# Decoding the Pricing of Uncertainty Shocks*

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**Abstract**

Uncertainty affects business cycles and asset prices. We estimate firm-level productivity growth and decompose total uncertainty risk measured as cross-sectional productivity dispersion into macro uncertainty (an aggregate component) and micro uncertainty (an idiosyncratic component). We find that macro uncertainty is multidimensional, strongly countercyclical, and priced among stocks, but micro uncertainty is acyclical and not priced. Moreover, we show that the expected investment growth factor proposed in Hou, Mo, Xue, and Zhang (2021) captures macro uncertainty risk, which helps us understand the success of the $q^5$-model.

JEL classification: G12, E20, E24, E32, D24

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Uncertainty coincides with business cycles (Bloom, 2009; Fernández-Villaverde et al., 2015; Basu and Bundick, 2017; Bloom et al., 2018; Diercks et al., 2024),[1] and affects asset prices as well (Bansal and Yaron, 2004; Segal et al., 2015; Bali et al., 2017, 2021; Bretscher et al., 2023). Uncertainty includes both macroeconomic and microeconomic components. Previous studies such as Bloom et al. (2018) assign a significant role for micro uncertainty relative to macro uncertainty under the assumption that both are driven by a common latent process, i.e., these two components are related. However, these two uncertainty measures seem to be distinct as discussed in Kozeniauskas et al. (2018) and the empirical measure of micro uncertainty is often contaminated with macro uncertainty. Given that the distinction between them is understudied, this paper aims to fill this gap by examining these two components from an asset pricing perspective. We first estimate firm-level productivity growth and then decompose uncertainty risk measured as cross-sectional productivity growth dispersion into macro uncertainty (an aggregate component) and micro uncertainty (an idiosyncratic component). We find that macro uncertainty is strongly countercyclical and priced among stocks, but micro uncertainty is acyclical and not priced. This challenges the importance of micro uncertainty over business cycles. Moreover, we show that the expected investment growth factor proposed in Hou, Mo, Xue, and Zhang (2021) captures macro uncertainty risk.

To motivate our empirical work, we consider a simple production economy with time-varying productivity volatilities to study the impact of macro uncertainty on consumption, investment, and asset prices. There are two different and yet related fundamental shocks in this economy, namely, a productivity shock and an uncertainty shock. An interplay between productivity shocks and uncertainty shocks, similar to the leverage effect (e.g., Black, 1976; Christie, 1982; Harvey and Shephard, 1996), is crucial to our analysis. For example, in recessions, low productivity often accompanies high economic uncertainty. The increasing risk caused by high uncertainty leads to

[1]Many papers find that the cross-sectional dispersions of firm- or establishment-level variables, like productivity, output, prices, employment, and business forecasts, appear to be countercyclical (Bloom, 2009; Bachmann and Bayer, 2014; Bloom et al., 2018; David et al., 2022). But the causality is unclear, as Bloom et al. (2018) discuss. Uncertainty might lead to business fluctuations. Alternatively, uncertainty may arise endogenously from business cycles.

a higher expected stock return and a lower current investment rate, which in turn implies higher expected investment growth in the future. Therefore, both the investment rate and expected investment growth are necessary to capture these two fundamental shocks. This in turn implies that expected stock returns positively covary with expected investment growth via an uncertainty channel. We test this prediction with the expected investment growth (EG) factor proposed in the $q^5$-model of Hou et al. (2021). We find that the pricing power of the EG factor is driven by macro uncertainty risk. This provides an alternative way to understand the success of the EG factor and the $q^5$-model.

Empirically, we follow Bloom (2014) to measure uncertainty as time-varying volatilities. Uncertainty contains two components — macro and micro uncertainty shocks. Macro uncertainty refers to the aggregate uncertainty in the economy, which is often measured over an aggregate index such as aggregate productivity or stock market volatility. Macro uncertainty is countercyclical (Bloom et al., 2018) and its asset pricing power is well documented as it changes investors' future consumption growth and investment opportunities (Bansal and Yaron, 2004; Segal et al., 2015; Bali et al., 2017, 2021). In contrast, micro uncertainty captures uncertainty about idiosyncratic volatility, which is often measured with micro-level data. For example, Bloom et al. (2018) uses the cross-sectional dispersion of establishment- or firm-level productivity to measure micro uncertainty. However, their micro uncertainty measure is contaminated by macro uncertainty, since micro-level productivity contains both systematic and idiosyncratic productivity. This calls for a clean measure of micro uncertainty to help us understand whether micro uncertainty matters.

Guided by this observation, we use firm-level data to differentiate micro and macro economic uncertainty in two steps. First, we estimate firm-level total factor productivity growth ($\Delta TFP$) following Olley and Pakes (1996) and İmrohoroğlu and Tüzel (2014) at an annual frequency. Second, we apply an asymptotic principal component analysis to estimate the systematic and idiosyncratic components of TFP growth across all firms. We identify six principal components of productivity growth. Macro (Micro) uncertainty is measured as the cross-sectional standard deviation of systematic (idiosyncratic) productivity growth, while total uncertainty is measured as the cross-sectional standard deviation of TFP growth. Figure 1 demonstrates that macro uncertainty is countercyclical, with a correlation coefficient of -0.26 with industrial production growth, but micro uncertainty is almost acyclical. This suggests that macro uncertainty and not micro uncertainty relates to business cycles. A decomposition of macro uncertainty further shows that its time variation is driven almost entirely by fluctuations in the principal components rather than by changes in the cross-sectional dispersion of factor loadings, so macro uncertainty reflects aggregate shocks embedded in the common factors.

