The Finance Uncertainty Multiplier

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We show how real and financial frictions amplify, prolong, and propagate the negative impact of uncertainty shocks. We 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. We show that financially constrained firms cut investment more than unconstrained firms following an uncertainty shock. We then build a general equilibrium heterogeneous firms model with real and financial frictions, finding that financial frictions (i) amplify uncertainty shocks by doubling their impact on output; (ii) increase persistence by doubling the duration of the drop; and (iii) propagate uncertainty shocks by spreading their impact onto financial variables.

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I. 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 second-moment uncertainty shocks is challenging because of correlated first-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 detrimental impact of uncertainty shocks, producing a larger recession and a slower recovery, as seen in the data. The amplified effects of uncertainty can be particularly damaging in periods when financial conditions tighten due to shocks in the banking sector, such as the recent collapse of Silicon Valley Bank in 2023. Furthermore, adding financial frictions to the model is crucial in generating a propagation of the harmful effects of uncertainty from real-only variables onto financial outcomes, for example, leading firms to hoarding corporate cash.

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, we propose a novel instrumentation strategy for uncertainty that exploits differential industry-level exposure to exchange rate, factor price, and policy uncertainty.[1] 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

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[1] For models and empirics on reverse causality with uncertainty and growth, see, e.g., Van Nieuwerburgh and Veldkamp (2006), Bachmann and Moscarini (2012), Pastor and Veronesi (2012), Orlik and Veldkamp (2015), Berger, Dew-Becker, and Giglio (2016), and Fajgelbaum, Schaal, and Taschereau-Dumouchel (2017).

oil price volatility. This key separation between first- and second-moment effects is crucial given that when commodity prices see upward or downward movement, 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.

Our identification strategy works well in delivering strong first-stage F-statistics and satisfying the exclusion restriction in Sargan-Hansen overidentification 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 ordinary least squares (OLS) regressions, by a factor of 1.7–2.4, 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 threefold during periods of increased financial frictions (e.g., 2008–9) compared with 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, and on the financing side, raising external funds involves costs so that firms have to manage liquidity by saving in cash.[2] 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 stochastic-volatility shocks—as in Dixit and Pindyck (1994), Abel and Eberly (1996), and Bloom (2009)—roughly doubles the negative impact of uncertainty shocks on investment. In our simulation, an

[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). Models with costs of raising external finance include Hennessy and Whited (2007) and Bolton, Chen, and Wang (2011). Models with firms holding cash include Froot, Scharfstein, and Stein (1993), Bolton, Chen, and Wang (2013), and Eisfeldt and Muir (2016).

uncertainty shock with real and financial frictions leads to a peak drop in output of 3.9% but a drop of 1.8% with only real frictions. 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 (table 1).

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 internal fund 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 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

TABLE 1
Impact of Uncertainty Shocks on Output in Simulation

	Drop in Output (%)
Real frictions	−1.8
Real + financial frictions	−3.9

Note.—Results from the average 500 simulations of the calibrated model (see sec. V.III).

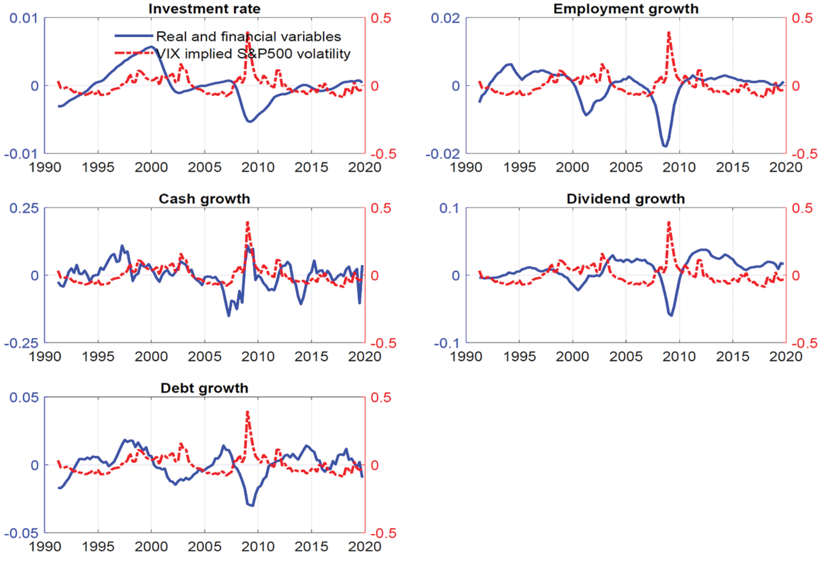

FIG. 1.—Uncertainty, real outcomes, and financial flows. Investment rate is from investment and capital data from the Bureau of Economic Analysis's National Income and Product Accounts (NIPA) tables. Employment is seasonally adjusted total private employment from the Bureau of Labor Statistics. Short-term debt, long-term debt, and cash are from NIPA Integrated Macroeconomic Accounts Table S.5.q nonfinancial corporate business, deflated by the consumer price index (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 Robert J. 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 the S&P 500. Sample period is 1991Q1–2019Q4.

assumptions. In particular, we ignore labor, as 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 is the uncertainty literature studying the interaction of uncertainty and adjustment costs for investment and employment.[3] This emphasizes the

[3] 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), and Fernandez-Villaverde et al. (2011, 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; e.g., 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, and Alfaro and Park (2019) more recently became the first to look at the effects of employer-level stock return volatility 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

"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 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 is the finance literature on firms' financial management of liquidity. The notion of liquidity management goes back at least to Keynes's general theory, which argues that precautionary cash saving and financing constraints are closely linked if financial markets are imperfect.[4] This literature highlights how firms will hoard cash in the presence of uncertainty and financial adjustment costs—that is, 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.[5]

Finally, our paper is also closely related to the recent literature on financial frictions and business cycles.[6] We build on this literature to argue it is not a choice between uncertainty shocks and financial shocks as to

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to stochastic volatility, 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 Di Tella (2017) explore the relations between uncertainty and the aggregate outcomes through the financial intermediary channel.

