.2. Instruments and their 1st-moment controls are also required. Collectively, these non-missing data requirements guarantee that the sample used across all outcome variables in Table 3 is the same, and thus the same 1st stage regression (i.e., same large $F-$statistic 79.68) across specifications.

The firm-level index $D^{Fin.Constrained}_{i,t-5} = \{0, 1\}$ that uses the consensus (i.e., mode) between 3 different firm-level proxies for financial constraints: $D^{Fin.Constrained}_{i,t-5} =$ mode$(D^{S\&P-credit-ratings}_{i,t-5}, D^{Whited-Wu}_{i,t-5}, D^{Size-Age}_{i,t-5})$ uses year $t-5$ information for any of the 3 indexes. To avoid losing observations for the very few cases where the lag 5 Whited-Wu index is missing, the consensus index takes value 1 if either of the S&P or the Size & Age indexes are equal to 1, zero otherwise. The Whited-Wu index is -0.091*$(OIBDP_t)/AT_{t-1}$ - 0.062*$payout\_dummy$+ 0.021*$(DLTT/AT_{t-1})$ - 0.044*$log(AT_{t-1})$ + 0.102*$\Delta(Ind\_SALE_t)$ - 0.035*$\Delta(SALE_t)$, where $OIBDP$ is operating income before depreciation, $payout\_dummy$ takes value 1 if firm pays dividends (common and/or preferred $DVC + DVP > 0$), zero otherwise, and $\Delta(Ind\_SALE)$ is the within-industry 3SIC average of sales growth. The Size & Age index is -0.737*SA_size_t + 0.043*$SA\_size_t^2$ - 0.040*SA_age_t, where $SA\_size = log(AT)$ with AT assets capped at 4.5 US$Billion, and SA_age is the firm age in years counted from the first non-missing market value from CRSP, with SA_age bounded above at 37 years.

Moody's Baa-Aaa corporate credit spread is from St. Louis Fed. We download the monthly time-series to construct annual calendar-year credit spreads using the simple 12-month average of monthly values from January to December. This series from 1993 to 2019 is standardized (i.e., rescaled to have a mean of zero and a standard deviation of one) prior to merging with the firm-year sample used in the regressions presented in Table 4. This is done to ease interpretation of coefficients in the interaction regressions and ease comparison across columns. The Romer-Romer U.S financial distress measure is from Romer and Romer (2017). The biannual series is extended in the latter years through 2019 with zero distress values. The annual calendar-year series is the simple average of the biannual data points. The Chicago Fed Adjusted National Financial Conditions (ANFCI) Index is from the Chicago Fed. We download weekly data and construct the annual series as the median of all weekly observations within each calendar year. As with the Moody's index, the Romer-Romer and the ANFCI series are standardized in the 1993 to 2019 period. When interacting the aggregate series with firm uncertainty shocks and the ex-ante financial constraints indicator in Table 4, all endogenous uncertainty terms of interest are estimated in 2SLS while other regressors are partialled out. By the Frisch-Waugh-Lovell theorem (e.g., ivreg2 documentation), in 2SLS, two-step GMM, and LIML estimation of coefficients not partialled out are the same as those obtained without partialling out any of the variables.

A.2 Timing alignment of firm-level volatility and instruments

The main empirical analysis examines the effect of changes in annual firm-level uncertainty $\Delta\sigma_{i,t-1}$ on the 1-year ahead 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 the outcomes $\Delta y_{i,t}$, lagged instruments for energy prices, exchange rates, and policy uncertainty,$\mid \beta^c_{j,t-3} \mid \cdot\Delta\sigma^c_{t-1}$, lagged price returns in the 1st moment controls of each instrument, $\beta^c_{j,t-3} \cdot r^c_{t-1}$, and the main uncertainty measure which is the the lagged growth in firm $i's$ realized annual stock return volatility, $\Delta\sigma_{i,t-1}$. Given that the regressions are predictive from year $t-1$ to year t, the first-stage 2SLS regressions implicitly 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 9 lagged composite exposures to aggregate uncertainty shocks $z^c_{t-1} = \mid \beta^c_{j,t-3} \mid \cdot\Delta\sigma^c_{t-1}$ where for instrument c the growth in the 1-year lagged uncertainty is $\Delta\sigma^c_{t-1} = (\sigma^c_{t-1} - \sigma^c_{t-2})/(\frac{1}{2}\sigma^c_{t-1} + \frac{1}{2}\sigma^c_{t-2})$ and measured in a monthly manner using information from month t-24 to month t-12, and $\mid \beta^c_{j,t-3} \mid$ is the cross-industry exposure estimated every month and timed exactly 36 months prior to the firm's fiscal-year end-month dependent variable, $\Delta y_{i,t}$.

It is important to highlight that the key date variable over which all variables are timed (e.g., rolling window sensitivities, 12-month compounded stock returns, outcome variables, controls, etc.,) for each firm is the year-month of variable *datadate* in Compustat. We use each firms' annual year-month to increase accuracy in matching firm accounting reports and volatility with the instruments. Therefore, by taking into account that firms may have different fiscal-year end dates within a calendar year, we allow firms that share the same 2SIC industry codes but have different fiscal-year end dates (e.g., firm A with fiscal-year end in October and B in December of year t) to use their exact timing when measuring the variables entering the instruments (e.g., the 36 month lag in $\beta^c_{j,t-3}$ for firm A is with respect to October in year t while $\beta^c_{j,t-3}$ for firm B is with respect to December of that year). Therefore, firms within the same 2SIC industry for any given calendar year may have different values for instruments and 1st moment controls depending on their fiscal-year endings.

Lastly, our daily data for the estimation of the sensitivities entering the regression (1) starts in January 1986. Given that the rolling windows use a 5-year window, the first set of sensitivities, $\beta^c_{j,\tau}$, start in December 1990, $\beta^c_{j,1990}$. We estimate the exposures every month in rolling windows of 5 years and merge with firm annual reports in Compustat using each firms' industry-by-year-month information (where the relevant date variable is 'datadate' from Compustat). With the first set of sensitivities, $\beta^c_{j,1990}$, we construct the first set of instruments appearing in the regression sample (from 1993 to 2019) as $z^c_{i,1992} = \mid \beta^c_{j,1990} \mid \cdot \Delta\sigma^c_{1992}$, which are used to instrument for firm uncertainty shocks measured in 1992, $\Delta\sigma_{i,1992}$, to forecast the 1-year ahead investment in 1993, $I/K_{i,1993}$. Note that in running the rolling windows in (1) on CRSP daily return data we restrict the daily sample to CRSP stocks (permno) that are mapped by year to Compustat firms (GVKEY), using (for consistency) Compustat SIC classification codes, require firms to have a minimum of 120 daily return observations (i.e., roughly 6 months of data) in the 5-year windows, and apply the standard filters that securities are listed in major US stock exchanges (EXCHCD codes 1,2, and 3 for NYSE, AMEX and the Nasdaq Stock Market (SM)) and with equity shares listed as ordinary common shares (SHRCD 10 or 11).

A.3 Risk adjusted returns

Using the same 5-year rolling window used in (1) we define firm daily risk-adjusted returns as the residuals of regressing firms' excess return on the daily Carhart factors:

$$r^{excess}_{i,t} = \alpha_i + \beta_{i,mkt} \cdot MKT_t + \beta_{i,HML} \cdot HML_t + \beta_{i,SMB} \cdot SMB_t + \beta_{i,UMD} \cdot UMD_t + \varepsilon_{i,t} \quad (22)$$

where $r^{excess}_{i,t}$ is firm i's daily CRSP stock return (including dividends and adjusted for delisting) in excess of the t-bill rate from CRSP, 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.[45]

Thus, by running (22) before the estimation of the sensitivities in (1) we effectively adjust firm-level returns for aggregate risk, which in turn addresses concerns over whether the sensitivities to energy, currencies, and policy - β^c_j in equation (1)- are capturing exposures to common risk factors in stock returns rather than exposures to those 9 factors of interest for the instrumentation strategy.

A.4 2SLS first stage results

The 2SLS first stage results for investment are shown in Table A.2. Columns 1,2, and 3 report the first stages for the IV columns 3,4, and 5 in Table 2. The F-statistics indicate a well identified first stage relevance condition, with 3SIC-clustered Kleibergen-Paap (KP) F values ranging from 69.91 to 87.22. Untabulated F values for the less strict Cragg-Donald (CD) (robust standard errors) are substantially larger and ranging from 119.7 to 299.6. Most instruments are individually positively correlated with firm uncertainty shocks and mostly significant at the 1% (offering incremental non-redundant relevance even when

[45] To reduce role of outliers and increase precision of industry sensitivity estimates we require firms to have a minimum of 120 daily CRSP returns in the rolling windows (i.e., about 6 months of trading return data in US public markets).

controlling for each other). The high significance of the individual instruments implies that identification comes from not one but from the collective set of exposures to different sources of aggregate uncertainty shocks. Using the motivation of our instruments presented in section 2.2, exogenous variation in uncertainty shocks for firms in, say, the manufacturing sector seems to stem not only from their exposure to oil uncertainty but also from exposure to bilateral exchange rate uncertainty affecting input and output prices for imports and exports with major countries/regions such as the Euro Area, and simultaneously also from exposure to policy uncertainty.

Moreover, we also find the Hansen-Sargen over-identification test does not reject the validity of the instruments, as shown by the p-values of the J statistic ranging from 0.462 to 0.665. Thus, we fail to reject the null that our instruments are exogenous. Altogether, even in the presence of an extensive set of controls (including 1st moment aggregate controls for each of the instruments), Table A.2 shows well satisfied relevance and exclusion restrictions for the set of 9 instruments for uncertainty.

A.5 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 in the case of omitted variable bias, 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 $I/K_{i,t+1} = \gamma_0 + \gamma_1 \Delta\sigma_{i,t} + \gamma_2 friction_{i,t} + \epsilon_{i,t+1}$. If a suitable proxy for $friction_{i,t}$ were available there is no omitted variable concern in estimating γ_1, by simply running investment rate on $\Delta\sigma_{i,t}$ and the proxy, which delivers a consistent estimator of γ_1. However, assuming the proxy is not available, then $friction_{i,t}$ is put into the error term, and we are left with the simple regression model $I/K_{i,t+1} = \gamma_0 + \gamma_1 \Delta\sigma_{i,t} + \mu_{i,t+1}$, where μ contains $friction$ and $\Delta\sigma_{i,t}$ is therefore endogenous. Of course, an OLS regression gives a biased and inconsistent estimator of γ_1. Therefore, the need for an instrument $z_{i,t}$ for $\Delta\sigma_{i,t}$.