Using the annual non-tradable uncertainty factor, we run Fama-MacBeth two-pass regressions to test its pricing power. We augment five commonly used factor models with the total uncertainty factor, the macro uncertainty factor, or the micro uncertainty factor. The factor models include the Fama and French (1993) three-factor model (FF3), the Carhart (1997) four-factor model (FF4), the Fama and French (2015) five-factor model (FF5), the Fama and French (2018) six-factor model (FF6), and the Hou et al. (2015) $q$-factor model (HXZ). We find that macro uncertainty is negatively priced, with a price of -8.29% to -13.93% per year, but micro uncertainty is not priced. A head-to-head test confirms that the pricing power of total uncertainty operates through its macro component. When total uncertainty is orthogonalized against macro uncertainty, the residual carries no risk premium, whereas macro uncertainty orthogonalized against total uncertainty retains a negative price. Augmenting these factor models with a macro uncertainty factor improves their performance. For example, pricing errors are insignificant for the augmented FF5, FF6, and HXZ models. We also show that our macro uncertainty measure exhibits stronger pricing performance than the Jurado et al. (2015) uncertainty measure.

To allow for empirical tests at the monthly frequency, we construct mimicking factors for total uncertainty, macro uncertainty, and micro uncertainty following Adrian et al. (2014) and Chen and

Yang (2019). The monthly Sharpe ratios of the total uncertainty and macro uncertainty factors are sizable, -0.35 and -0.39, respectively, but micro uncertainty has a Sharpe ratio of only -0.03. Cross-sectional asset pricing tests further show that macro uncertainty is negatively priced. Small, high book-to-market, low investment rate, more profitable, high momentum, high expected investment growth, and low accruals stocks tend to have a negative loading on the macro uncertainty factor. Pricing errors are insignificant for the FF3, FF4, FF5, FF6 and HXZ models augmented with macro uncertainty. Our results are robust to different numbers of principal components, different base assets, tests for noisy factors, and the three-pass regression approach of (Giglio and Xiu, 2021).

We also show an economic linkage between macro uncertainty and the expected investment growth factor in Hou et al. (2021). First, we show that high expected investment growth firms are more exposed to macro uncertainty shocks. Second, we find that the predictors of expected investment growth in Hou et al. (2021) capture macro uncertainty, especially the operating cash flow component. Finally, we show that after controlling for macro uncertainty, the residual of the expected investment growth factor is not priced. Overall, we provide evidence that the expected investment growth factor captures macro uncertainty risk.

Our paper belongs to a growing literature on economic uncertainty. Bloom (2009), Fernández-Villaverde et al. (2015), Basu and Bundick (2017), Bloom et al. (2018), and Diercks et al. (2024) study the impact of uncertainty on business cycles. Kozeniauskas et al. (2018) shows that various macro uncertainty, micro uncertainty, and higher-order uncertainty measures are distinct and some are statistically uncorrelated. Dew-Becker and Giglio (2023) shows that cross-sectional uncertainty, measured using option data, does not forecast overall economic activity as well as aggregate uncertainty.

Other works examine the asset pricing implications of aggregate uncertainty shocks. For example, Bali and Zhou (2016) shows that economic uncertainty, proxied by the variance risk premium, is significantly priced. Dew-Becker et al. (2017), Berger et al. (2019), and Dew-Becker et al. (2021)

differentiate between uncertainty and realized variance using data from equity derivative markets. They show that realized variance has a negative premium, while aggregate uncertainty carries a zero or a positive premium. Segal et al. (2015) differentiate good and bad uncertainty arising from positive and negative industrial production growth. Bretscher et al. (2023) show that uncertainty shock affects risk premium, especially when it is combined with countercyclical risk aversion. Alfaro et al. (2024) consider real and financial frictions to amplify the impacts of uncertainty shocks. More closely related to our work, Bali et al. (2017) and Bali et al. (2021) find that macroeconomic uncertainty is priced in the cross section of stocks and corporate bonds using the Jurado et al. (2015) uncertainty index. Herskovic et al. (2023) consider uncertainties of aggregate consumption growth and firm-specific productivity shocks, and show that the former drives the size and the value premia while the latter contributes to the equity premium. Our paper contributes to this literature by differentiating macro and micro uncertainty and shows that micro uncertainty does not matter for asset prices.

Our paper also follows in the tradition of the production-based asset pricing literature such as Cochrane (1991, 1996), Zhang (2005), and Liu et al. (2009). The neoclassical theory of investment stresses that production risks drive stock risks. Hou et al. (2015) and Hou et al. (2021) construct pricing factors based on firm investment, profitability, and expected investment growth.[2] Our paper adds to this literature by studying the role of uncertainty risk and its relation to expected investment growth.

The rest of the paper proceeds as follows. Section 1 presents a production-based model to explore the linkage between uncertainty shocks, expected investment growth, and asset prices. Section 2 describes the data and the procedures used for estimating various uncertainty measures and their estimates. Section 3 presents cross-sectional asset pricing tests, using non-tradable uncertainty factors. Section 4 tests the pricing power of the uncertainty factors, using mimicking portfolios.

[2] Li et al. (2021) consider the impact of investment lags and show that aggregate expected investment growth negatively predicts future market returns due to firms' investment plans.

Section 5 explores the relationship between the macro uncertainty factor and the expected investment growth factor. Finally, Section 6 concludes.

# 1. Macro uncertainty shocks, expected investment growth, and asset prices: A motivating model

We consider a simple production economy to illustrate the role of uncertainty shocks on expected investment growth and asset prices.[3] We assume an all-equity representative firm that operates in discrete time with an infinite horizon. The firm generates output at time $t$ according to a constant returns to scale production function: $Y_t = X_t\, K_t$, where $Y_t$ is the firm's output, $X_t$ is total factor productivity which can be viewed as the economy's systematic productivity, and $K_t$ is the productive capital at the beginning of time $t$.