[4] The recent development in the finance literature on liquidity management and financial constraints include the theoretical work of Riddick and Whited (2009), Bolton, Chen, and Wang (2011), and Bolton, Wang, and Yang (2019) and the empirical work of Almeida, Campello, and Weisbach (2005) and Bates, Kahle, and Stulz (2009).

[5] There is a large literature—Gomes (2001), Rampini and Viswanathan (2013), etc.—studying the impact of various frictions on firms' financing policies.

[6] For example, Lhuissier and Tripier (2016) and Alessandri and Mumtaz (2018) show in value-at-risk estimates a strong interaction effect of financial constraints on uncertainty. More generally, Gilchrist and Zakrajsek (2012) and 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.

which drives recessions, but instead these shocks amplify each other. So they should not be considered individually, rather jointly. Authors with related work that links uncertainty and financial frictions include the following: 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 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 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 (2020), who investigate the relationship between financial frictions and firm heterogeneity and the impact of monetary policy on firms' investment. Although we share with Christiano, Motto, and Rostagno (2014), Gilchrist, Sim, and Zakrajsek (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.[7] 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 United States and Europe, with rising uncertainty one suggested reason.[8]

The rest of the paper is laid out as follows. Section II describes the instrumentation strategy and data. Section III presents the empirical findings on the effects of uncertainty shocks on both real and financial activities of firms. In section IV, we write down the model. Section V presents the main quantitative results of the model. Section VI concludes.

[7] The typical prior approach in this literature to instrumentation—e.g., Leahy and Whited (1996), Bloom, Bond, and Reenen (2007), and Gilchrist, Sim, and Zakrajsek (2014)—is to use lagged values of uncertainty as instruments in OLS regressions. We propose instruments that capture exogenous variation in uncertainty in a two-stage least squares (2SLS) framework.

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

II. Data, Instruments, and Addressing Endogeneity

This section discusses the instrumentation strategy, construction of instruments, and data sources used in the empirical analysis.[9]

A. Data

Stock returns are from the Center for Research in Security Prices (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 firms, utilities, and public-sector firms are excluded from the main sample (i.e., Standard Industrial Classification [SIC] between 6,000 and 6,999, between 4,950 and 4,999, and equal to or greater than 9,000). 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.[10] 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 $(252)^{1/2}$ (a year typically spans 252 trading days).[11] 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 forward 365-day-horizon at-the-money (ATM) call and put options.[12] Data from OptionMetrics is available starting January 1996.

[9] Full replication code and data for this paper are available at https://nbloom.people.stanford.edu/research.

[10] We lag the firm uncertainty measure by 1 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 biannually, on average (Altig et al. 2021), and capital decisions often have long lags from decision to implementation, so that a 1-year lag also appears economically appropriate.

[11] 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, the sample uses securities appearing on CRSP for firms listed on major US stock exchanges (EXCHCD codes 1–3 for NYSE, AMEX, and Nasdaq) and equity shares listed as ordinary common shares (SHRCD 10 or 11).

[12] As with the construction of the aggregate VIX, using a two-sided mix of call and put options is preferable (e.g., unlike a call or a put, it is not a one-sided uncertainty measure, while it also reduces the influence of smirks or other asymmetries in implied volatility). Moreover,

Changes in variables x_t are measured in annual growth rates $\Delta x_t = x_t - x_{t-1}/(1/2)(x_{t-1} + x_t)$, which for positive values of x_t and x_{t-1} yield 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 $I_t/(1/2)(K_{t-1} + K_t)$, where I_t is the flow of capital expenditures (CAPX from Compustat) over the course of fiscal year t, and $(1/2)(K_{t-1} + K_t)$ 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 appendix, available online. 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. The appendix presents a battery of robustness tests on data and variable construction choices (e.g., variable definitions, filters, instrumental variables used, subsample analyses, and winsorization).

Table 2 reports summary statistics for the main sample of firm-year observations in 2SLS regressions.[13]

B. *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), some are negatively sensitive (e.g., airlines and energy-intensive manufacturing firms), and 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 nondirectionally 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 observes upward simultaneous shifts. Our strategy allows us to tease

the use of ATM options has the benefit of having the highest Black-Scholes vega (the sensitivity of options prices to implied volatility).

[13] Additional variables and summary statistics are presented in the appendix.

TABLE 2
Descriptive Statistics

	Mean	SD	Observations
Dependent:			
Investment rate$_{i,t}$	.229	.142	56,172
ΔIntangible investment$_{i,t}$	.057	.233	56,172
ΔEmployment$_{i,t}$	.024	.222	56,172
ΔCost of goods sold$_{i,t}$	.057	.277	56,172
ΔSales$_{i,t}$	.058	.263	56,172
ΔPayout$_{i,t}$	.054	.947	56,172
ΔDebt$_{i,t}$	.035	.688	56,172
ΔCash holdings$_{i,t}$	.045	.686	56,172
Independent:			
ΔRealized volatility$_{i,t-1}$	−.013	.308	56,172
ΔImplied volatility$_{i,t-1}$	−.020	.308	26,977

Note.—Table reports summary statistics for the main sample of firm-year observations in 2SLS regressions from 1993 to 2019. For variable details, see sec. II and the appendix.