The concern with simultaneity bias is that, for example, firms cut investment upon higher uncertainty ($\uparrow \Delta\sigma_{i,t} \Rightarrow \downarrow I/K_{i,t+1}$), but stock return volatility might also have risen because the market saw earlier *persistent* cuts in investment for the same firm ($\downarrow I/K_{i,t-1} \Rightarrow \uparrow \Delta\sigma_{i,t}$), 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 $\Delta\sigma_{i,t}$.[46]

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 in Table A.2 indicate that the relevance condition is well satisfied jointly by the instruments $z_{i,t} = \mid \beta^c_{j,t-2} \mid \cdot \Delta\sigma^c_t$, with most being highly positively correlated with

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

firm uncertainty shocks at the 1% even in the presence of each other (i.e., incremental non-redundant relevance).

The exclusion restriction in the omitted variable example requires that our candidate instruments are not correlated with the unobserved $friction$ and have no direct effect on investment. In our setting, it's hard to see why firm-specific agency frictions, $friction_{i,t}$, or more broadly firm-specific unobservables that influence idiosyncratic investment rates, would be correlated with the composite terms that capture the non-directional industry-level exposures to aggregate sources of uncertainty, $z_{i,t} = \mid \beta^c_{j,t-2} \mid \cdot \Delta\sigma^c_t$. For instance, for the above scenario to happen the idiosyncratic agency frictions at time t would have to be 1) correlated with the aggregate shocks to the realized volatility of WTI crude oil spot price contracts, $\Delta\sigma^{oil}_t$, and 2) cross-sectionally correlated with the non-directional industry-level exposures to oil, $\mid \beta^{oil}_{j,t-2} \mid$. For the latter it is hard to see why the time t level of idiosyncratic frictions would systematically line-up nicely in the cross-section with the industry-wide exposures measured in absolute terms, i.e., $\mid \beta^{oil}_{j,t-2} \mid$. In addition, the timing setup of the rolling windows guarantees that the 5 year information used in estimating the exposures $\beta^c_{j,t-2}$ does not overlap with any of the dependent or independent variables at time $t+1$ and t in the investment regression. Lastly, to the extent that we have more instruments than the endogenous firm uncertainty variable, we can test for instrument exogeneity using the Hansen-Sargan over-identification $J-$ test, which as reported in Table 2 strongly fails to reject the validity of the instruments.

A.6 Robustness tests: instrumentation strategy, functional form, credit supply, data and variable choices, implied volatility, single index of currencies

This section presents robustness checks to 1) the instrumentation strategy, 2) uncertainty functional form, 3) leverage-adjusted volatility and additional controls for credit supply and financial constraints, 4) data and variable choices for 4.i) the investment results presented in Table 2 and 4.ii) the amplification results presented in Table 4, 5) robustness to different definitions when measuring firm-level implied volatility from OptionMetrics, 6) robustness to using an index of currencies as instrument with currencies weighted by US Fed trade weights.

A.6.1 Instrumentation strategy

The instrumentation strategy relies on identifying cross-sectional exogenous variation in firm volatility shocks, $\Delta\sigma_{i,t-1}$, from non-directional exposure to 9 different aggregate volatility shocks, $z_{i,t-1} = \mid \beta^c_{j,t-3} \mid \cdot \Delta\sigma^c_{t-1}$. Even though our 1st stage results show strong relevance F-tests and high significance of most of the individual instruments in accounting for non-redundant exogenous variation, a first concern is whether the uncertainty effects examined in the baseline regressions go away once we drop any particular instrument or a combination of instruments from the 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? We address this concern in Table A.3. Column 1 presents the baseline realized 2SLS results (with full set of controls) presented in Table 3. Columns 2 to 10 present the results that drop each instrument one-by-one, starting with the implied volatility of the Canadian Dollar-USD exchange rate in column 2 and ending with the oil volatility in column 10. Results are largely robust and with similar points estimates. Therefore the instrumentation strategy does not depend on any single instrument. Columns 11 and 12 drop a combination of instruments, with oil and policy (i.e., non-currency) instruments dropped in column 11, while column 12 drops all 7 currency instruments and keeps only oil and policy. Results are largely robust, and in the case of dropping all 7 currencies at the same time the F-test is the lowest across all columns in the Table. The latter indicates that the collective set of instruments helps increase the relevance condition in identification and is preferable to using a substantially reduced set of IVs. Moreover, the over-identification J tests are very similar to the baseline and strongly fail to reject the validity of the instruments used across columns. Taken together, the results across all columns in Appendix Table A.3 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, and policy 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.

A second questions is whether potential multicollinearity and noise in the estimation of sensitivities in regression (1) play a role in our results. As discussed in the paper we address this by adjusting the raw sensitivities for statistical significance. In particular, each sensitivity, β_j^c, is adjusted by its statistical significance within each industry, $\beta_j^{c,weighted} = \omega_j^c \cdot \beta_j^c$. The sensitivity weight $\omega_j^c = \mid t_j^c \mid / \sum^c \mid t_k^c \mid$ is the ratio of the absolute value of the t-statistic of each instrument's sensitivity to the sum of all t-statistics in absolute value of instruments within the industry, with insignificant sensitivities at the 10% set to zero. Therefore, the adjusted instruments are $z_{i,t-1} = \mid \beta_{j,t-3}^{c,weighted} \mid \cdot \Delta\sigma_{t-1}^c$ for which we also adjust the 1st-moment controls $\beta_{j,t-3}^{c,weighted} \cdot r_{t-1}^c$. Results that use the significance-adjusted instruments and 1st moment controls are presented for the key investment regressions in columns 2 of Tables A.6 and A.7. Results are largely similar and robust to using the weighting scheme.

A.6.2 Uncertainty functional form

Another concern is whether the instrumented real and financial results depend on the precise functional form used in measuring the endogenous RHS variable for uncertainty. In Appendix Table A.4 we relax the assumption on using annual changes in firm volatility, $\Delta\sigma_{i,t-1}$, and explore different reasonable transformations of this variable. In particular, Column 1 presents the baseline 2SLS multivariate coefficients shown in Table 3, in which the instrumented volatility variable is the lagged-by-1-year annual growth in realized stock return volatility from CRSP, $\Delta\sigma_{i,t-1}$. Column 2 instruments the lagged annual growth in the square of realized return volatility, $\Delta(\sigma_{i,t-1}^2)$, column 3 the level of volatility, $\sigma_{i,t-1}$, column 4 the square in the level of volatility, $\sigma_{i,t-1}^2$, and column 5 the natural log of volatility, $log(\sigma_{i,t-1})$. Regardless of how uncertainty is measured, results are largely robust across all outcome variables. Columns 1A to 5A are similar to columns 1 to 5, but use idiosyncratic stock return volatility to proxy for uncertainty. While columns 1 to 5 measure annual volatility as the 12-month standard deviation of daily firm returns and annualized by multiplying by $\sqrt{252}$, columns 1A to 5A measure firm volatility as firms' idiosyncratic volatility with respect to a Carhart 4 factor model. In particular, firm annual idiosyncratic volatility is the annualized standard deviation of the 12-month residuals (i.e., $\sigma(\varepsilon_{i,t}) \cdot \sqrt{252}$) from the following firm-by-firm regression of daily firm returns in excess of the risk-free rate on the 4 Carhart factors from CRSP: $r_{i,t}^{excess} = \alpha_i + \beta_{i,mkt} \cdot MKT_t + \beta_{i,HML} \cdot HML_t + \beta_{i,SMB} \cdot SMB_t + \beta_{i,UMD} \cdot UMD_t + \varepsilon_{i,t}$. Columns 1A to 5A isolate the idiosyncratic component in firm stock returns that is not systematic and explained by the 4 aggregate factors. 2SLS sample across all columns in the Table are identical to the baseline specification in column 1 and from 1993 to 2019. Results using idiosyncratic volatility are largely robust for all outcome variables and not affected by the different permutations done on how firm volatility is defined. 1st-stage F tests and the over-identification J test also indicate a well performing instrumentation strategy.

A.6.3 Leverage-adjusted volatility and additional controls for credit supply and financial constraints

Appendix Table A.5 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. For comparison, column 1 presents the baseline 2SLS multivariate coefficients shown in Table 3. Columns 2 and 3 check whether the effects are robust to adjusting firm volatility for firm market- and book-leverage, respectively. In particular, when constructing the volatility shock annual volatility is first adjusted by $\sigma_{i,t} \cdot \frac{E_{i,t}}{E_{i,t}+D_{i,t}}$ where E is market equity in column 2 and book equity in column 3, and D is total debt. As shown, the results for the different outcome variables are largely robust to adjusting volatility for leverage. Moreover, one concern could be that uncertainty reduces financial supply - for example, banks are unwilling to lend in periods of high uncertainty and aggregate market risk - which then affects investment and other results we observe. Columns 4 to 7 run the baseline specification in column 1 but adding additional controls that include: the covariance of firm returns with the market in column 4 –where covariance is the firm lagged CAPM beta that controls for firm loadings on the market price of risk (e.g., control for 1st moment effects)–, controls for firm-level financial constraint indexes in column 5 – which include the lagged Whited-Wu and Size and Age indexes–, and controlling for the S&P credit ratings of firms in column 6 – which adds a full set of dummies based on every possible credit rating category given by S&P on long-term debt, where the omitted dummy is for no credit ratings–. Lastly, column 7 includes all the previous controls in columns 4,5, and 6 together. 2SLS sample across all columns is from 1993 to 2019. As shown, the results for the different outcome variables are largely robust to the addition of controls for covariance with the market and credit and financial frictions.

A.6.4 Robustness to data and variable choices

We perform a battery of robustness checks for the data and variable choices used in the key investment results documented in the paper, where we change one data or variable choice at a time and compare that to the baseline specification. We perform a total of 13 checks for both i) the baseline investment specification presented in column 4 in Table 2 and ii) the baseline triple-interaction specification that documents an amplification effect from financial frictions as presented in column 4 of Table 4. The 13 checks are presented in Tables A.6 and A.7.