Logarithmic productivity, $ln\, X_t$, follows a first-order autoregressive model (AR(1)), with time-varying volatility $\sigma_t$:

$$\begin{aligned} ln\, X_{t+1} &= \rho_x\, ln\, X_t + \eta\, (\sigma_t^2 - \sigma^2) + \sigma_t\, \varepsilon_{x,t+1}, && (1) \\ \sigma_{t+1}^2 &= (1-\rho_\sigma)\, \sigma^2 + \rho_\sigma\, \sigma_t^2 + \upsilon\, \varepsilon_{\sigma,t+1}, && (2) \end{aligned}$$

where $0 < \rho_x < 1$ and $0 < \rho_\sigma < 1$ are AR(1) coefficients, $\sigma^2$ is the long-run average volatility, $\upsilon$ is a constant, and $\varepsilon_{x,t+1}$ and $\varepsilon_{\sigma,t+1}$ are i.i.d. $N(0,1)$ exogenous shocks. Eq. (2) assumes a stochastic volatility process (see, e.g., Fernández-Villaverde and Guerrón-Quintana (2020)) which describes the macro uncertainty shock. Similar to Bansal and Yaron (2004), for analytical tractability, we assume an AR(1) process for uncertainty.[4] We also assume $0 < \rho_\sigma < 1$, which is similar to the consecutive

[3]For simplicity, this model is not designed to capture all empirical features. See Appendix A for a general equilibrium model.

[4]Admittedly, the realizations of volatility could be negative in this case. This assumption can be easily relaxed by assuming the logarithmic volatility satisfies an AR(1) process or adopting an autoregressive gamma process for volatility.

uncertainty shocks considered by Diercks et al. (2024).[5] One important feature of the model is that uncertainty affects productivity growth, as captured by the second term in the right-hand side of Eq. (1). This is similar to the leverage effect (e.g. Black, 1976; Christie, 1982; Harvey and Shephard, 1996). Economic recessions often feature high uncertainty and low productivity contemporaneously with productivity increasing in the future. Therefore, high uncertainty is associated with low productivity contemporaneously but high productivity in the future, suggesting that $\eta > 0$ in Eq. (1).

Productive capital evolves as $K_{t+1} = I_t + (1-\delta)K_t$, with a quadratic capital adjustment cost of $\frac{a}{2}\left(\frac{I_t}{K_t}\right)^2 K_t$, where $I_t$ is time $t$ investment, $\delta$ is the depreciation rate, and $a$ is a constant.[6] The dividend is given by $D_t = Y_t - I_t - \frac{a}{2}\left(\frac{I_t}{K_t}\right)^2 K_t$. For a given stochastic discount factor $M_{t+i}$, the firm chooses the optimal investment to maximize the present value of future dividends:

$$\max_{I_t} \; D_t + \mathbb{E}_t \sum_{i=1}^{\infty} [M_{t+i} D_{t+i}]. \tag{3}$$

From the firm's first-order conditions, the marginal cost at time $t$ of adding an additional unit of productive capital at time $t+1$ is $1 + a\frac{I_t}{K_t}$, which defines the marginal $q$ at time $t$:

$$q_t \equiv 1 + a\frac{I_t}{K_t}. \tag{4}$$

The value of an additional unit of productive capital at time $t+1$ is $X_{t+1} + \frac{a}{2}\left(\frac{I_{t+1}}{K_{t+1}}\right)^2 + (1-\delta)\left[1 + a\left(\frac{I_{t+1}}{K_{t+1}}\right)\right]$, where the first term captures the marginal productivity, the second term captures the capital adjustment costs that are saved, and the last term captures the continuation value of

[5] Diercks et al. (2024) show that uncertainty shocks in consecutive periods are superadditive, i.e., amplifying uncertainty effects.

[6] We do not consider time-to-build. Chen (2016) and Li et al. (2021) consider investment lags.

productive capital. Therefore, the real investment return, $R^I_{t+1}$, is

$$R^I_{t+1} = \frac{X_{t+1} + \frac{a}{2}\left(\frac{I_{t+1}}{K_{t+1}}\right)^2 + (1-\delta)\left[1 + a\left(\frac{I_{t+1}}{K_{t+1}}\right)\right]}{1 + a\frac{I_t}{K_t}}. \tag{5}$$

Cochrane (1991) and Restoy and Rockinger (1994) show that stock returns equal real investment returns when production exhibits constant returns to scale. Therefore, Eq. (5) also computes the stock return $R_{t+1}$.

Using a log-linearized version of the economy, we solve for the investment rate, expected investment growth, and the expected stock return. Let $\hat{V}_t$ denote logarithmic deviations of variable $V$ from its steady state. Given the three state variables (productivity $\hat{X}_t$, productive capital $\hat{K}_t$, and uncertainty $\sigma_t^2$), optimal investment can be approximated as:

$$\hat{I}_t = I_0 + I_x\hat{X}_t + I_k\hat{K}_t + I_\sigma\sigma_t^2, \tag{6}$$

where $I_0$, $I_x$, $I_k$, and $I_\sigma$ are coefficients to be solved (in fact, $I_k = 1$ due to constant returns to scale production). Therefore, the optimal investment rate is

$$\widehat{\frac{I_t}{K_t}} = \hat{I}_t - \hat{K}_t = I_0 + I_x\hat{X}_t + I_\sigma\sigma_t^2. \tag{7}$$

Appendix A shows that $I_x > 0$ and $I_\sigma < 0$ under very mild technical conditions. That is, the investment rate increases with productivity shocks but decreases with uncertainty shocks. Expected investment growth is

$$\mathbb{E}_t\left[\widehat{\frac{I_{t+1}}{K_{t+1}}} - \widehat{\frac{I_t}{K_t}}\right] = I_\sigma(1-\rho_\sigma)\sigma^2 + (\rho_x - 1)\, I_x\hat{X}_t + \left[(\rho_\sigma - 1)\, I_\sigma + I_x\eta\right]\sigma_t^2. \tag{8}$$

As $I_x > 0$, $0 < \rho_x < 1$, $\eta > 0$, $I_\sigma < 0$ and $0 < \rho_\sigma < 1$, expected investment growth decreases with productivity shocks but increases with uncertainty shocks.