out second-moment uncertainty effects while controlling explicitly for correlated first-moment effects, for example, control for economic downturns while isolating effects of heightened uncertainty. We extend the oil example to nine sources of uncertainty—oil, seven widely traded currencies, and policy—to generate nine 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-à-vis the euro, while identification comes from uncertainty suddenly increasing in the bilateral exchange rate.[14]

1. 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, seven currencies, and changes in daily policy uncertainty. That is, for firm i in industry j, $\text{sensitivity}_i^c = \beta_j^c$ is estimated as follows:

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

[14] 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 $r_{i,t}^{\text{risk\_adj}}$ 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, thus 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 $r_{i,t}^{\text{risk\_adj}}$ 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 the appendix). 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 seven widely traded currencies defined as "major" currencies by the Federal Reserve Board (FRB), and the growth in US economic policy uncertainty (EPU) from Baker, Bloom, and Davis (2016).[15]

2. Construction of Instruments

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

$$z_{i,t-1}^c = \left|\beta_{j,\tau}^c\right| \times \Delta\sigma_{t-1}^c. \tag{2}$$

For the volatilities, σ_{t-1}^c, of oil and the seven 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 the 252-day standard deviation of daily changes in bilateral exchange rates against the US dollar (foreign currency units per US$1; data from the FRB and

[15] See http://www.federalreserve.gov/pubs/bulletin/2005/winter05_index.pdf. These include the euro, Canadian dollar, Japanese yen, British pound, Swiss franc, Australian dollar, and Swedish krona. Each of these trade widely in currency markets outside their respective home areas and (along with the US dollar) are referred to by Board staff as major currencies.

downloaded from CRSP). For economic policy uncertainty, we use the 252-day average of trading-day EPU from Baker, Bloom, and Davis (2016).[16]

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 3 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 overlap 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 nine uncertainty instruments for firm-level lagged uncertainty shocks, $\Delta\sigma_{i,t-1}$, are $z^c_{i,t-1} = |\beta^c_{j,t-3}| \times \Delta\sigma^c_{t-1}$. In other words, this is the 3-year lagged cross-industry nondirectional exposure times the lagged change in volatility for oil prices, seven leading currencies, and policy uncertainty.[17] We show in the appendix 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).[18]

The baseline multivariate specifications include four important and extensive sets of controls. First are controls for the first-moment effects of each of the nine 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 $\beta^c_{j,t-3} \times r^c_{t-1}$, 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 $\Delta\sigma^c_{t-1}$).[19] These

[16] Trading days for EPU are defined as calendar days in which FRB exchange rate daily data are available from Wharton Research Data Services (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 appendix presents robustness tests using implied volatilities of the instruments instead of realized volatilities.

[17] For accuracy in matching the timing of firms' accounting reports and volatility with the instruments, the rolling-window sensitivities and the aggregate volatility shocks entering the instruments are timed to exactly match firms' accounting report dates (i.e., year-month of the datadate variable in Compustat). See the appendix for details on timing and measurement.

[18] In particular, each sensitivity, β^c_j, is adjusted by its statistical significance within each industry, $\beta^{c,\text{weighted}}_j = \omega^c_j \times \beta^c_j$. The sensitivity weight $\omega^c_j = |t^c_j|/\Sigma^c|t^c_k|$ 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% level set to zero.

[19] 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 gross domestic product (see variable A822RE1Q156NBEA from the St. Louis Fed, shares of GDP: government consumption expenditures and gross investment). This share is countercyclical and controls for first-moment economic effects (e.g., downturns when policy uncertainty is high).

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, that is, 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 Tangibility$_{i,t-1}$, Book leverage$_{i,t-1}$, Return on assets$_{i,t-1}$, and Firm size$_{i,t-1}$. Fourth, to account for potential autocorrelation in the eight outcome variables explored in the paper, we further include the 1-year lags for each: Investment rate$_{i,t-1}$, 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$_{i,t-1}$. Therefore, in addition to the full set of firm and time fixed effects, the baseline specification includes a total of 23 controls $X_{i,t-1}$ (nine aggregate first-moment controls, two firm-level first-moment controls, four standard controls in finance, and eight 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 allows 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 firms' real and financial activity.

III. 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 financial variables (debt, payout, and cash holdings).

A. Investment Results

Table 3 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 level, 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 1-unit increase in the growth of 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 2),

TABLE 3
FIRM INVESTMENT AND UNCERTAINTY SHOCKS

	OLS REALIZED		IV REALIZED		IV IMPLIED
INVESTMENT RATE$_{i,t}$	(1)	(2)	(3)	(4)	(5)
ΔVolatility$_{i,t-1}$	−.023***	−.024***	−.057***	−.041***	−.058**
	(.002)	(.002)	(.014)	(.014)	(.022)
Firm-level controls$_{i,t-1}$	No	No	No	Yes	Yes
IV$_{i,t-1}$ first-moment controls	No	No	Yes	Yes	Yes
Firm, time fixed effects	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
First-stage F-test			87.22	79.68	69.91
p-value Sargan-Hansen J-test			.462	.665	.572

NOTE.—Annual realized volatility is the 12-month standard deviation of firms' cum-dividend daily stock returns from CRSP and annualized by multiplying by $(252)^{1/2}$. Annual implied volatility is the 12-month average of firms' daily option-implied volatility from OptionMetrics. Standard errors are clustered by 2-digit SIC industry. See sec. II and the appendix for information on variable construction and data details.
** $p < .05$.
*** $p < .01$.

this is a decline of 10.04% per year. In standard deviation units, firm investment drops by 0.16 standard deviations in response to a 1-unit increase in shock to 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, inferences from OLS results are likely to suffer from endogeneity bias (see the appendix for how our instruments help address endogeneity). Therefore, columns 3 and 4 instrument firm-realized volatility shocks using the instrumentation strategy discussed in section II.B, with sample years 1993–2019. Column 3 is the 2SLS analogue of column 2 that includes the full set of first-moment aggregate controls to identify and disentangle the second-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% level) in firm-level investment rates that are larger than those 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 1.7–2.4 depending on model specification and controls included. Column 5 runs an analogue to column 4, but instrumenting firm level implied volatility shocks, with sample period 1998–2019.[20] 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 1-unit increase in the shock to volatility.[21]

Importantly, the instrumentation strategy across all 2SLS specifications in table 3 seems to work well, as seen by the large first-stage F-tests, with values ranging from 69.91 to 87.22, and a Sargan-Hansen overidentification J-test that does not reject the validity of the instruments, with p-values ranging from .462 to .665. The full 2SLS first-stage results are discussed and presented in the appendix.