Column 1 presents the baseline specifications, while columns 2 to 14 perform various robustness checks that change one specific criteria at a time regarding data and/or variable construction. Col. 2 adjusts the set of baseline instruments for the statistical significance of each exposure within the industry, where betas are weighted by their statistical significance within the industry with weight zero for insignificant exposures at the 10%. Col. 3 uses 10-year rolling windows in the IVs instead of 5yrs. Col. 4 uses implied volatilities to construct the IVs instead of the baseline realized volatilities. To increase the range of the sample as far as possible, the set of implied IVs include only that of the 7 major currencies, sample is 2000 to 2019. Col. 5 adjusts the baseline measure of investment $\text{rate}_{i,t} = \frac{I_t}{\frac{1}{2}(K_{t-1}+K_t)}$ (capx/average of current and lagged property plant & equipment from Compustat) to be net of sale of property plant & equipment, i.e., $\frac{I_t - SPPE_t}{\frac{1}{2}(K_{t-1}+K_t)}$ (where SPPE is sale of property plant & equipment). Col. 6 defines investment rate as $\frac{I_t}{K_{t-1}}$(capx/lagged property plant & equipment). Col. 7 relaxes the baseline winsorization of outliers in investment rate from [-0.5,+0.5] to [-1,+1]. Column 8 drops penny stocks with share price below $USD 1 from the sample of firms. These penny stock firms are generally tiny firms whose trading in the stock market and price volatility are likely influenced by other issues such as stock illiquidity. Col. 9 clusters the standard errors at the industry-by-year level instead of at the 2-digit industry level only. Col. 10 runs on the subsample of firm years from 2002 to 2019, hence drops the Dot-Com bubble of year 2000 and the 9/11 event in 2001. Although these events came with significant movements in volatility, financial conditions remained relatively stable those years. Col. 11 drops year 2008 which largely represents the peak of the financial crisis and is the only year of the crisis in which all quarters in the year are defined as recession quarters by NBER recession indicators. Cols. 12 to 14 add additional sectors excluded from the baseline sample, expanding to government firms in (12) (i.e., SIC codes >=9000), utilities in (13) (i.e., SIC 4950-4999), and financial firms in (14).(i.e., SIC 6000-6999).

As shown in Tables A.6 and A.7, the key baseline effects of uncertainty on investment are largely robust to various transformations done on data and variable choices.

A.6.5 Different definitions when measuring firm-level implied volatility from OptionMetrics

Table A.8.presents robustness to various definitions of firm-level option-implied volatilities. As show, the key investment regression results presented in column 5 of Table 2 that use a 2-sided mix of at-the-money (ATM) put and call options are robust to different permutations of option data from OptionMetrics. For comparison, column 1 presents the baseline results in column 5 of Table 2. This specification uses an ATM option-implied volatility measure that is constructed as the simple average between a firm's 365-day call and put options. As stressed, a mix of ATM forward 365-day call and puts is preferable because: (I) a 2-sided mix of puts and calls (as in the construction of the VIX) reduces any influences of smirks or other asymmetries, and (II) ATM options have the nice feature of the Black-Scholes Vega (the sensitivity of options prices to implied volatility) being the highest among other type of options (e.g., out-of-the-money (OTM) and in-the-money (ITM))

Columns 2 and 3 in Table A.8 each use only ATM call and ATM put options, respectively. We see that regardless of which one-sided measure is used (e.g., a bullish expectation with the call versus a bearish put) the effect of uncertainty is negative. Moreover, the call generates a slightly larger drop in investment (6 percentage point drop in column 2) than the put (5.7 pp in col. 3), while the baseline measure that uses the average in column 1 shows a coefficient that falls in between the 2 prior effects (drop of 5.8 pp in column 1). In addition to choosing between calls and puts, there is another degree of freedom in using ATM, OTM, ITM, or all the above. We explore these choices in columns 4 to 12, where columns 4 to 6 are similar to 1 to 3 but use only OTM options in measuring implied volatility, while columns 7 to 9 use only ITM options, and 10 to 12 make use of all the above call and put options in column 10, only calls in 11, and only puts in 12.

As shown, regardless of the combination between puts, calls, ATM, OTM, or ITM options, we see robust negative effects of option-implied uncertainty on firm investment – in some cases even larger than the preferred specification in column 1. Lastly, in all columns the 1st stage relevance F-test and over-identification tests indicate a well-performing IV strategy.

A.6.6 Using an index of currencies as instrument, with currencies weighted by US Fed trade weights

The 7 major currencies used as instrumental variables (IVs) may include large and common movements in bilateral exchange rates that might affect the precision of the industry-level exposures that are key in the IV strategy. We explore the results to using an index of currencies as IV instead of the 7 individual currency IVs. Individual currencies entering the index are weighted by US Fed trade-weights. The results are presented in Table A.9. Panel A presents the results for key outcomes presented in Table 3 but using only 3 IVs: oil, policy, and the currency index constructed from a weighted average of the 7 major currencies weighted by FED US trade-weights. Panel B does a similar exercise, but further includes the Mexican MXN Peso and the Chinese CNY Yuan in the weighted index. Although these are historically non-major currencies as defined by the US Fed, their economies have become more important over time. The data availability of these 2 additional currencies only starts in 1994, thus their weights in the index are zero before that year. 2SLS sample across columns is identical to the baseline specification in Table 3 and from 1993 to 2019.

Compared to the baseline 1st -stage F-tests in Table 3 that use the full set of IVs, the F-tests in both Panels A and B are weaker and down from 79.68 to 30.92 and 42.03, respectively. Therefore, the relevance condition suggests its preferable to use the individual IVs for identification of exogenous variation in firm volatility shocks. Despite the lower 1st-stage F-tests all coefficient signs remain unchanged and with comparable magnitudes relative to the baseline specifications.

Moreover, although using a single currency IV with trade weights reduces the complexity and data requirement for the IV strategy, it comes with an important economic caveat. Using the currency index forces first to have the same exposures to currency volatility of different regions, say, Europe's Euro and Mexico's Peso. In practice, it is more plausible that firms differ in their exposure to those regions depending on their production-channels, supply chains, demand, etc., For example, a firm importing raw materials from Mexico and selling in the US may be highly exposed to the Mexican Peso but not much to European exchange rates. The much larger 1st-stage F-test in our baseline instrumentation strategy suggests this might be true because it reveals that firms do have different exposures to bilateral currencies.

B Appendix Numerical algorithm

This appendix describes the solution algorithm for the model, which follows the generalized Krusell and Smith (1998) approach as implemented in Khan and Thomas (2008) and Bloom, Floetotto, Jaimovich, Saporta and Terry (2018). The full program, which runs on Matlab 64-bit, is at http://www.stanford.edu/~nbloom/.

B.1 Solution algorithm

We transform the Bellman equation for the firm problem so that the problem has a constant discount rate with the period dividends transformed by a marginal utility price p :

$$\tilde{V}\left(k,n,z,\sigma^{z};X,\sigma^{X},\eta,\mu\right)=\max_{\{i,h\}}\left\{\begin{array}{c} p\left(X,\sigma^{X},\eta,\mu\right)(y-i-h-g-\psi) \\ +\beta E\left[\tilde{V}\left(k',n',z',\sigma^{z'};X',\sigma^{X'},\eta',\mu'\right)\right]\end{array}\right\}.$$

The aggregate state of the economy is $\left(X,\sigma^{X},\eta,\mu\right)$ and the marginal utility price implied from the household optimization problem is given by

$$p\left(X,\sigma^{X},\eta,\mu\right)=\frac{1}{C\left(X,\sigma^{X},\eta,\mu\right)}.$$

Then the evolution of the aggregate economy can be characterized by the mappings below:

$$\begin{aligned} p &= \Gamma_{p}\left(X,\sigma^{X},\eta,\mu\right) \\ \mu' &= \Gamma_{\mu}\left(X,\sigma^{X},\eta,\mu\right). \end{aligned}$$

Note that the cross-sectional distribution μ is generally intractable as a state variable, so we approximate the cross-sectional distribution μ in the aggregate state space by the aggregate capital $K=\int k\left(k,n,z,\sigma^{z}\right)d\mu$, which implies that the approximate aggregate state vector is given by $\left(X,\sigma^{X},\eta,K\right)$. We then define the approximation to the equilibrium mapping Γ_{p} and Γ_{μ} using the log-linear rules as below:

$$\begin{aligned} \hat{\Gamma}_{p} &: \log(\hat{p})=\alpha_{p}\left(X,\sigma^{X},\eta\right)+\beta_{p}\left(X,\sigma^{X},\eta\right)\log(K) \\ \hat{\Gamma}_{K} &: \log(\hat{K}^{'})=\alpha_{K}\left(X,\sigma^{X},\eta\right)+\beta_{K}\left(X,\sigma^{X},\eta\right)\log(K). \end{aligned}$$

We test the internal accuracy of the approximation using statistics commonly used in the literature on heterogeneous agents models with aggregate uncertainty. Now the approximated Bellman equation is given by

$$\tilde{V}\left(k,n,z,\sigma^{z};X,\sigma^{X},\eta,K\right)=\max_{\{i,h\}}\left\{\begin{array}{c} p\left(X,\sigma^{X},\eta,K\right)(y-i-h-g-\psi) \\ +\beta E\left[\tilde{V}\left(k',n',z',\sigma^{z'};X',\sigma^{X'},\eta',K'\right)\right]\end{array}\right\}.$$

Now we describe our solution algorithm details, which closely follow Bloom, Floetotto, Jaimovich, Saporta and Terry (2018). We first initialize the forecast rules $\hat{\Gamma}_{p}^{(1)}$ and $\hat{\Gamma}_{K}^{(1)}$ with guessed initial coefficients $\alpha_{p}^{(1)}\left(X,\sigma^{X},\eta\right)$ and $\beta_{p}^{(1)}\left(X,\sigma^{X},\eta\right)$, and $\alpha_{K}^{(1)}\left(X,\sigma^{X},\eta\right)$ and $\beta_{K}^{(1)}\left(X,\sigma^{X},\eta\right)$. Then the follow steps are performed with iteration $q=1,2,...$to implement the algorithm:

Step 1: Solve the firm problem as in the Bellman equation for $\tilde{V}$ given the forecast rules $\hat{\Gamma}_{p}^{(q)}$ and $\hat{\Gamma}_{K}^{(q)}$. This gives approximated firm value function $\tilde{V}^{(q)}$ and policy functions $\left(\hat{\imath}^{(q)},\hat{h}^{(q)}\right)$.

Step 2: Simulate the economy for T periods unconditionally. During this simulation, we do not impose adherence of the assumed equilibrium pricing mapping $\hat{\Gamma}_{p}$.

Step 3: Update the forecast rules of $\hat{\Gamma}_p^{(q)}$ and $\hat{\Gamma}_K^{(q)}$ to get $\hat{\Gamma}_p^{(q+1)}$ and $\hat{\Gamma}_K^{(q+1)}$ using the simulated data from step 2.

Step 4: Check the convergence. Keep doing the iteration until the difference between $(\hat{\Gamma}_p^{(q)}, \hat{\Gamma}_K^{(q)})$ and $(\hat{\Gamma}_p^{(q+1)}, \hat{\Gamma}_K^{(q+1)})$ is smaller than a predeterrmined criterion ϵ_Γ, then stop and exit the algorithm.