Log-linearizing Eq. (5) gives the expected stock return:

$$
\begin{aligned}
\mathbb{E}_t[\hat{R}_{t+1}] \;=\;& \left(h - \frac{a\delta}{1+a\delta}\right) I_0 + \left[hI_\sigma(1-\rho_\sigma) - \left(\frac{h}{a\delta} + hI_x\right)\eta\right]\sigma^2 \\
&+ \underbrace{\left[\frac{h}{a\delta}\rho_x + hI_x\rho_x - \frac{a\delta}{1+a\delta}I_x\right]\hat{X}_t}_{\text{productivity shock}} + \underbrace{\left\{\left[h\rho_\sigma - \frac{a\delta}{1+a\delta}\right]I_\sigma + \left(\frac{h}{a\delta} + hI_x\right)\eta\right\}\sigma_t^2}_{\text{uncertainty shock}}, \quad (9)
\end{aligned}
$$

where $h = \frac{a\delta}{2-\frac{a}{2}\delta^2+(a-1)\delta}$. Since $0 < h < \frac{a\delta}{1+a\delta}$, $0 < \rho_\sigma < 1$, $I_\sigma < 0$, $I_x > 0$ and $\eta > 0$, the expected stock return increases with uncertainty shocks.

In this economy, two fundamental risks drive the investment rate, expected investment growth, and the expected stock return, namely the productivity shock $\hat{X}_t$ and the uncertainty shock $\sigma_t^2$.[7] Taking Eq. (7), (8), and (9) together, we see that when there are productivity shocks only (i.e., no uncertainty shocks), either the investment rate or the expected investment growth rate alone is a sufficient statistic for productivity shocks. That is, either the investment rate or the expected investment growth rate is sufficient to fully capture expected stock returns. However, in the presence of uncertainty shocks, both the investment rate and expected investment growth are necessary and sufficient to fully capture these two shocks and hence expected stock returns. This suggests using firm characteristics such as the investment rate and expected investment growth rate as pricing factors. In other words, the pricing power of the investment factor and the expected investment growth factor in the $q^5$-model is due to their abilities to capture the fundamental risks, i.e., productivity shocks and uncertainty shocks. In a similar vein, other empirical factors (for example, the profitability factor) might also incorporate these two risk sources and appear to be priced.

Examining the impact of the uncertainty shock, i.e., the coefficients of $\sigma_t^2$ in Eq. (7), (8), and (9), we see that when uncertainty increases, the investment rate decreases while expected investment

[7] Again, due to constant returns to scale production, the capital stock does not affect expected stock returns, i.e., no size effect. Empirically, the capital stock generally matters for asset prices, providing a potential explanation of the size factor.

growth and the expected stock return increase. That is, investment and the stock return are negatively correlated while expected investment growth covaries positively with the expected stock return. This provides additional support to the investment factor and expected investment growth factor used in the $q^5$-model of Hou et al. (2021), i.e., via an uncertainty channel.

## 2. Estimating uncertainty shocks

Following Bloom et al. (2018), we first estimate firm-level total factor productivity growth ($\Delta TFP$), the productivity shock. The cross-sectional dispersion of TFP growth is then used as a total uncertainty measure. Next, we decompose total uncertainty into macro and micro uncertainty.

### *2.1. Estimating firm-level TFP and the total uncertainty*

We closely follow Olley and Pakes (1996) and İmrohoroğlu and Tüzel (2014) to estimate firm-level TFP. Olley and Pakes (1996) address two endogeneity issues involving TFP estimation. First, since input factors (labor and capital stock) are contemporaneously correlated, there is a simultaneity bias. They estimate the production function parameters for each input factor separately to address this bias. Second, there is a selection bias, because firms enter or exit the market depending on their productivity. Olley and Pakes (1996) assume TFP is a function of a firm's survival probability and include that in the TFP estimation. İmrohoroğlu and Tüzel (2014) apply Olley and Pakes (1996) to estimate firm-level TFP. We follow their estimation procedures with some modifications (see Appendix B for more details).

Assume a Cobb-Douglas production function:

$$Y_{it} = Z_{it} L_{it}^{\beta_L} K_{it}^{\beta_K}, \tag{10}$$

where $Y_{it}$, $Z_{it}$, $L_{it}$, and $K_{it}$ are value-added, productivity, labor, and capital stock of a firm $i$ at time $t$. The productivity contains both systematic and idiosyncratic components. Next, we scale the production function by its capital stock and take logarithms. We perform this scaling for three reasons. First, since TFP is the residual term, it is highly correlated with firm size. Second, the scaling avoids estimating the capital coefficient directly. Third, it mitigates an upward bias in the labor coefficient. Eq. (10) can be rewritten as

$$Log\frac{Y_{it}}{K_{it}} = \beta_L Log\frac{L_{it}}{K_{it}} + (\beta_K + \beta_L - 1)LogK_{it} + LogZ_{it}. \tag{11}$$