In summary, table 3 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 2.5–3.6 percentage points, respectively. These may be modest compared with the unconditional mean of firm-level investment of 22.9% (see table 2) but large in comparison to the 3.3 percentage point total drop in aggregate investment during recessions.[22] 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 cols. 4 and 5, respectively).

B. Other Real and Financial Outcomes

Table 4 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 × XSGA)),[23] 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

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

[21] The raw coefficient on the growth in implied volatility in col. 5 (i.e., run on the raw sample of growth in implied volatility that has not first been rescaled to have the same standard deviation of growth in realized volatility in col. 4) is −0.093 with same significance at the 5% level.

[22] The average total drop in National Income and Product Accounts (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 4 quarters prior to the onset of a recession.

[23] Measured following Peters and Taylor (2017) as R&D + (0.3 × XSGA), where R&D is research and development in Compustat and 30% of XSGA (i.e., sales and general and administration expenses) is intangible investment (for details, see the appendix)

TABLE 4

REAL AND FINANCIAL OUTCOMES

	Investment Rate$_{i,t}$ (1)	ΔIntangible Investment$_{i,t}$ (2)	ΔEmployment$_{i,t}$ (3)	ΔCOGS$_{i,t}$ (4)	ΔSales$_{i,t}$ (5)	ΔCorporate Payout$_{i,t}$ (6)	ΔDebt$_{i,t}$ (7)	ΔCash holdings$_{i,t}$ (8)
	A. Baseline IV Regressions							
ΔVolatility$_{i,t-1}$	−.041***	−.052***	−.032*	−.151***	−.217**	−.423***	−.137**	.167**
	(.014)	(.016)	(.016)	(.019)	(.082)	(.085)	(.053)	(.067)
Firm-level controls$_{i,t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IV$_{i,t-1}$ first-moment controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm, time fixed effects	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
First-stage F-test	79.68	79.68	79.68	79.68	79.68	79.68	79.68	79.68
p-value Sargan-Hansen J-test	.665	.469	.538	.097	.279	.891	.073	.161
	B. Effect of a 2 SD Volatility Shock (of Size .616)							
Magnitude of effect	−.025	−.032	−.020	−.093	−.134	−.261	−.084	.103
Response of outcome in SD units	−.178	−.138	−.089	−.336	−.509	−.275	−.123	.150

NOTE.—Table presents 2SLS regressions. Volatility is the 12-month standard deviation of firms' cum-dividend daily stock returns from CRSP and annualized by multiplying by $(252)^{1/2}$. Standard errors clustered by the 2-digit SIC industry. See sec. II and the appendix for information on variable construction and data details.

* $p < .10$.

** $p < .05$.

*** $p < .01$.

sum 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 3. Using the same preferred 2SLS specification, columns 2–5 present the responses of the other real variables, while columns 6–8 present 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 nonmissing outcomes and controls guarantee that all columns in table 4 have the same firm-year sample and thus the same first-stage regression that shows a large first-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 (R&D, intellectual property, brand 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 IV reconciles and provides intuition into these dynamics in firms' 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 4 compares the magnitudes of the economic effects of uncertainty shocks on all the different outcomes, showing sizable magnitudes of responses, with, for example, a 2 standard deviation volatility shock leading to changes in real and financial activity typically between 0.1 and 0.3 standard deviations.

Overall, table 4 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 the 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.

C. *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 the appendix for data details. We expect that firms cut investment, $I/K_{i,t}$, after increased uncertainty shocks, $\Delta\sigma_{i,t-1}$, and that this cut is amplified further during periods of high aggregate Fin_index$_t$.

Table 5 presents the interaction results using our baseline 2SLS regression with the full set of controls and firm and time fixed effects. For comparison, column 1 repeats the noninteracted baseline regression discussed above and presented in column 1 of table 4. Column 2 presents the interaction of firm uncertainty and aggregate financial frictions.[24] 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 with years of normal aggregate financial frictions (i.e., a multiplier of $-0.045/-0.022 = 2.05$).

Second, we investigate whether 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, $D^{\text{fin.constrained}}_{i,t-5} = \{0, 1\}$, which is a dummy that takes the value one for firms classified as ex ante financially constrained using information in fiscal year $t - 5$ 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

[24] The yearly Fin_index$_t$ is collinear with the year fixed effects and so neither included nor reported. The specification has two endogenous terms (*a*) volatility shock and (*b*) its interaction with Fin_index$_t$, both of which are instrumented with two analogue sets of instruments: (*a*) the IVs and (*b*) their interaction with Fin_index$_t$. Controls, including first moment, are similarly interacted.