In the following, we discuss how we implement each step in detail numerically.

Firm Problem We use the value function iteration procedure to solve the firm's maximization problem numerically. We specify the grids of 200 points for capital and 6 points for cash, respectively, with upper bounds $\bar{k}$ and $\bar{n}$ that are large enough to be non-binding. The grid for capital is constructed recursively given the pre-specified lower and upper bounds $\underline{k}$ and $\bar{k}$, following $k_i = k_{i-1}/(1-\delta)$, where $i = 1,...,s$ is the index of grids points. The grid for cash is constructed log-linearly allowing for zero cash. We discretize the aggregate and firm-specific productivities with two-state Markov processes of time-varying conditional volatility into a 5 (productivity level) by 2 grid, respectively. 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.

Unconditional Simulation and Market Clearing We simulate the model for $T = 5000$ periods of aggregate productivity, uncertainty and financial cost realizations $\left(X_t, \sigma_t^X, \eta_t\right)$, $t = 1,..,T$ following the exogenous processes which remain the same for steps 1-4. To compute the aggregate variables, we follow the histogram-based approach by Young (2010), which avoids the Monte Carlo sampling error in the simulation of individual firms. Specifically, we compute the distribution (histogram) on the firm-specific state points (k, n, z, σ^z) in each period, i.e., $\mu_{t+1}\left((k', n', z', \sigma^{z'})_j\right) = \sum \mu_t\left((k, n, z, \sigma^z)_i\right) \prod(z_i, z_j'; \sigma_i^z) \prod(\sigma_i^z, \sigma_j^{z\prime}) 1\left(k_j' = k_t'\left((k, n, z, \sigma^z)_i\right), n_j' = n_t'\left((k, n, z, \sigma^z)_i\right)\right)$ where $(k, n, z, \sigma^z)_i$ are discretized individual states for i=1,...,$\mathrm{n}_k\mathrm{n}_n\mathrm{n}_z\mathrm{n}_{\sigma^z}$ and $\prod(z_i, z_j'; \sigma_i^z)$ and $\prod(\sigma_i^z, \sigma_j^{z\prime})$ are transition matrix for firm-specific productivity and firm-specific uncertainty.

In each simulation period t, we make the individual firm policy functions to be consistent with market clearing and the firm optimization, that is the simulated consumption C_t and the market clearing marginal utility price $p = 1/C$ are consistent with the approximate cross-sectional distribution and the firm individual policy rules. To do this, we must find the market clearing price p using the continuation value $\hat{V}^{(q)}$. For a given p̃, we re-optimize the Bellman equation to compute the firm policy functions using $\hat{\mathrm{V}}^{(q)}$ in the right side of Bellman equation (we do not solve for a new value function), i.e.,

$$\max_{\{i,h\}} \left\{\tilde{p}\left(X, \sigma^X, \eta, \mu\right)(y - i - h - g - \psi) + \beta E\left[\hat{V}^q\left(k', n', z', \sigma^{z'}; X', \sigma^{X'}, \eta', K^{(q)\prime}\right)\right]\right\}.$$

Market clears when the consumption $C(\tilde{p}) = 1/\tilde{p}$ for the price $\tilde{p}$. However due to discontinuities associated firm distribution shifting with small price shift, the excess demand function e($\tilde{p}$) does not always clear to zero. Therefore we follow Bloom, Floetotto, Jaimovich, Saporta and Terry (2018) to convexify the firm policies and the excess demand function, which allows us to clear the market at a high precision.

1. Specifically, we first set up a grid for the marginal utility price $\{\tilde{p}_i\}$ of size N_p. Then

we recompute the firm policies for each price $\tilde{p}_i$ as described in the above, and compute the values of consumption and aggregate capital $C(\tilde{p}_i)$ and $K'(\tilde{p}_i)$, where

$$\begin{aligned} C(\tilde{p}_i) &= \sum_{(k,n,z,\sigma^z)_i} \mu_t\left((k,n,z,\sigma^z)_i\right)\left[y-(k'-(1-\delta k)-(n'-(1+r_n)n)-g-\psi\right] \\ K'(\tilde{p}_i) &= \sum_{(k,n,z,\sigma^z)_i} \mu_t\left((k,n,z,\sigma^z)_i\right)k'. \end{aligned}$$

2. Then for $\{\tilde{p}_i, C(\tilde{p}_i)\}$, we linearly interpolate the consumption function $\tilde{C}(\tilde{p}_i)$ for the candidate price $\tilde{p}$ outside the grid for the price. Then we define the convexified excess demand function as

$$e(\tilde{p}) = 1/\tilde{p} - \tilde{C}(\tilde{p})$$

which is continuous in $\tilde{p}$ because the functions of $1/\tilde{p}$ and $\tilde{C}(\tilde{p})$ are continuous.

3. Next we clear the market in each period using a hybrid bisection/inverse quadratic interpolation algorithm solve for p^* such that the excess demand function $e(\tilde{p}) = 0$ at arbitrary precision.

4. Given the market clear price p^*, we update the firm distribution and aggregate quantities consistent with the construction of the excess demand function by linearly interpolating at $\tilde{p}^*$. Specifically, for the nearest interval $[p_{i^*-1}, p_{i^*}]$ where p^* is on the grid, we compute the weight $w(p^*) = \frac{p^*-p_{i^*-1}}{p_{i^*}-p_{i^*-1}}$, and this also implies that $\tilde{C}(p^*) = (1-w(p^*))\tilde{C}(p_{i^*-1}) + w(p^*)\tilde{C}(p_{i^*})$. Similarly, we update the cross-sectional distribution μ_{t+1} and aggregate capital K_{t+1} for the next period as $\mu_{t+1}(p^*) = (1-w(p^*))\mu'(p_{i^*-1}) + w(p^*)\mu'(p_{i^*})$ and $K_{t+1}(p^*) = (1-w(p^*))K'(p_{i^*-1}) + w(p^*)K'(p_{i^*})$.

In practice, we set $N_p = 20$ and the market clearing error tolerance at 0.00001, and we find the result are robust to larger grid for p.

Equilibrium Mapping Update To update the equilibrium mappings $\hat{\Gamma}_p^{(q)}$ and $\hat{\Gamma}_K^{(q)}$, we first discard the 500 initial periods in simulation, then we run the following regressions on the simulated data to $\hat{\Gamma}_p^{(q)}$ and $\hat{\Gamma}_K^{(q)}$,

$$\begin{aligned} \log(p_t) &= \alpha_p\left(\left(X,\sigma^X,\eta\right)_i\right) + \beta_p\left(\left(X,\sigma^X,\eta\right)_i\right)\log(K_t) \\ \log(K_{t+1}) &= \alpha_K\left(\left(X,\sigma^X,\eta\right)_i\right) + \beta_K\left(\left(X,\sigma^X,\eta\right)_i\right)\log(K_t). \end{aligned}$$

After collecting the estimated coefficients, we get updated forecasted rules $\hat{\Gamma}_p^{(q+1)}$ and $\hat{\Gamma}_K^{(q+1)}$.

Test for Convergence To determine convergence, one can check if the maximum absolute difference between two forecasting rules is smaller than a predetermined tolerance. Following we use a commonly accepted practice to check the internal accuracy of a forecast mapping based on the maximum Den Haan (2010) statistics. Let $\mathrm{DH}_k^{\max}$ and $\mathrm{DH}_p^{\max}$ denote the Den Haan statistics for aggregate capital K and price p, respectively, which are maximum absolute log difference between actual simulated (K_t, p_t) and the forecasted (K_t, p_t) using the equilibrium mappings $\hat{\Gamma}_p$ and $\hat{\Gamma}_K$.The forecast mapping converge when

$$\max\{|DH_k^{\max,q+1} - DH_k^{\max,1}|, |DH_p^{\max,q+1} - DH_p^{\max,1}|\} < \epsilon,$$

where $\epsilon = 1\%$.

B.2 Internal accuracy of the approximation

This section reports the basic accuracy statistics to evaluate the accuracy of heterogeneous agents models with aggregate uncertainty used in the literature.

We show that the R2 implied by the following forecasting regressions for price $\hat{p}_t$ and aggregate capital $\hat{K}_{t+1}$ are close to 1.

$$\begin{aligned} \log(\hat{p}_t) &= \alpha_p\left(X, \sigma^X, \eta\right) + \beta_p\left(X, \sigma^X, \eta\right)\log(K_t) \\ \log(\hat{K}_{t+1}) &= \alpha_K\left(X, \sigma^X, \eta\right) + \beta_K\left(X, \sigma^X, \eta\right)\log(K_t). \end{aligned}$$

B.3 Impulse response simulation

This section describes the calculations of the impulse responses of the economy to uncertainty shocks. After solving the model using the algorithm, we compute the conditional response of the economy to uncertainty shocks (aggregate and firm-specific uncertainty shocks combined) by simulating 500 economies of length 230 periods, where the shocks occur at period 200 with market clearing within each period. After the shocks, each economy evolves normally, so effectively we simulate shocks and their gradual decay. Impulse responses are computed as the average aggregate series of interest scaled by the average level of the variable in the pre-shock period.

B.4 Calibration details

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

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

- Return on saving R_n: Return on saving is assumed to be less than the risk-free rate because of the wedge between the two, which can be due to the tax disadvantage of carrying cash for firms or agency frictions. Unfortunately, there is no readily available value for return on cash saving. In the model it determines firms' choice on cash saving, so we set $R_n = 97\%R$ to match the cash-to-revenue ratio of 0.29 in Compustat firms. We also tried no cash model as a robustness check.

- Returns-to-scale α. Since our model is a single capital model, we follow the estimated value by Cooper and Ejarque (2001) and Hennessy and Whited (2007), in both the production-function is decreasing returns to scale with capital as the only input and set $\alpha = 0.7$.

- Depreciation rate δ . We set the capital depreciation rate δ at 0.05, consistent with Caballero and Engel (1999).

- Real adjustment cost c_k. We calibrate the real adjustment cost parameter in the real-only model to match the implied coefficient in the regression where firmlevel investment rate $\frac{i_{j,t}}{k_{j,t}}$ is regressed on firm-specific uncertainty shocks $\frac{\sigma^Z_{j,t}-\sigma^Z_{j,t-1}}{\sigma^Z_{j,t}+\sigma^Z_{j,t-1}}$. The data moment to match is from the multivariate IV regression. The calibration leads to $c_k = 0.20$.

- Real and financial adjustment cost $\{c_k, \eta_L, \eta_H\}$ .In the baseline model with both real and financial adjustment costs, we calibrate the real adjustment costs, the low and high financing costs to match the investment slope in the multi-variate IV regression in the data and the cash-to-sales ratio. This implies that $c_k = 0.03, \eta_L = 0.03$, and $\eta_H = 0.06$.