Denote $Log\frac{Y_{it}}{K_{it}}$, $Log\frac{L_{it}}{K_{it}}$, $LogK_{it}$, and $LogZ_{it}$ as $yk_{it}$, $lk_{it}$, $k_{it}$, and $z_{it}$. Also, let $\beta_L$ and $(\beta_K+\beta_L-1)$ be $\beta_l$ and $\beta_k$. Rewrite Eq. (11) as follows:

$$yk_{it} = \beta_l lk_{it} + \beta_k k_{it} + z_{it}. \tag{12}$$

We estimate the labor coefficient ($\beta_l$) and capital coefficient ($\beta_k$) using linear regressions. Then, the logarithmic TFP, $z_{it}$, is $yk_{it} - \beta_l lk_{i,t} - \beta_k k_{it}$. We use a 5-year rolling window to estimate TFP, then compute TFP growth ($\Delta TFP$) which measures productivity shocks. Similar to Bloom et al. (2018), we define the cross-sectional standard deviation of TFP growth at time $t$ as the cross-sectional TFP growth dispersion, i.e., total uncertainty (denoted as $UNC$). We take the first difference of this cross-sectional TFP growth dispersion as the total uncertainty shock (denoted as $\Delta UNC$). Note that this firm-level TFP growth dispersion is often used as micro uncertainty in the literature. However, as we show below, this measure contains macro uncertainty also.

We use annual Compustat data to estimate TFP for common stocks from the NYSE, Amex, and Nasdaq. To obtain stable estimates, following Bloom et al. (2018), we assume all firms follow the same production function. This will introduce some noise in our estimates, since production functions may vary across industries and over time. However, as we decompose total uncertainty into micro and macro components, we expect the measurement errors to be small, especially for macro uncertainty.

We include all firms except for financial and utility firms (four-digit SIC codes between 6000 - 6999 and between 4900 - 4999).[8] We exclude firms with assets or sales below \$1 million or year-end stock price lower than \$5. We also exclude firms with asset or sales growth rates exceeding 100% to avoid potential business discontinuities that might be caused by mergers and acquisitions. The sample period is from 1966 to 2016. The TFP estimates are from 1972 to 2016. The estimated labor coefficient $\beta_l$ is 0.56 and the estimated capital coefficient $\beta_k$ is 0.38. These estimates are similar to those reported in Olley and Pakes (1996), and are in line with neoclassical models (e.g., Bloom et al. (2018)).

### *2.2. Estimating macro and micro uncertainty*

Following Herskovic et al. (2016), we decompose firm-level TFP growth (productivity shocks) into systematic and idiosyncratic components via the asymptotic principal component analysis of Connor and Korajczyk (1987). This is analogous to the standard decomposition in the Arbitrage Pricing Theory (Connor and Korajczyk, 1988), where the systematic return of stock $i$ is $\beta_i' F_t$ (a product of firm-specific loadings and common factors). That is, we decompose firm-level TFP growth as follows:

$$\Delta \mathrm{TFP}_{i,t} = B_i' \times \mathrm{PC}_t + \varepsilon_{i,t}, \tag{13}$$

where $\Delta\mathrm{TFP}_{i,t}$ is the TFP growth of firm $i$ $(i = 1, 2, ..., N)$ at time $t$ $(t = 1, 2, ..., T)$, $\mathrm{PC}_t \in \mathbb{R}^k$ is a vector of $k$ aggregate shocks (principal components) at $t$, $B_i \in \mathbb{R}^k$ is the vector of firm-specific loadings for firm $i$, and $\varepsilon_{i,t}$ is an idiosyncratic shock to TFP growth, orthogonal to $\mathrm{PC}_t$.

To more precisely estimate the systematic components of TFP growth, we use firms with more than 10 years of data. We choose six principal components ($k$=6) for two reasons. First, statistically, Bai and Ng (2002) suggest six statistical criteria to determine the number of principal components,

[8] The results are qualitatively similar if we restrict our sample to manufacturing firms only.

including three panel $C_p$ criteria and three panel information criteria.[9] We apply their criteria, which suggest the number of principal components as six. Second, economically, Chen and Kim (2020) find that (1) there is a positive contemporaneous correlation between stock returns and systematic components of TFP growth; and (2) these six components are related to commonly used asset pricing factors. Overall, these findings suggest that there are multiple sources of productivity shocks and six principal components reasonably approximate the systematic productivity shocks.

After we estimate the systematic component of TFP growth (i.e., $B_i' \times PC_t$) and idiosyncratic TFP growth (i.e., $\epsilon_{i,t}$), we calculate the cross-sectional standard deviations of systematic TFP growth and idiosyncratic TFP growth, which we define as macro uncertainty and micro uncertainty, respectively. Although $k$ systematic components are common in origin, firms' exposures ($B_i$) to them are heterogeneous. In practice, firms face multiple aggregate shocks—such as investment-specific technology shocks (Papanikolaou, 2011), demand shocks, and policy shocks—and their structural characteristics determine how they respond to each. The cross-sectional dispersion of $B_i' \times PC_t$ therefore reflects the heterogeneous transmission of aggregate shocks ($PC_t$) across firms, not firm-specific idiosyncratic variation. We label this measure "macro uncertainty" to distinguish it from "micro uncertainty" (the dispersion of the idiosyncratic residual $\epsilon_{i,t}$), following the convention in the macro-finance literature (Bloom, 2009; Bloom et al., 2018; Kozeniauskas et al., 2018). Next, we take their first differences to compute macro and micro uncertainty shocks, denoted as $\Delta UNC^{ma}$ and $\Delta UNC^{mi}$, respectively. Although idiosyncratic productivity shocks are not themselves priced, it remains an open question if micro uncertainty is priced, since it may correlate with other priced state variables.

[9] Appendix C further discusses the eigenvalues and proportions of TFP growth variations explained by principal components. We see that the first principal component is insufficient and additional principal components are necessary to capture the TFP growth variations. Chen and Kim (2020) provide some empirical explanations of the six principal components.