TABLE 5
EFFECT OF UNCERTAINTY SHOCKS AMPLIFIED BY FINANCIAL FRICTIONS

AGGREGATE FINANCIAL CONDITIONS INDEX$_t$	MOODY'S BAA-AAA CREDIT SPREAD				ROMER AND ROMER'S US FINANCIAL DISTRESS MEASURE	CHICAGO FED ANFCI INDEX	MOODY'S PLACEBO TESTS: FIN_INDEX SHIFTED $t-3$	
Investment rate$_{i,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta\sigma_{i,t-1}$	−.041***	−.022**	−.034***	−.023**	−.028**	−.027**	−.039***	−.031***
	(.014)	(.010)	(.012)	(.010)	(.012)	(.012)	(.013)	(.011)
$\Delta\sigma_{i,t-1} \times$ Fin_index$_t$		−.023**		−.019**	−.006	−.008	.008	.006
		(.009)		(.008)	(.007)	(.007)	(.007)	(.005)
$\Delta\sigma_{i,t-1} \times D_{i,t-5}^{\text{fin.constrained}}$			−.020***	.002	−.001	−.004		−.019***
			(.006)	(.009)	(.011)	(.010)		(.007)
$\Delta\sigma_{i,t-1} \times D_{i,t-5}^{\text{fin.constrained}} \times$ Fin_index$_t$				−.014***	−.016**	−.014***		.004
				(.005)	(.006)	(.005)		(.006)
Observations	56,172	56,172	56,172	56,172	56,172	56,172	56,172	56,172
First-stage F-test	79.68	27.25	58.30	39.45	44.25	36.71	35.88	36.74
p-value Sargan-Hansen J-test	.665	.531	.723	.509	.547	.665	.932	.844

NOTE.—Table presents 2SLS regression results of firm investment rate on changes in firm realized volatility of daily CRSP returns, $\Delta\sigma_{i,t-1}$, and its interaction with aggregate financial frictions indexes Fin_index$_t$ and with a firm-level dummy, $D_{i,t-5}^{\text{fin.constrained}}$, that takes value one for firms classified as ex ante financially constrained using information in year $t-5$, zero otherwise. Standard errors are clustered by 2-digit SIC industry. See sec. II and the appendix for information on variable construction and data details.

** $p < .05$.

*** $p < .01$.

of financial constraints. This financial constraint measure $D_{i,t-5}^{\text{fin.constrained}}$ 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 $t-5$;[25] 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.[26] In column 3, we see that, indeed, financially constrained firms show a significantly larger response to uncertainty (coefficient of -0.020), which is about 60% higher than nonconstrained firms, $(-0.020-0.034)/-0.034 = 1.59$.[27]

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, $D_{i,t-5}^{\text{fin.constrained}}$ (we also include all lower-level pairwise interactions and the financial constraint indicator but, for brevity, report only those coefficients involving uncertainty in the table).[28] 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 -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 levels 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 5. The figure uses the

[25] See, e.g., 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 WRDS, using variable SPLTICRM (S&P Domestic Long-Term Issuer Credit Ratings).

[26] 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; 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 a cutoff to classify firms.

[27] The indicator $D_{i,t-5}^{\text{fin.constrained}}$ is included but not reported for brevity. Moreover, the two endogenous terms involving firm volatility shocks are instrumented with two analogue sets of instruments: (*a*) the IVs and (*b*) their interaction with the indicator $D_{i,t-5}^{\text{fin.constrained}}$. Controls are similarly interacted.

[28] The specification includes four endogenous terms involving firm uncertainty shocks, which are instrumented with four sets of IVs with similar functional forms: (*a*) IVs, (*b*) the IVs interacted with Fin_index$_t$, (*c*) IVs interacted with firm indicator $D_{i,t-5}^{\text{fin.constrained}}$, and (*d*) the IVs in a triple interaction. Indicator $D_{i,t-5}^{\text{fin.constrained}}$ and its interaction with Fin_index$_t$ are also included but not reported for brevity. The specification in col. 4 therefore nests the models in cols. 3, 2, and 1.

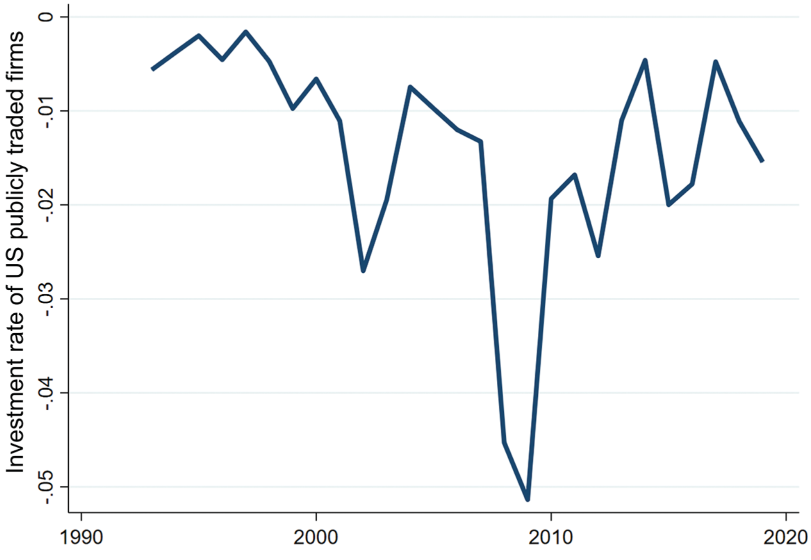

FIG. 2.—Implied effect of uncertainty shocks on investment rates of US publicly listed firms. The graph plots the average investment rate of all sample Compustat firms (weighted by tangible fixed assets) using the results from table 5, column 4, where the response of firms to uncertainty depends on both the binding of firm financial constraints (as measured by an index based on the consensus between S&P credit ratings, Whited-Wu, and size and age 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.

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 2008–9 crisis, because of both the worsening in the market-wide credit conditions and the binding of 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 one another—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 Federal Reserve Bank of Chicago's Adjusted National Financial Conditions Index (ANFCI) in column 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 two 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 1.4–1.6 percentage points more than otherwise similar, albeit less constrained firms.