- *Stochastic processes.* We set the persistence of aggregate and firm-specific productivities as $\rho^X = 0.95$ and $\rho^Z = 0.95$ following Khan and Thomas (2008). Following Bloom et al. (2018), we set the baseline aggregate and firm-specific volatilities as $\sigma^X_L = 0.0067$ and $\sigma^Z_L = 0.051$, respectively, the high uncertainty state $\sigma^X_H = 1.6 * \sigma^X_L$ and $\sigma^Z_H = 4.1 * \sigma^Z_L$, and the transition probabilities of $\pi^{\sigma^X}_{L,H} = 0.026$, $\pi^{\sigma^Z}_{L,H} = 0.026$ and $\pi^{\sigma^X}_{H,H} = 0.943$, and $\pi^{\sigma^Z}_{H,H} = 0.943$. Because there is no readily available estimate for the transition probabilities of financial shock in the data, we set $\pi^{\eta}_{L,H} = 0.05$ and $\pi^{\eta}_{H,H} = 0.50$ so that the high financial costs state is expected to happen every 20 quarters and the expected length of the high financial costs state is 2 quarters.

B.5 Model robustness

In this section we consider changes in parameter values in the general equilibrium model.

Changes in parameter values We start by re-solving the model by changing a series of the parameter values listed in Table 5. The broad summary is that while the quantitative results vary somewhat across different models, the qualitative results are robust - uncertainty shocks lead to drops and rebounds in output, capital and labor (alongside rises in cash and drops in equity payouts), and adding in financial adjustment costs make the impact larger and more persistent. We report the output response of these models in Figure 5.

1. Different transition matrix for financial shocks. We set the transition probabilities of the financial shock to be the same as the uncertainty shock. As we see (black line with crosses) this leads to a slightly smaller drop and similarly slow recovery from the uncertainty-finance shock because the finance shocks is still persistent.

2. Zero cash model. Next, we remove the cash saving choice from the model. We see a similar drop in output of around 4.0% (3.9% in the baseline) and a slower recovery after the uncertainty-finance shock (green line with cirlcles).

3. Constant financing cost. In addition, rather than assuming stochastic financing costs, we set financing costs constant (equal to the unconditional expected stochastic financing costs in the baseline model). This also leads to a slightly smaller drop in output but similar persistent response afterwards (brown line with pluses).

4. Nonconvex financial adjustment costs model . We also solved a model with nonconvex financial adjustment cost model with $\psi_{j,t} = \phi(\eta_t) y_{j,t} \mathbf{1}_{\{e_{j,t}<0\}}$. We calibrate the financial adjustment costs so that they are comparable to the baseline model with linear financial adjustment costs. We see that the peak drop in output is slightly larger than the baseline model (black line with triangles).

5. Smaller and bigger financial adjustment costs. We also tried financial adjustment costs as 90% and 110% of the baseline calibration. We see these two model calibrations (blue line with squares for 90% of the baseline and blue line with rhombuses for 110% of the baseline) produce similar drops and almost identical recovery of output to the baseline calibration from the uncertainty-finance shocks because financial constraints are not significantly loosened or tightened with a smaller changes, which also show the robustness of the finance-uncertainty multiplier effect.

6. Smaller and bigger real adjustment costs. We also tried real adjustment costs as 90% and 110% of the baseline calibration. We see these two model calibrations (mageta line with triangles for 90% of the baseline and purple line with triangles for 110% of the baseline) produce similar drops and recovery to the baseline calibration.

Table A.1
Descriptive statistics

	N Obs.	Mean	S. Dev	Min	P1	P25	P50	P75	P99	Max
Dependent										
Investment Rate$_{i,t}$	56,172	0.229	0.142	-0.238	0.013	0.117	0.195	0.321	0.500	0.500
ΔIntangible Invest$_{i,t}$	56,172	0.057	0.233	-1.282	-0.663	-0.018	0.046	0.138	0.785	1.677
ΔEmployment$_{i,t}$	56,172	0.024	0.222	-1.145	-0.756	-0.048	0.019	0.100	0.738	1.214
ΔCost of Goods Sold$_{i,t}$	56,172	0.057	0.277	-1.490	-0.950	-0.031	0.060	0.158	0.898	1.571
ΔSales$_{i,t}$	56,172	0.058	0.263	-1.326	-0.845	-0.028	0.060	0.155	0.854	1.528
ΔPayout$_{i,t}$	56,172	0.054	0.947	-2.000	-2.000	-0.133	0.000	0.327	2.000	2.000
ΔDebt$_{i,t}$	56,172	0.035	0.688	-2.000	-2.000	-0.134	0.000	0.173	2.000	2.000
ΔCash Holdings$_{i,t}$	56,172	0.045	0.686	-1.937	-1.782	-0.318	0.044	0.397	1.837	1.941
Independent										
ΔRealized Volatility$_{i,t-1}$	56,172	-0.013	0.308	-0.877	-0.722	-0.215	-0.022	0.174	0.824	1.072
ΔImplied Volatility$_{i,t-1}$	26,977	-0.020	0.308	-0.857	-0.693	-0.221	-0.037	0.151	0.844	1.038
Tobin's Q$_{i,t-1}$	56,172	1.612	0.855	0.133	0.608	1.054	1.352	1.887	4.824	9.003
Book Leverage$_{i,t-1}$	56,172	0.326	0.323	-0.050	0.000	0.047	0.284	0.495	1.562	2.205
Stock Return$_{i,t-1}$	56,172	0.168	0.629	-0.893	-0.786	-0.185	0.073	0.355	2.976	3.909
Log Sales$_{i,t-1}$	56,172	5.971	2.188	-2.254	0.573	4.484	6.053	7.491	10.843	11.018
Return on Assets$_{i,t-1}$	56,172	0.059	0.180	-1.177	-0.701	0.023	0.080	0.138	0.422	0.580
Tangibility$_{i,t-1}$	56,172	0.611	0.448	0.000	0.033	0.265	0.503	0.869	2.114	2.563
Instruments										
Cad IV ΔVol$_{i,t-1}$	56,172	0.001	0.019	-0.070	-0.054	-0.006	0.000	0.007	0.071	0.085
Euro IV ΔVol$_{i,t-1}$	56,172	-0.003	0.030	-0.105	-0.084	-0.012	-0.002	0.004	0.129	0.173
Jpy IV ΔVol$_{i,t-1}$	56,172	-0.001	0.014	-0.071	-0.050	-0.005	-0.001	0.004	0.048	0.067
Aud IV ΔVol$_{i,t-1}$	56,172	-0.001	0.020	-0.071	-0.066	-0.008	0.000	0.006	0.068	0.073
Sek IV ΔVol$_{i,t-1}$	56,172	-0.001	0.021	-0.073	-0.060	-0.008	0.000	0.004	0.094	0.099
Chf IV ΔVol$_{i,t-1}$	56,172	-0.001	0.031	-0.105	-0.088	-0.011	-0.001	0.004	0.149	0.174
Gbp IV ΔVol$_{i,t-1}$	56,172	-0.001	0.016	-0.060	-0.050	-0.006	-0.001	0.004	0.056	0.081
Oil IV ΔVol$_{i,t-1}$	56,172	0.000	0.011	-0.086	-0.044	-0.002	0.000	0.001	0.035	0.073
Policy IV ΔVol$_{i,t-1}$ ‡	56,172	-0.001	0.009	-0.046	-0.032	-0.003	-0.001	0.002	0.030	0.042

Notes: Table reports summary statistics for the main sample of firm-year observations in 2SLS regressions from 1993 to 2019. Investment rate at year t is defined as $\frac{I_t}{\frac{1}{2}(K_{t-1}+K_t)}$ (i.e., capx/average of current and lagged property plant & equipment from Compustat). Changes in variables, Δx, are annual growth rates defined as $\frac{x_t - x_{t-1}}{\frac{1}{2}(x_t + x_{t-1})}$. Annual realized volatility is the 12-month standard deviation of firms' cum-dividend daily stock returns from CRSP, and annualized by multiplying by $\sqrt{252}$. Annual implied volatility is the 12-month average of firms' daily option-implied volatility from OptionMetrics, where the daily observations are the average of 365-day-horizon at-the-money call and put options. To ease comparison across realized and implied volatility effects, the growth in option implied volatility is scaled to have the same standard deviation as the growth in realized volatility in their respective regression samples. Definition of other variables in the Table, including uncertainty instruments for currencies, oil, and policy are described in detail in Section 2 and Online Appendix A. Variables are winsorized at the 0.5 and 99.5 percentiles. Standard deviation is S. Dev and P1, P25, P50, P75, P99 stand for the 1, 25, 50, 75, and 99 percentiles, respectively. ‡ : For presentational purposes moments for policy IV are multiplied by 100.

Table A.2
Investment rate - 2SLS 1st stage results

	(1)	(2)	(3)
Set-up: ΔVolatility$_{i,t-1}$	Realized		Implied
Cad IV ΔVol$_{i,t-1}$	-0.101	-0.060	-0.485*
	(0.203)	(0.196)	(0.287)
Euro IV ΔVol$_{i,t-1}$	0.578***	0.572***	0.799***
	(0.205)	(0.208)	(0.162)
Jpy IV ΔVol$_{i,t-1}$	0.377*	0.385*	0.676***
	(0.226)	(0.219)	(0.196)
Aud IV ΔVol$_{i,t-1}$	1.874***	1.861***	0.670***
	(0.233)	(0.230)	(0.208)
Sek IV ΔVol$_{i,t-1}$	1.126***	1.127***	0.326
	(0.282)	(0.277)	(0.254)
Chf IV ΔVol$_{i,t-1}$	0.457***	0.413***	0.297*
	(0.155)	(0.160)	(0.157)
Gbp IV ΔVol$_{i,t-1}$	0.057	0.026	0.716***
	(0.236)	(0.226)	(0.237)
Oil IV ΔVol$_{i,t-1}$	1.646***	1.588***	1.251***
	(0.469)	(0.457)	(0.407)
Policy IV ΔVol$_{i,t-1}$‡	1.225***	1.164***	0.043
	(0.390)	(0.377)	(0.324)
Firm-level controls$_{i,t-1}$	No	Yes	Yes
IV$_{i,t-1}$ 1st moment controls	Yes	Yes	Yes
Firm, time FEs	Yes	Yes	Yes
SE cluster industry	Yes	Yes	Yes
Sample years	1993-2019	1993-2019	1998-2019
Observations	56,172	56,172	26,977
1st stage $F-$test	87.22	79.68	69.91
$p-$val Sargan–Hansen $J-$test	0.462	0.665	0.572

Notes: Table reports the first stage regression results of the excluded instruments used in the 2SLS firm-level investment rate regressions presented in Table 2. Therefore, columns (1) and (2) are the first stage results for columns (3) and (4) in Table 2, respectively, that instrument the shocks to *realized* stock return volatility of firms. In contrast, column (3) is the first stage of column (5) in Table 2 that instruments the option-*implied* volatility shocks of firms. See notes in Table 2 for additional details on the specifications ran in each column. We normalize implied volatility growth to have the same standard deviation as realized volatility growth to ease comparison of coefficients across columns. Sample period is reported in row "Sample years". All columns include firm and calendar-year fixed effects, and controls for 1st moment effects of each of the 9 aggregate instruments (i.e., 1st moment returns) labeled "IV$_{i,t-1}$ 1st moment", with SEs clustered at industry 2SIC level. 2SLS first-stage $F-$statistics are Kleibergen-Paap (KP) that cluster standard errors at the industry-level (2SIC). Overidentification test for the validity of instruments is the $p-$value for the Sargan-Hansen overidentification $J-$test. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1, † p<0.15. See section 2 and Online Appendix A for information on variable construction and data details. ‡ : For presentational purposes coefficients and standard errors for policy IV are divided by 100.