## 2.3. Uncertainty estimates

Panel A of Table 1 shows that TFP growth ($\Delta TFP$) has a mean of 0.01 and a standard deviation of 0.21. TFP growth varies over both the cross section and the time series. The next three rows present descriptive statistics for uncertainty shocks. Total uncertainty ($\Delta UNC$) has a mean of 0.00 with a standard deviation of 0.05. Macro uncertainty ($\Delta UNC^{ma}$) has a larger standard deviation of 0.07, while micro uncertainty ($\Delta UNC^{mi}$) only has a standard deviation of 0.03. Figure 1 shows the time series of the uncertainty shocks and industrial production growth ($IP$), including total uncertainty, macro uncertainty, and micro uncertainty. We apply the band-pass filter of Christiano and Fitzgerald (2003) to these series. Similar to findings in Bloom et al. (2018), total uncertainty ($UNC$) is countercyclical, with a correlation coefficient of -0.10 with IP growth. Therefore, uncertainty is high during recessions. Moreover, we see that macro uncertainty ($UNC^{ma}$) is strongly countercyclical, with a correlation coefficient of -0.26, but micro uncertainty ($UNC^{mi}$) is barely correlated with IP growth, with a correlation coefficient of 0.004. Total uncertainty being countercyclical is mainly due to macro uncertainty.

A decomposition of macro uncertainty further shows that the time-series variation in $UNC^{ma}$ is mainly driven by the aggregate components $PC_t$ rather than by changes in the cross-sectional dispersion of factor loadings (see Appendix D). When the principal components are held fixed and only the cross-sectional distribution of loadings is allowed to vary, the resulting counterfactual measure is uncorrelated with the actual series and with the business cycle.

Next, we compare our uncertainty measures with other commonly used uncertainty measures in the literature, including Jurado et al. (2015) aggregate uncertainty (denoted as $UNC^{JLN}$ ), the aggregate uncertainty ($UNC^{agg}$) as in Bloom et al. (2018), and the VIX. We see that $UNC^{ma}$ positively correlates with $UNC^{JLN}$, $UNC^{agg}$, and VIX (with a correlation $\rho = 0.36, 0.32, 0.37$, respectively). But $UNC^{mi}$ barely correlates with them. Overall, we find that our macro uncertainty measure reasonably captures those aggregate uncertainty measures but not micro uncertainty (see

Appendix E for details).

Panel B of Table 1 summarizes the annual correlation coefficients between the uncertainty measures and cross-sectional asset pricing factors. We consider eleven pricing factors, including: (1) the six factors in Fama and French (2018) — the market portfolio (MKT), the size factor (SMB), the value factor (HML), the investment factor (CMA), the profitability factor (RMW), and the momentum factor (UMD); (2) the five factors from Hou et al. (2021) — the market portfolio (MKT), the size factor ($Q_{ME}$), the investment factor ($Q_{IA}$), the profitability factor ($Q_{ROE}$), and the expected investment growth factor (EG); and (3) the univariate mispricing factor (MIS) from Stambaugh and Yuan (2017).

Consistent with the predictions in Section 1, Panel B shows that total uncertainty ($\Delta UNC$) is positively related to the expected investment growth factor (EG) (a correlation coefficient of 0.29). We also see that macro uncertainty ($\Delta UNC^{ma}$) is highly correlated with $\Delta UNC$, with a correlation coefficient of 0.87. This high correlation is expected: in a factor model, the systematic component often explains the majority of total variance, so the dispersion of the systematic component naturally tracks total dispersion closely. This confirms that total uncertainty is primarily driven by macro uncertainty. Despite the high correlation, the decomposition provides a clear value-add: as we show in Section 3, micro uncertainty is not priced, and macro uncertainty subsumes the Jurado et al. (2015) measure while total uncertainty does not. Also, $\Delta UNC^{ma}$ has a pronounced correlation coefficient with EG, 0.25. Turning to micro uncertainty ($\Delta UNC^{mi}$), it has negative correlations with $\Delta UNC$ and $\Delta UNC^{ma}$. Also, $\Delta UNC^{mi}$ does not have a strong correlation with $EG$. Overall, Panel B provides evidence that $\Delta UNC^{ma}$ captures most of $\Delta UNC$ and both measures have a significant relationship with the EG factor.

# 3. Pricing of uncertainty shocks: Using annual non-tradable uncertainty factors

We run Fama-MacBeth two-stage regressions to examine the pricing power of uncertainty shocks using annual non-tradable uncertainty factors, including total uncertainty, macro uncertainty, and micro uncertainty. We use forty-five portfolios, including six size and book-to-market sorted portfolios, six size and operating profitability sorted portfolios, six size and investment sorted portfolios, six size and momentum sorted portfolios, six size and expected investment growth sorted portfolios, ten operating accrual sorted portfolios, and five Fama-French industry portfolios.[10] Following Lewellen et al. (2010), we add the pricing factors of tested factor models to test assets in order to restrict the price of risk to be equal to the average factor return. To ensure that uncertainty risk is strictly observable, we match the uncertainty estimates and stock returns with a six-month lag.

We augment the prevailing factor models with the total uncertainty factor, macro uncertainty factor, or micro uncertainty factor, and compare them to the prevailing factor models. Seven factor models are considered, including the Fama and French (1993) three-factor model (FF3), the Carhart (1997) four-factor model (FF4), the Fama and French (2015) five-factor model (FF5), the Fama and French (2018) six-factor model (FF6), the Stambaugh and Yuan (2017) mispricing factor model (SY),[11] the Hou et al. (2015) $q$-factor model (HXZ), and the Hou et al. (2021) $q^5$ model (HMXZ). We do not augment the Hou et al. (2021) $q^5$ model (HMXZ) since EG and $\Delta UNC^{ma}$ are highly correlated. We leave our discussion of the $q^5$ model for Section 5. For example, the total

[10] We download these portfolios from the following websites:
http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html; http://global-q.org/index.html.