In all, columns 4–6 indicate that the causal effects of uncertainty on investment differ 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 2008–9 financial crisis to instead be measured in 2005–6 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 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 noninteracted 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 5 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 III.B, 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 4.

IV. Model

The model features a large number 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 shown by 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.

A. 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 in which α is a constant, with $0 < \alpha < 1$.

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

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

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

in which ε_{t+1}^X is an i.i.d. standard normal aggregate productivity shock and $\varepsilon_{j,t+1}^z$ is 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

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

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

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, and 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.

B. *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 $R = 1/\beta$, that is, $R_n = \kappa R$, 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^S_{t+1} follows a constant elasticity of supply function,

$$N^S_{t+1} = \vartheta R^{\zeta}_{f,t}, \tag{11}$$

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

C. *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, in the manner of 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 (e.g., flotation costs—underwriting, legal and registration fees) and indirect (unobserved) costs due to asymmetric information and managerial incentive problems, among others.[29]

Because external financing costs will be paid only if payouts are negative, we define the firm's payout before financing cost ($e_{j,t}$) 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.[30] The microfoundations 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; 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 that changes in information symmetries between firms and investors are likely to vary over time.[31]

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

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

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

[29] These costs are estimated to be substantial. For example, Altinkilic and Hansen (2000) estimate the underwriting fee to range 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 that this price reduction as a fraction of the new equity issue is, on average, −31%.

[30] 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 likely be the primary cause for the reduction in firms' capital expenditures in 2007–8.

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

negative. Specifically, the external financing costs $\psi_{j,t}$ are assumed to be proportional to the proceeds raised:[32]

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

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.

D. *Firm's Problem*

We denote the firm's value function by $v(k_{j,t}, n_{j,t}, z_{j,t}, \sigma^z_{j,t}; X_t, \sigma^X_t, \eta_t, \mu_t)$. The state variables are given by (i) a firm's capital stock, $k_{j,t}$; (ii) a firm's cash holding $n_{j,t}$; (iii) the firm's idiosyncratic productivity, $z_{j,t}$; (iv) the current value of micro uncertainty, $\sigma^z_{j,t}$; (v) aggregate productivity, X_t; (vi) the current value of macro uncertainty, σ^X_t; (vii) the current value of financing wedge, η_t; and (viii) the joint distribution of idiosyncratic productivity, micro uncertainty, and firm-level capital stocks and cash holding, μ_t, which is defined for the space $\mathrm{S} = \mathrm{R}_+ \times \mathrm{R}_+ \times \mathrm{R}_+ \times \{0 \cup \mathrm{R}_+\}$.

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,

$$\mu_{t+1} = \Gamma(X_t, \sigma^X_t, \eta_t, \mu_t), \tag{16}$$

and $M_{t,t+1}$ is the stochastic discount factor from the household problem in section IV.E.

E. *Households*

There is a continuum of identical households of measure unity. Households choose consumption and investment in firm shares to maximize

[32] 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.

the lifetime utility. Let $\phi_{j,t}$ denote the shares households invest in firms. The household problem is given by

$$U_t = \max_{C_t, \phi_{j,t+1}} \{\log(C_t) + \beta \mathbb{E}_t U_{t+1}\}. \tag{17}$$

The household budget constraint is

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

where $q_{j,t}$ is 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

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

- Equity market clears

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

- Liquid asset market clears

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

V. Main Results

This section presents the model solution and the main results.[33] 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.

A. *Calibration*

The baseline parameters of the model are presented in table 6. We briefly discuss their calibration in this section and present a detailed discussion in the appendix.

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

TABLE 6
Predetermined Parameter Values under Baseline Calibration

Description	Notation	Value	Justification
Technology:			
Subjective discount factor	β	.988	Long-run average of US firm-level discount rate
Return on saving	κ	.97	97% of the subjective discount rate and cash/revenue ratio
Share on capital	α	.70	Cooper and Ejarque 2001; Hennessy and Whited 2007
Rate of depreciation for capital	δ	.05	Capital depreciation rate assumed 5% per quarter (Caballero and Engel 1999)
Fixed real adjustment cost	c_k	.03	Investment slope in the multivariate IV regression and cash/revenue ratio
Uncertainty shock (two-state Markov):			
Conditional macro volatility of productivity	σ_{L}^{X}	.0067	Baseline macro uncertainty (Bloom et al. 2018)
Conditional macro volatility in high uncertainty state	σ_{H}	.0107	Macro uncertainty shocks 1.6× baseline uncertainty (Bloom et al. 2018)
Transition probability low to high uncertainty	$\pi_{\mathrm{L,H}}^{\sigma^X}$	2.60%	Uncertainty shocks expected every 9.6 years (Bloom et al. 2018)
Transition probability remaining in high uncertainty	$\pi_{\mathrm{H,H}}^{\sigma^X}$	94.3%	Quarterly probability of remaining in high uncertainty (Bloom et al. 2018)
Conditional micro volatility of productivity	σ_{L}^{z}	.051	Baseline micro uncertainty (Bloom et al. 2018)
Conditional micro volatility in high uncertainty state	σ_{L}^{z}	.209	Micro uncertainty shocks 4.1 × baseline uncertainty (Bloom et al. 2018)
Transition probability low to high uncertainty	$\pi_{\mathrm{L,H}}^{\sigma^z}$	2.60%	Uncertainty shocks expected every 9.6 years (Bloom et al. 2018)
Transition probability remaining in high uncertainty	$\pi_{\mathrm{H,H}}^{\sigma^z}$	94.3%	Quarterly probability 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 (two-state Markov):			
Low fixed financial adjustment cost	η_{L}	.03	Investment slope in the multivariate IV regression and cash/revenue ratio
High fixed financial adjustment cost	η_{H}	.06	Investment slope in the multivariate IV regression and cash/revenue ratio
Transition probability low to high financing cost state	$\pi_{\mathrm{L,H}}^{\eta}$	5%	High financial cost state expected every 5 years (also tried $\pi_{\mathrm{L,H}}^{\sigma^X}$)
Transition probability remaining in high financing cost state	$\pi_{\mathrm{H,H}}^{\eta}$	50%	Expected length of high financial cost state for 2 quarters (also tried $\pi_{\mathrm{H,H}}^{\sigma^X}$)

Note.—Presented are the predetermined and the calibrated parameter values of the baseline model. Full details are in the appendix.