Table A.3
2SLS sensitivity to dropping instruments from the full set of IVs

IV Dropped	(1) None	(2) Cad	(3) Euro	(4) Jpy	(5) Aud	(6) Sek	(7) Chf	(8) Gbp	(9) Policy	(10) Oil	(11) Policy+Oil	(12) All 7 curs
Real Variables												
Investment rate$_{i,t}$	-0.041***	-0.041***	-0.042***	-0.042***	-0.046***	-0.042***	-0.039***	-0.041***	-0.039***	-0.032***	-0.030***	-0.085***
ΔIntang.$_{i,t}$	-0.052***	-0.054***	-0.055***	-0.055***	-0.059***	-0.044**	-0.055***	-0.052***	-0.051***	-0.044**	-0.042**	-0.086***
ΔEmp$_{i,t}$	-0.032*	-0.033**	-0.037**	-0.034*	-0.035*	-0.029†	-0.034**	-0.033*	-0.030*	-0.012	-0.009	-0.128**
ΔCOGS$_{i,t}$	-0.151***	-0.153***	-0.141***	-0.148***	-0.184***	-0.154***	-0.149***	-0.151***	-0.149***	-0.129***	-0.127***	-0.186†
ΔSales$_{i,t}$	-0.217**	-0.220**	-0.218**	-0.221**	-0.243**	-0.224**	-0.218**	-0.218**	-0.214**	-0.148***	-0.142***	-0.580***
Financial Variables												
ΔPayout$_{i,t}$	-0.423***	-0.419***	-0.423***	-0.422***	-0.445***	-0.438***	-0.412***	-0.423***	-0.409***	-0.382***	-0.368***	-0.561***
ΔDebt$_{i,t}$	-0.137**	-0.134**	-0.131***	-0.146***	-0.198***	-0.114**	-0.132**	-0.137**	-0.121**	-0.117**	-0.099*	-0.284***
ΔCash $_{i,t}$	0.167**	0.167**	0.170**	0.172**	0.177**	0.169**	0.161**	0.166**	0.160**	0.187***	0.183***	0.026
Firm-level controls$_{i,t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IV$_{i,t-1}$ 1st moment	Yes	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	Yes
SE cluster industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investment Rate Regression												
Observations	56,172	56,172	56,172	56,172	56,172	56,172	56,172	56,172	56,172	56,172	56,172	56,172
1st stage $F-$test	79.68	74.22	70.99	67.62	46.09	45.34	87.50	73.54	87.26	80.73	87.18	43.93
$p-$val Sargan–H test	0.665	0.571	0.668	0.586	0.557	0.580	0.613	0.578	0.924	0.649	0.888	0.938

Notes: Table reports 2SLS robustness tests to the instrumentation strategy used in all real and financial outcome results (with full set of controls) presented in Table 3. Column (1) presents the baseline 2SLS multivariate coefficients shown in Table 3 that use the full set of 9 instrumental variables (IVs) to instrument firm-level realized volatility shocks. Columns (2 to 10) examine the robustness of the results when dropping individual instruments one at a time from the full set of 9 instruments (as indicated by row "IV Dropped"). Column (11) drops both the Policy and Oil IVs while keeping only currency IVs. Column (12) drops all 7 major currencies and keeps only Policy and Oil IVs. 2SLS sample across columns is identical to the baseline specification in column (1) and from 1993 to 2019. The statistics under "Investment Rate Stats" correspond to the 1st stage results and overidentification test of the 2SLS investment rate regressions. See notes in Table 3 for additional details on the specifications ran for each outcome variable. All columns include firm and calendar-year fixed effects, and controls for 1st moment effects of each of the instruments used in the regression (i.e., 1st moment returns) labeled "IV$_{i,t-1}$ 1st moment", with SEs clustered at industry 2SIC level. 2SLS first-stage $F-$statistics are Kleibergen-Paap (KP) that cluster standard errors at the industry-level (2SIC). Overidentification test for the validity of instruments is the $p-$value for the Sargan-Hansen overidentification $J-$test. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1, † p<0.15. See section 2 and Online Appendix A for information on variable construction and data details.

Table A.4
2SLS robustness to changing functional form when measuring uncertainty

	(1)	(2)	(3)	(4)	(5)	(1A)	(2A)	(3A)	(4A)	(5A)
Firm-level Volatility	$\Delta\sigma_{i,t-1}$	$\Delta(\sigma^2_{i,t-1})$	$\sigma_{i,t-1}$	$\sigma^2_{i,t-1}$	$log(\sigma_{i,t-1})$	$\Delta\sigma_{i,t-1}$	$\Delta(\sigma^2_{i,t-1})$	$\sigma_{i,t-1}$	$\sigma^2_{i,t-1}$	$log(\sigma_{i,t-1})$
Volatility source	Realized *total* stock return volatility (1-5)					Realized *idiosyncratic* stock return volatility (1A-5A)				
Real Variables										
Investment rate$_{i,t}$	-0.041***	-0.022***	-0.116***	-0.075***	-0.073***	-0.063***	-0.034***	-0.178***	-0.118***	-0.101***
ΔIntang.$_{i,t}$	-0.052***	-0.029***	-0.125**	-0.083**	-0.079**	-0.079***	-0.044***	-0.194***	-0.142***	-0.101**
ΔEmp$_{i,t}$	-0.032*	-0.018**	-0.086*	-0.053*	-0.056*	-0.052**	-0.030**	-0.135*	-0.087*	-0.081*
ΔCOGS$_{i,t}$	-0.151***	-0.081***	-0.483***	-0.315***	-0.308***	-0.234***	-0.125***	-0.728***	-0.488***	-0.409***
ΔSales$_{i,t}$	-0.217**	-0.118**	-0.637***	-0.402***	-0.412***	-0.344***	-0.188***	-0.976***	-0.624***	-0.579***
Financial Variables										
ΔPayout$_{i,t}$	-0.423***	-0.229***	-1.173***	-0.758***	-0.752***	-0.633***	-0.344***	-1.762***	-1.190***	-0.980***
ΔDebt$_{i,t}$	-0.137**	-0.073**	-0.513***	-0.334***	-0.321***	-0.221***	-0.118***	-0.828***	-0.554***	-0.467***
ΔCash $_{i,t}$	0.167**	0.090**	0.454**	0.300**	0.287**	0.233**	0.125**	0.673*	0.488**	0.343*
Firm-level controls$_{i,t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IV$_{i,t-1}$ 1st moment	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm, time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE cluster industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investment Rate Stats										
Observations	56,172	56,172	56,172	56,172	56,172	56,172	56,172	56,172	56,172	56,172
1st stage $F-$test	79.68	80.66	55.67	43.97	37.93	74.76	73.86	47.93	30.52	33.59
$p-$val Sargan–H test	0.665	0.662	0.759	0.776	0.732	0.646	0.656	0.759	0.799	0.699

Notes: Table reports 2SLS robustness tests that change the functional form when measuring firm-level uncertainty and its effect on all real and financial outcomes (with full set of controls) presented in Table 3. Column (1) presents the baseline 2SLS multivariate coefficients shown in Table 3, in which the instrumented volatility variable is the lagged-by-1-year annual growth in realized stock return volatility from CRSP, $\Delta\sigma_{i,t-1}$. Column (2) instruments the lagged annual growth in the square of realized return volatility, $\Delta(\sigma^2_{i,t-1})$, column (3) the level of volatility, $\sigma_{i,t-1}$, column (4) the square in the level of volatility, $\sigma^2_{i,t-1}$, and column (5) the natural log of volatility, $log(\sigma_{i,t-1})$. Columns (1A) to (5A) are similar to columns (1) to (5), but use idiosyncratic stock return volatility to proxy for uncertainty. While columns (1) to (5) measure annual volatility as the 12-month standard deviation of daily firm returns and annualized by multiplying by $\sqrt{252}$, columns (1A) to (5A) measure firm volatility as firms' idiosyncratic volatility with respect to a Carhart 4 factor model. In particular, firm annual idiosyncratic volatility is the annualized standard deviation of the 12-month residuals (i.e., $\sigma(\varepsilon_{i,t})\cdot\sqrt{252}$) from the following firm-by-firm regression of daily firm returns in excess of the risk-free rate on the 4 Carhart factors from CRSP: $r^{excess}_{i,t} = \alpha_i + \beta_{i,mkt}\cdot MKT_t + \beta_{i,HML}\cdot HML_t + \beta_{i,SMB}\cdot SMB_t + \beta_{i,UMD}\cdot UMD_t + \varepsilon_{i,t}$. Columns (1A) to (5A) isolate the idiosyncratic component in firm stock returns that is not systematic and explained by the 4 aggregate factors. 2SLS sample across columns is identical to the baseline specification in column (1) and from 1993 to 2019. The statistics under "Investment Rate Stats" correspond to the 1st stage results and overidentification test of the 2SLS investment rate regressions. See notes in Table 3 for additional details on the specifications ran for each outcome variable. All columns include firm and calendar-year fixed effects, and controls for 1st moment effects of each of the 9 aggregate instruments (i.e., 1st moment returns) labeled "IV$_{i,t-1}$ 1st moment", with SEs clustered at industry 2SIC level. 2SLS first-stage $F-$statistics are Kleibergen-Paap (KP) that cluster standard errors at the industry-level (2SIC). Overidentification test for the validity of instruments is the $p-$value for the Sargan-Hansen overidentification $J-$test. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1, † p<0.15. See section 2 and Online Appendix A for information on variable construction and data details.