[11] For the Stambaugh and Yuan (2017) mispricing factor model, we only perform asset pricing tests on monthly mimicking portfolios for the uncertainty factors in Section 4 as we do not have the constituent portfolios available to construct annual data.

uncertainty ($\Delta UNC$) augmented factor models are as follows:

$$
\begin{aligned}
\text{FF3+}\Delta UNC\text{:} \quad & R_{it} = \gamma_0 + \gamma_{MKT}\hat{\beta}_{MKT,i} + \gamma_{SMB}\hat{\beta}_{SMB,i} + \gamma_{HML}\hat{\beta}_{HML,i} + \gamma_{UNC}\hat{\beta}_{UNC,i} + \epsilon_{it}; \\
\text{FF4+}\Delta UNC\text{:} \quad & R_{it} = \gamma_0 + \gamma_{MKT}\hat{\beta}_{MKT,i} + \gamma_{SMB}\hat{\beta}_{SMB,i} + \gamma_{HML}\hat{\beta}_{HML,i} + \gamma_{UMD}\hat{\beta}_{UMD,i} + \gamma_{UNC}\hat{\beta}_{UNC,i} + \epsilon_{it}; \\
\text{FF5+}\Delta UNC\text{:} \quad & R_{it} = \gamma_0 + \gamma_{MKT}\hat{\beta}_{MKT,i} + \gamma_{SMB}\hat{\beta}_{SMB,i} + \gamma_{HML}\hat{\beta}_{HML,i} + \gamma_{CMA}\hat{\beta}_{CMA,i} + \gamma_{RMW}\hat{\beta}_{RMW,i} \\
& \quad + \gamma_{UNC}\hat{\beta}_{UNC,i} + \epsilon_{it}; \\
\text{FF6+}\Delta UNC\text{:} \quad & R_{it} = \gamma_0 + \gamma_{MKT}\hat{\beta}_{MKT,i} + \gamma_{SMB}\hat{\beta}_{SMB,i} + \gamma_{HML}\hat{\beta}_{HML,i} + \gamma_{CMA}\hat{\beta}_{CMA,i} + \gamma_{RMW}\hat{\beta}_{RMW,i} \\
& \quad + \gamma_{UMD}\hat{\beta}_{UMD,i} + \gamma_{UNC}\hat{\beta}_{UNC,i} + \epsilon_{it}; \\
\text{HXZ+}\Delta UNC\text{:} \quad & R_{it} = \gamma_0 + \gamma_{MKT}\hat{\beta}_{MKT,i} + \gamma_{Q_{ME}}\hat{\beta}_{Q_{ME},i} + \gamma_{Q_{IA}}\hat{\beta}_{Q_{IA},i} + \gamma_{Q_{ROE}}\hat{\beta}_{Q_{ROE},i} + \gamma_{UNC}\hat{\beta}_{UNC,i} + \epsilon_{it}; \\
\text{SY+}\Delta UNC\text{:} \quad & R_{it} = \gamma_0 + \gamma_{MKT}\hat{\beta}_{MKT,i} + \gamma_{MIS_{ME}}\hat{\beta}_{MIS_{ME},i} + \gamma_{MGMT}\hat{\beta}_{MGMT,i} + \gamma_{PERF}\hat{\beta}_{PERF,i} \\
& \quad + \gamma_{UNC}\hat{\beta}_{UNC,i} + \epsilon_{it}.
\end{aligned}
$$

We have similar equations for macro uncertainty ($\Delta UNC^{ma}$) or micro uncertainty ($\Delta UNC^{mi}$) augmented factor models.

In the first stage, we run the time-series regression of each model to estimate the factor loadings for each asset using the full sample. In the second stage, we run the cross-sectional regression of all test assets on the factor loadings each year and then compute the time-series average of the prices of risk. We adjust the $t$-statistics following Shanken (1992). We report the adjusted $R^2$ from Jagannathan and Wang (1996). Following Lewellen et al. (2010), we construct a sampling distribution of the adjusted $R^2$ by bootstrapping the time-series return data and factors by sampling with replacement to estimate the adjusted $R^2$. We repeat this procedure 10,000 times and report the $5^{th}$ and $95^{th}$ percentiles of the sampling distribution of the adjusted $R^2$. The testing period is from July 1973 to June 2018.

We report regression results for the total uncertainty factor in Panel A of Table 2. We find $\gamma_{UNC}$ is significantly priced across different factor models. The price of total uncertainty risk ranges from -9.32% to -4.55% per year. The total uncertainty factor also improves model fit. For example, after adding the total uncertainty factor to FF6, the intercept $\gamma_0$ becomes insignificant ($t$-statistic=1.52) while the adjusted $R^2$ increases from 0.71 to 0.78.

Panel B of Table 2 reports results for the macro uncertainty factor. First, we see that macro uncertainty is negatively priced in all models. The price of macro uncertainty risk $\gamma_{UNC^{ma}}$ is sizable, ranging from -13.93% to -8.29% per year across different augmented factor models. Second, we see that $\Delta UNC^{ma}$ improves model performance. For example, the pricing error is insignificant in FF5+$\Delta UNC^{ma}$ (0.71% per year, $t$-statistic=1.64) and FF6+$\Delta UNC^{ma}$ (0.58% per year, $t$-statistic=1.54). The results in Panels A and B of Table 2 are similar, which again suggests that the pricing power of total uncertainty is mainly from macro uncertainty risk. In Panel C of Table 2, we replace the macro uncertainty factor with the micro uncertainty factor. The price of micro uncertainty risk is negligible and insignificant.