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 savings 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 $R_n = 97\% \, R$, $c_k = 0.03$, $\eta_{\mathrm{L}} = 0.03$, and $\eta_{\mathrm{H}} = 0.06$ to match the investment slope in the multivariate instrumental variables (IV) regression and the cash-to-revenue ratio in the data. The model-implied moments are -0.125 and 0.27, respectively, close to the data counterparts at -0.09 and 0.29. We also check the robustness of these parameters in section V.C. 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 $\sigma_{\mathrm{L}}^X = 0.0067$ and $\sigma_{\mathrm{L}}^Z = 0.051$, respectively; the high uncertainty state as $\sigma_{\mathrm{H}}^X = 1.6 \times \sigma_{\mathrm{L}}^X$ and $\sigma_{\mathrm{H}}^Z = 4.1 \times \sigma_{\mathrm{L}}^Z$; and transition probabilities of $\pi_{\mathrm{L,H}}^{\sigma^X} = 0.026$, $\pi_{\mathrm{L,H}}^{\sigma^Z} = 0.026$ and $\pi_{\mathrm{H,H}}^{\sigma^X} = 0.943$, $\pi_{\mathrm{H,H}}^{\sigma^Z} = 0.943$. Because there is no readily available estimate for the transition probabilities of financial shock in the data, we set $\pi_{\mathrm{L,H}}^{\eta} = 0.05$ and $\pi_{\mathrm{H,H}}^{\eta} = 0.50$ 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.[34]

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.[35]

B. *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. Figure 3 plots the optimal investment policies associated with low and

[34] 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 fig. 5.

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

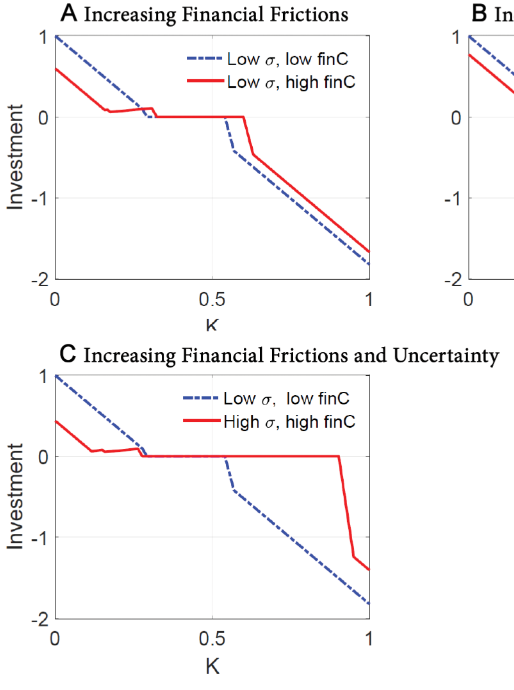

FIG. 3.—Investment policy functions. Plotted are the optimal investment policies associated with low and high financial adjustment costs states (*A*), low and high uncertainty states (*B*), and low and high financial adjustment costs and low and high uncertainty states (*C*) of the model with real adjustment costs and financial adjustment costs. In all panels, we fix the aggregate and idiosyncratic productivities, aggregate capital, and cash at their median grid points.

high financial adjustment costs states (fig. 3*A*), low and high uncertainty states (fig. 3*B*), and low-low financial and uncertainty states and high-high financial costs and uncertainty states (fig. 3*C*).[36] In all figures, we fix the aggregate and idiosyncratic productivities, aggregate capital, and firm cash at their median grid points.

In figure 3*A*, 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 cost 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

[36] We set both macro and micro uncertainties to either low or high state together in this analysis.

region in the high financing cost state, which arises when the firm is investing but only financed by internal funds. Turning to figure 3*B*, we see that the Ss band associated with high uncertainty states (both macro and micro uncertainty) is bigger than the low uncertainty state. Last, in figure 3*C*, 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 3*A*, 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 detail.

C. Inspecting the Mechanism

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

1. Impulse Responses

We simulate the impulse responses of the baseline model and the model with real frictions only. We run 500 simulations each with 230 periods and then kick both macro and micro uncertainties and/or financing costs up to their high level in period 201 and then let the model continue to run as before. Hence, we are simulating the response to a 1-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 as well as 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). Total factor productivity falls and recovers due to