Table A.5
2SLS Robustness tests: leverage-adjusted volatility and additional controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Real Variables							
Investment rate$_{i,t}$	-0.041***	-0.045***	-0.044***	-0.040***	-0.040***	-0.041***	-0.039***
ΔIntangible Cap. Invest.$_{i,t}$	-0.052***	-0.065***	-0.062***	-0.052***	-0.050***	-0.053***	-0.050***
ΔEmployment$_{i,t}$	-0.032*	-0.041**	-0.042**	-0.032**	-0.031*	-0.032*	-0.030*
ΔCOGS$_{i,t}$	-0.151***	-0.163***	-0.160***	-0.150***	-0.148***	-0.151***	-0.146***
ΔSales$_{i,t}$	-0.217**	-0.241**	-0.246**	-0.214**	-0.213**	-0.216**	-0.209**
Financial Variables							
ΔPayout$_{i,t}$	-0.423***	-0.484***	-0.459***	-0.408***	-0.418***	-0.422***	-0.403***
ΔDebt$_{i,t}$	-0.137**	-0.132**	-0.131**	-0.137**	-0.131**	-0.138**	-0.132**
ΔCash Holdings$_{i,t}$	0.167**	0.184**	0.178**	0.166**	0.163**	0.170**	0.166**
Firm-level controls$_{i,t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IV$_{i,t-1}$ 1st moment controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm, time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE cluster industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market-leverage adjusted ΔVolatility$_{i,t-1}$		Yes					
Book-leverage adjusted ΔVolatility$_{i,t-1}$			Yes				
Covariance w/ market$_{i,t-1}$				Yes			Yes
Financial constraint indexes$_{i,t-1}$					Yes		Yes
S&P credit ratings$_{i,t-1}$						Yes	Yes
Investment Rate Stats							
Observations	56,172	56,172	56,172	56,172	55,933	56,172	55,933
1st stage $F-$test	79.68	52.52	40.84	83.11	81.69	79.64	85.52
$p-$val Sargan–Hansen $J-$test	0.665	0.580	0.656	0.677	0.593	0.669	0.604

Notes: Table reports 2SLS robustness checks for the effects of firm uncertainty shocks on all real and financial outcomes (with full set of controls) presented in Table 3. Column (1) presents the baseline 2SLS multivariate coefficients shown in Table 3, in which the instrumented volatility variable is the lagged-by-1-year annual growth in realized stock return volatility from CRSP, $\Delta\sigma_{i,t-1}$. Columns (2) and (3) check whether the effects are robust to adjusting firm volatility for firm market- and book-leverage, respectively. In particular, when constructing the volatility shock annual volatility is first adjusted by $\sigma_{i,t} \cdot \frac{E_{i,t}}{E_{i,t}+D_{i,t}}$ where E is market equity in column (2) and book equity in column (3), and D is total debt. Columns (4) to (7) run the baseline specification in column (1) but adding additional controls that include: the covariance of firm returns with the market in column (4) –where covariance is the firm lagged CAPM beta that controls for firm loadings on the market price of risk (e.g., control for 1st moment effects)–, controls for firm-level financial constraint indexes in column (5) – which include the lagged Whited-Wu and Size and Age indexes–, and controlling for the S&P credit ratings of firms in column (6) – which adds a full set of dummies based on every possible credit rating category given by S&P on long-term debt, where the omitted dummy is for no credit ratings–. Lastly, column (7) includes all the previous controls in columns (4,5,6) together. 2SLS sample across columns is from 1993 to 2019. The statistics under "Investment Rate Stats" correspond to the 1st stage results and overidentification test of the 2SLS investment rate regressions. See notes in Table 3 for additional details on the specifications ran for each outcome variable. All columns include firm and calendar-year fixed effects, and controls for 1st moment effects of each of the 9 aggregate instruments (i.e., 1st moment returns) labeled "IV$_{i,t-1}$ 1st moment", with SEs clustered at industry 2SIC level. 2SLS first-stage $F-$statistics are Kleibergen-Paap (KP) that cluster standard errors at the industry-level (2SIC). Overidentification test for the validity of instruments is the $p-$value for the Sargan-Hansen overidentification $J-$test. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1, † p<0.15. See section 2 and Online Appendix A for information on variable construction and data details.

Table A.6
Robustness Investment Rate results

Investment rate$_{i,t}$	(1) Baseline	(2) IVs 10% signf.	(3) 10yr roll windows	(4) IVs Implied	(5) $\frac{I_t - SPPE_t}{\frac{1}{2}(K_{t-1}+K_t)}$	(6) $\frac{I_t}{K_{t-1}}$	(7) Winsr Invt rate [-1,+1]	(8) Drop penny	(9) 2SIC-year cluster	(10) Post 2001	(11) Drop peak fin.crisis	(12) Add govrmt	(13) Add utilities	(14) Add financial
ΔVol$_{i,t-1}$	-0.041***	-0.040***	-0.035***	-0.033***	-0.041***	-0.045***	-0.033**	-0.039***	-0.041***	-0.044***	-0.043***	-0.040***	-0.041***	-0.041***
	(0.014)	(0.014)	(0.013)	(0.009)	(0.014)	(0.016)	(0.015)	(0.012)	(0.010)	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)
Obs.	56,172	56,172	44,707	41,016	56,172	56,172	56,172	52,389	56,172	36,932	53,996	56,287	56,632	60,321
Start year	1993	1993	1998	2000	1993	1993	1993	1993	1993	2002	1993	1993	1993	1993
End year	2019	2019	2019	2019	2019	2019	2019	2019	2019	2019	2019	2019	2019	2019
1st stage F	79.68	33.22	38.27	52.14	79.68	79.63	79.73	78.53	35.91	85.15	72.98	80.78	78.93	73.97
$p-$val Sargan	0.665	0.623	0.266	0.736	0.665	0.630	0.790	0.600	0.164	0.340	0.652	0.659	0.676	0.758

Notes: Table reports 2SLS robustness checks to the baseline investment rate results (with full set of controls) presented in column (1) of Table 3. For comparison across columns, col. (1) repeats the baseline 2SLS multivariate results in col. (1) of Table 3. This baseline instruments firm-level realized volatility shocks using all 9 instrumental variables (IVs) as estimated at the 2-digit SIC industry-levels and described in section 2. Sample start and end years are specified in bottom rows and from 1993 to 2019 for the baseline col. (1). From cols. (2) to (14) we perform various robustness checks that change one specific criteria at a time regarding data and/or variable construction. Col. (2) adjusts the set of baseline instruments for the statistical significance of each exposure within the industry, where betas are weighted by their statistical significance within the industry with weight zero for insignificant exposures at the 10%. Col. (3) uses 10-year rolling windows in the IVs instead of 5yrs. Col. (4) uses implied volatilities to construct the IVs instead of the baseline realized volatilities. To increase the range of the sample as far as possible, the set of implied IVs include only that of the 7 major currencies, sample is 2000 to 2019. Col. (5) adjusts the baseline measure of investment rate$_{i,t}$ $= \frac{I_t}{\frac{1}{2}(K_{t-1}+K_t)}$ (capx/average of current and lagged property plant & equipment from Compustat) to be net of sale of property plant & equipment, i.e., $\frac{I_t - SPPE_t}{\frac{1}{2}(K_{t-1}+K_t)}$ (where SPPE is sale of property plant & equipment). Col. (6) defines investment rate as $\frac{I_t}{K_{t-1}}$(capx/lagged property plant & equipment). Col. (7) relaxes the baseline winsorization [-0.5,+0.5] of investment rate to [-1,+1]. Column (8) drops penny stocks with share price below $USD 1 from the sample of firms. These penny stock firms are generally tiny firms whose trading in the stock market and price volatility are likely influenced by other issues such as stock illiquidity. Col. (9) clusters the standard errors at the industry-by-year level instead of at the 2-digit industry level only. Col. (10) runs on the subsample of firm years from 2002 to 2019, hence drops the Dot-Com bubble of year 2000 and the 9/11 event in 2001. Although these events came with significant movements in volatility, financial conditions remained relatively stable those years. Col. (11) drops year 2008 which largely represents the peak of the financial crisis and is the only year of the crisis in which all quarters in the year are defined as recession quarters by NBER recession indicators. Cols. (12) to (14) add additional sectors excluded from the baseline sample, expanding to government firms in (12) (i.e., SIC codes >=9000), utilities in (13) (i.e., SIC 4950-4999), and financial firms in (14).(i.e., SIC 6000-6999) See notes in Table 2 for additional details on the baseline investment regression. All columns include firm and calendar-year fixed effects, and controls for 1st moment effects of each of the 9 aggregate instruments (i.e., 1st moment returns), with SEs clustered at industry 2SIC level. 2SLS first-stage $F-$statistics are Kleibergen-Paap (KP) that cluster SEs at the industry-level (2SIC). Overidentification test is the $p-$value for the Sargan-Hansen overidentification $J-$test. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1, † p<0.15. See section 2 and Online Appendix A for information on variable construction and data details.