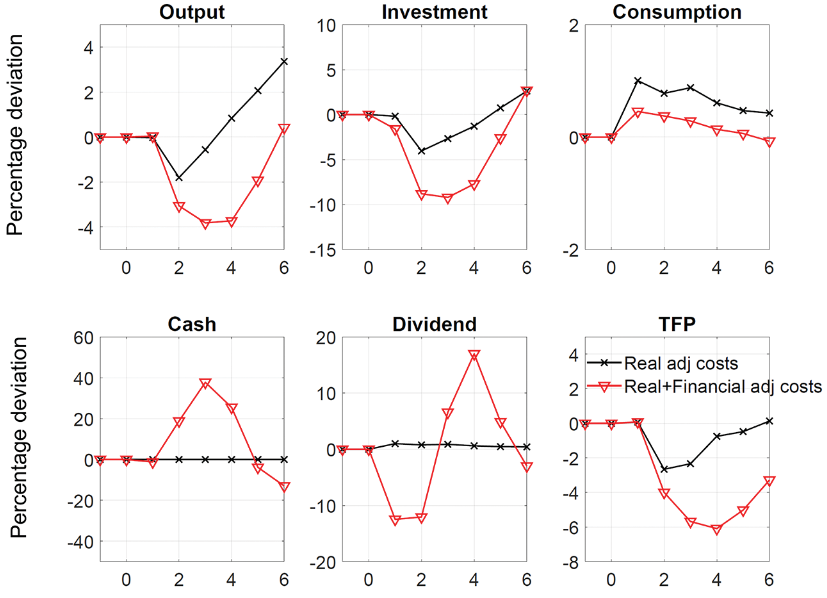

Fig. 4.—Impact of a pure uncertainty shock. We plot the percentage deviations of the average output, investment, consumption, cash, dividend, and aggregate total factor productivity (TFP) from their values in quarter 0 of two model specifications: (i) the model with real adjustment costs only (x's) and (ii) the benchmark model with both real and financial adjustment costs (triangles). All plots are based on 500 simulations of 200-quarter length. We impose an uncertainty shock in the quarter labeled 1, allowing normal evolution of the economy afterward.

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 a 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.[37]

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

[37] 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).

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. The duration of impact roughly triples compared with the baseline—output and investment fall for 3 periods rather than 1, while output remains below steady state for 4 periods rather than 2.

Robustness.—We examine robustness of results of our baseline model to changes in parameter values (details in the appendix). These changes 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) a 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) a 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 and investment (alongside rises in cash and drops in equity payouts), and adding in financial adjustment costs make the impact larger and more persistent.

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 from costlessly buffering uncertainty shocks via financial channels.[38]

VI. Conclusion

This paper studies the impact of uncertainty shocks on firms' real and financial activity. We first take endogeneity concerns in measuring the

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

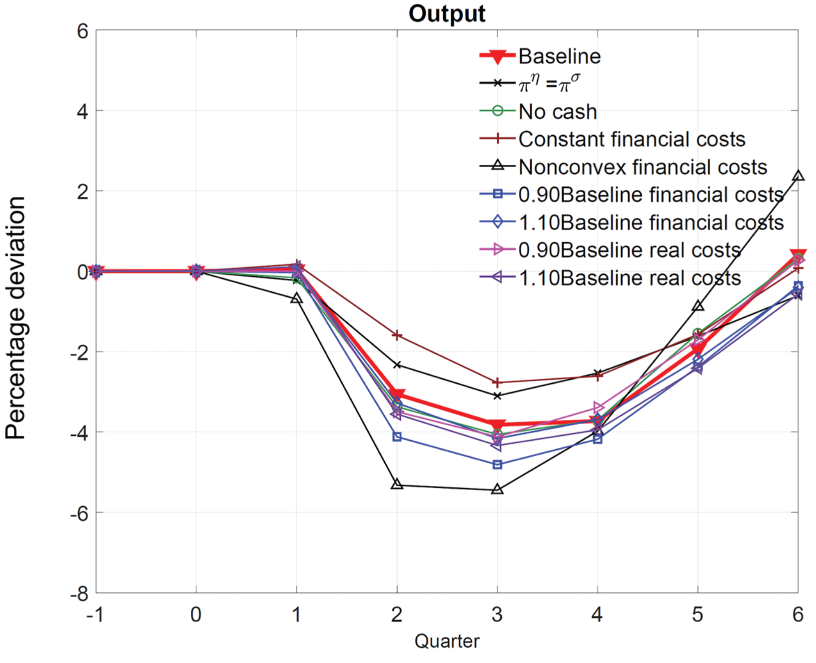

FIG. 5.—Robustness check of the impact of uncertainty shocks. We plot the percent deviations of average output from their values in quarter 0 of the benchmark model with both real and financial costs (baseline; inverted triangles), the model with the transition matrix of financial shocks the same as the uncertainty shocks (x's), the model without cash (circles), the model with constant financial costs (plus signs), and the model with nonconvex financial adjustment costs (triangles), the model with the financial adjustment costs as 90% of the baseline (squares), the model with the financial adjustment costs as 110% of the baseline (rhombuses), the model with the real adjustment costs as 90% of the baseline (right arrowheads), and the model with the real adjustment costs as 110% of the baseline (left arrowheads). All plots are based on the average of 500 simulations of 200-quarter length. We impose an uncertainty shock in the quarter labeled 0, allowing normal evolution of the economy afterward.

effects of uncertainty seriously by employing a novel instrumentation strategy that exploits cross-sectional nondirectional 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 goods 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 threefold during periods of increased financial frictions (e.g., 2008–9) compared with 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 that 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. Second, persistence—adding financial frictions roughly doubles the duration of drops after an uncertainty shock. This is because financial frictions lead firms to become more financially conservative after an uncertainty shock, reducing investment rates during the rebound. Finally, propagation—financial frictions spread the impact of uncertainty shocks to financial outcomes as well as real outcomes. In this model, uncertainty shocks not only reduce investment and hiring but also raise firms' cash holding, while cutting equity payouts. Collectively, these predictions of a large, persistent, and widespread impact of uncertainty shocks on real and financial variables matches the evidence from the recent financial crisis.

Given these, 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 2008–9 crisis, we should recognize and estimate their interactive amplification effects.

Data Availability

Code replicating the tables and figures in this article can be found in Alfaro, Bloom, and Lin (2023) in the Harvard Dataverse, https://doi.org/10.7910/DVN/0IRS7Z.

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