Table A.7
Robustness amplification effect results

Investment rate$_{i,t}$	(1) Baseline	(2) IVs 10% signf.	(3) 10yr roll windws	(4) IVs Implied	(5) $\frac{I_t - SPPE_t}{\frac{1}{2}(K_{t-1}+K_t)}$	(6) $\frac{I_t}{K_{t-1}}$	(7) Winsr Invt rate [-1,+1]	(8) Drop penny	(9) 2SIC-year cluster	(10) Post 2001	(11) Drop peak fin.crisis	(12) Add govrmt	(13) Add utilities	(14) Add financial
$\Delta\sigma_{i,t-1}$	-0.023**	-0.036***	-0.018**	-0.022**	-0.023**	-0.023*	-0.022*	-0.021**	-0.023**	-0.024***	-0.022**	-0.021*	-0.024**	-0.018*
	(0.010)	(0.012)	(0.008)	(0.009)	(0.010)	(0.012)	(0.013)	(0.010)	(0.009)	(0.008)	(0.011)	(0.011)	(0.010)	(0.010)
$\Delta\sigma_{i,t-1} \cdot CS_t$	-0.019**	-0.012	-0.019**	-0.007	-0.019**	-0.020**	-0.022**	-0.022***	-0.019**	-0.016*	-0.022**	-0.020**	-0.018**	-0.022**
	(0.008)	(0.009)	(0.007)	(0.011)	(0.008)	(0.009)	(0.011)	(0.008)	(0.009)	(0.008)	(0.010)	(0.009)	(0.008)	(0.009)
$\Delta\sigma_{i,t-1} \cdot D^{FC}_{i,t-5}$	0.002	0.016†	-0.002	-0.003	0.002	0.004	0.012	0.004	0.002	-0.002	-0.002	0.001	0.003	-0.002
	(0.009)	(0.011)	(0.011)	(0.014)	(0.009)	(0.010)	(0.014)	(0.009)	(0.012)	(0.011)	(0.009)	(0.009)	(0.009)	(0.010)
$\Delta\sigma_{i,t-1} \cdot D^{FC}_{i,t-5} \cdot CS_t$	-0.014***	-0.018***	-0.010*	-0.010†	-0.014***	-0.019***	-0.020**	-0.015***	-0.014**	-0.011**	-0.010*	-0.014**	-0.014***	-0.011**
	(0.005)	(0.007)	(0.005)	(0.006)	(0.005)	(0.006)	(0.008)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)
Obs.	56,172	56,172	44,707	41,016	56,172	56,172	56,172	52,389	56,172	36,932	53,996	56,287	56,632	60,321
Start year	1993	1993	1998	2000	1993	1993	1993	1993	1993	2002	1993	1993	1993	1993
End year	2019	2019	2019	2019	2019	2019	2019	2019	2019	2019	2019	2019	2019	2019
1st stage F	39.45	11.06	35.23	21.41	39.45	39.45	39.58	38.60	12.53	41.45	42.10	40.31	36.88	33.71
$p-$val Sargan	0.509	0.292	0.550	0.889	0.509	0.436	0.555	0.266	0.561	0.612	0.357	0.436	0.510	0.462

Notes: Table reports 2SLS robustness checks to the baseline triple interaction regression (with full set of controls) presented in column (4) of Table 4. For comparison across columns, col. (1) repeats the baseline 2SLS results in col. (4) of Table 4. This baseline instruments firm-level realized volatility shocks (and its interactions) using all 9 instrumental variables (IVs) as estimated at the 2-digit SIC industry and described in section 2. Sample start and end years are in bottom rows, and 1993-2019 for the baseline col. (1). From cols. (2) to (14) we perform robustness checks that change one specific criteria at a time regarding data and/or variable construction. Col. (2) adjusts the set of baseline IVs for the statistical significance of each exposure within the industry, where betas are weighted by their statistical significance within the industry with weight zero for insignificant exposures at the 10%. Col. (3) uses 10-year rolling windows in the IVs instead of 5yrs. Col. (4) uses implied volatilities to construct the IVs instead of the baseline realized volatilities. To increase the range of the sample as far as possible, the set of implied IVs include only that of the 7 major currencies, sample is 2000 to 2019. Col. (5) adjusts the baseline measure of investment rate$_{i,t} = \frac{I_t}{\frac{1}{2}(K_{t-1}+K_t)}$ (capx/average of current and lagged property plant & equipment from Compustat) to be net of sale of property plant & equipment, i.e., $\frac{I_t - SPPE_t}{\frac{1}{2}(K_{t-1}+K_t)}$ (where SPPE is sale of property plant & equipment). Col. (6) defines investment rate as $\frac{I_t}{K_{t-1}}$(capx/lagged property plant & equipment). Col. (7) relaxes the baseline winsorization [-0.5,+0.5] of investment rate to [-1,+1]. Column (8) drops penny stocks with share price below $USD 1 from the sample of firms. These penny stock firms are generally tiny firms whose trading in the stock market and price volatility are likely influenced by other issues such as stock illiquidity. Col. (9) clusters the standard errors at the industry-by-year level instead of at the 2-digit industry level only. Col. (10) runs on the subsample of firm years from 2002 to 2019, hence drops the Dot-Com bubble of year 2000 and the 9/11 event in 2001. Although these events came with significant movements in volatility, financial conditions remained relatively stable those years. Col. (11) drops year 2008 which largely represents the peak of the financial crisis and is the only year of the crisis in which all quarters in the year are defined as recession quarters by NBER recession indicators. Cols. (12) to (14) add additional sectors excluded from the baseline sample, government firms in (12) (i.e., SIC codes >=9000), utilities in (13) (i.e., SIC 4950-4999), and financial firms in (14).(i.e., SIC 6000-6999) See notes in Table 2 for additional details on the baseline investment regression. All columns include firm and calendar-year fixed effects, and controls for 1st moment effects of each of the 9 aggregate instruments (i.e., 1st moment returns), with SEs clustered at 2SIC level. 2SLS first-stage $F-$statistics are Kleibergen-Paap (KP), with 2SIC clustering of SEs. Overidentification test is the $p-$value for the Sargan-Hansen $J-$test. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1, † p<0.15. See section 2 and Online Appendix A for information on variable construction and data details.

Table A.8
Implied volatility robustness, calls & puts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Implied	ATM	ATM	ATM	OTM	OTM	OTM	ITM	ITM	ITM	All	All	All
Volatility	Call & Put	Call	Put	Calls & Puts	Calls	Puts	Calls & Puts	Calls	Puts	Calls & Puts	Calls	Puts
Investment rate$_{i,t}$												
$\Delta\text{Vol}_{i,t-1}$	-0.058**	-0.060**	-0.057**	-0.062**	-0.064**	-0.061***	-0.058**	-0.061**	-0.058**	-0.059**	-0.061**	-0.058**
	(0.022)	(0.024)	(0.022)	(0.024)	(0.025)	(0.023)	(0.023)	(0.025)	(0.022)	(0.023)	(0.024)	(0.022)
Obs.	26,977	26,977	26,977	26,977	26,977	26,977	26,977	26,977	26,977	26,977	26,977	26,977
Start year	1998	1998	1998	1998	1998	1998	1998	1998	1998	1998	1998	1998
End year	2019	2019	2019	2019	2019	2019	2019	2019	2019	2019	2019	2019
1st stage $F-$test	69.91	68.35	62.38	66.28	61.91	66.35	65.68	70.60	48.68	68.95	69.02	60.44
$p-$val Sargan–H	0.572	0.577	0.567	0.563	0.552	0.571	0.574	0.571	0.576	0.571	0.567	0.571

Notes: Table reports 2SLS robustness checks to the measurement of option-implied volatility shocks and their effect on firm investment rates. For comparison across robustness checks, column (1) repeats the implied specification presented in column (5) of Table 2. This specification uses an average of both put and call at-the-money (ATM) options to measure firm implied volatility. In particular, annual implied volatility is the 12-month average of firms' daily option-implied volatility from OptionMetrics, where the daily observations are the simple average of 365-day-horizon at-the-money call and put options. Columns (2) and (3) use only and separately ATM call and ATM put options, respectively. Columns (4) to (6) are similar to (1) to (3) but use only out-of-the-money (OTM) options in measuring implied volatility, while columns (7) to (9) use only in-the-money (ITM) options. Lastly, columns (10) to (12) make use of all the above call and put options (10), only calls (11), and only puts (12). See notes in Table 2 for additional details on the specification of firm investment. All columns include firm and calendar-year fixed effects, and controls for 1st moment effects of each of the 9 aggregate instruments (i.e., 1st moment returns), with SEs clustered at industry 2SIC level. 2SLS first-stage $F-$statistics are Kleibergen-Paap (KP) that cluster standard errors at the industry-level (2SIC). Overidentification test for the validity of instruments is the $p-$value for the Sargan-Hansen overidentification $J-$test. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1, † p<0.15. See section 2 and Online Appendix A for information on variable construction and data details.

Table A.9
Robustness weighted average of currencies, using FED bilateral trade weights

	(1) Investment rate$_{i,t}$	(2) ΔIntang$._{i,t}$	(3) ΔEmp$_{i,t}$	(4) ΔCOGS$_{i,t}$	(5) ΔSales$_{i,t}$	(6) ΔPayout$_{i,t}$	(7) ΔDebt$_{i,t}$	(8) ΔCash $_{i,t}$
Panel A: IVs oil, policy, and a weighted average of the 7 US FED major curencies								
ΔVol$_{i,t-1}$	-0.052**	-0.051*	-0.059†	-0.159***	-0.330**	-0.319***	-0.182**	0.085
	(0.026)	(0.026)	(0.038)	(0.059)	(0.130)	(0.090)	(0.073)	(0.126)
Obs.	56,172	56,172	56,172	56,172	56,172	56,172	56,172	56,172
1st stage $F-$test	30.92	30.92	30.92	30.92	30.92	30.92	30.92	30.92
$p-$val Sargan–H	0.051	0.411	0.301	0.363	0.105	0.080	0.215	0.447
Panel B: Add Mexican MXN Peso and Chinese CNY Yuan								
ΔVol$_{i,t-1}$	-0.044*	-0.037†	-0.032	-0.143***	-0.264**	-0.283***	-0.135**	0.128
	(0.024)	(0.025)	(0.033)	(0.044)	(0.111)	(0.081)	(0.065)	(0.110)
Obs.	56,172	56,172	56,172	56,172	56,172	56,172	56,172	56,172
1st stage $F-$test	42.03	42.03	42.03	42.03	42.03	42.03	42.03	42.03
$p-$val Sargan–H	0.065	0.385	0.237	0.264	0.083	0.076	0.077	0.428

Notes: Table reports 2SLS robustness tests to the instrumentation strategy used in all real and financial outcome results (with full set of controls) presented in Table 3. The motivation is that the 7 major currencies used as instrumental variables (IVs) may include large and common movements in bilateral exchange rates that might affect the precision of the industry-level exposures that are key in the IV strategy. Thus, the Table replaces all 7 currency instruments with a single US FED trade-weighted currency index. Panel A presents the results for all baseline outcomes presented in Table 3 but using only 3 IVs: Oil, Policy, and the currency index constructed from a weighted average of the 7 major currencies weighted by FED US trade-weights. Panel B does a similar exercise, but further includes the Mexican MXN Peso and the Chinese CNY Yuan in the weighted index. Although these are historically non-major currencies as defined by the US Fed their economies have become more important over time. The data availability of these 2 additional currencies only starts in 1994, thus their weights in the index are zero before that year. 2SLS sample across columns is identical to the baseline specification in Table 3 and from 1993 to 2019. See notes in Table 3 for additional details on the specifications ran for each outcome variable. All columns include firm and calendar-year fixed effects, and controls for 1st moment effects of each of the instruments used in the regression (i.e., 1st moment returns), with SEs clustered at industry 2SIC level. 2SLS first-stage $F-$statistics are Kleibergen-Paap (KP) that cluster standard errors at the industry-level (2SIC). Overidentification test for the validity of instruments is the $p-$value for the Sargan-Hansen overidentification $J-$test. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1, † p<0.15. See section 2 and Online Appendix A for information on variable construction and data details.