Next, we run a horse race between the Jurado et al. (2015) uncertainty measure and our TFP-based uncertainty measures to alleviate concerns that the Jurado et al. (2015) uncertainty measure subsumes our measures. We estimate the uncertainty beta as Equation (1) of Bali et al. (2017) and construct the pricing factor ($UNC^{JLN}$) following Fama and French (1993). We use the Hou et al. (2015) $q$-factor model as the base model and augment it with Jurado et al. (2015) uncertainty ($UNC^{JLN}$), total uncertainty ($\Delta UNC$), macro uncertainty ($UNC^{ma}$), or micro uncertainty ($UNC^{mi}$). We run the Fama-MacBeth regressions, using the full-sample estimation. Panel A of Table 3 reports the results. Column (1) shows that $UNC^{JLN}$ is negatively priced, with a magnitude similar to the findings in Bali et al. (2017). Column (2) adds the total uncertainty factor, $UNC$. We see that $UNC$ is negatively priced, while $UNC^{JLN}$ remains marginally significant in Column (2). However, once we use macro uncertainty in Column (3), we see that $UNC^{JLN}$ becomes insignificant, while $UNC^{ma}$ is negatively priced. If we include micro uncertainty, Column (4) shows that $UNC^{JLN}$ remains significant but $UNC^{mi}$ is insignificantly priced.

Another concern is whether macro uncertainty contains pricing information beyond what total uncertainty already conveys, given the 0.87 correlation between the two measures. We address this by orthogonalizing each series against the other and re-running the pricing tests. We first regress total uncertainty on macro uncertainty and compute the residuals, denoted $UNC_{res}$. If the pricing power of total uncertainty is driven by macro uncertainty, the first differences $\Delta UNC_{res}$ should not be priced. Symmetrically, we regress macro uncertainty on total uncertainty and compute the residuals, denoted $UNC^{ma}_{res}$; if total uncertainty is too noisy, then $\Delta UNC^{ma}_{res}$ should remain priced. We again use the Hou et al. (2015) $q$-factor model as the base model and augment it with each pair of regressors. Panel B of Table 3 reports the Fama-MacBeth results. The price of $\Delta UNC_{res}$ is statistically indistinguishable from zero ($\gamma_{UNC_{res}} = 1.94$, $t = 1.16$), while the price of $\Delta UNC^{ma}$ remains significantly negative ($-11.15$, $t = -2.68$). Reversing the orthogonalization direction, the price of $\Delta UNC^{ma}_{res}$ remains negative ($-3.95$, $t = -1.83$). The orthogonalization direction therefore does not drive the result: total uncertainty contains no additional pricing information beyond macro uncertainty, while macro uncertainty carries incremental information beyond total uncertainty.

Overall, these results provide evidence that our TFP-based macro uncertainty factor explains the various test assets with a significantly negative price of risk, while the micro uncertainty factor does not.

## 4. Pricing of uncertainty shocks: Mimicking uncertainty factors

The previous section used annual non-tradable uncertainty factors to perform asset pricing tests. However, their statistical power might be limited by the sample size. We now construct monthly mimicking portfolios for the uncertainty factors. We use mimicking uncertainty factors as our main estimates in the rest of the paper as the monthly mimicking factors have more statistical power and allow us to perform additional empirical tests.

## 4.1. *Constructing mimicking uncertainty factors*

As the productivity dispersion shocks are annual, to construct monthly mimicking portfolios, we follow Adrian et al. (2014) and Chen and Yang (2019) by using a projection method. First, we project the uncertainty shocks ($\Delta UNC$) onto a set of annual base asset returns:

$$\Delta UNC = \kappa_{0,UNC} + \kappa'_{x,UNC} X_t^a + u_t, \tag{14}$$

where $X_t^a$ denotes the annual returns of some base assets in year $t$, and $\kappa_{0,UNC}$ and $\kappa_{x,UNC}$ are OLS regression coefficients.

We select base assets from Hou et al. (2015) and Hou et al. (2021) to track information in productivity dispersion. As discussed in Section 1 and confirmed in Panel B of Table 1, uncertainty is highly correlated with the investment factor, the profitability factor, and the expected investment factor. Therefore, we consider eighteen size, investment, and profitability-sorted portfolios (2-by-3-by-3) from Hou et al. (2015) as well as the EG factor from Hou et al. (2021) to extract as much information as possible from $\Delta UNC$.[12] However, we cannot include all eighteen portfolios as it induces a multicollinearity problem. Also, we are limited by degrees of freedom as we only have forty-five annual uncertainty shocks.

We start by projecting uncertainty shocks onto each of the eighteen portfolios and the EG factor. Then we select five of the eighteen portfolios that have significant coefficients. The base assets are $X_t^a$ = [BMH, BLL, BLM, SLM, BLH, EG]. For the first five portfolios, the first letter indicates the size group, small (S) or big (B); the second letter indicates the investment group, low (L), medium (M), or high (H); and the third letter indicates the profitability group, low (L), medium (M), and high (H). After we estimate $\kappa_{x,UNC}$ at an annual frequency, we normalize those coefficients: $\tilde{\kappa}_{x,UNC} = \frac{\kappa_{x,UNC}}{|\Sigma \kappa_{x,UNC}|}$. The denominator is the sum of the absolute value of the coefficients. The

[12]We further discuss the rational of using the EG factor as a base asset in Section 5. Limited by data availability, we do not consider the mispricing portfolio as a base asset.

last step is to build the mimicking uncertainty portfolio at a monthly frequency, by multiplying the normalized coefficients and the monthly base asset returns:

$$\Delta UNC_t = \tilde{\kappa}'_{x,UNC} X_t^m \tag{15}$$

where $X_t^m$ is the monthly returns of the base assets. When we construct the monthly uncertainty factor, we assume a six-month reporting gap between uncertainty shocks and stock returns, following Fama and French (1993). We use the monthly mimicking portfolios for the rest of asset pricing tests. We construct the mimicking macro (micro) uncertainty factor similarly, using the same base assets.

We estimate the coefficients of Eq. (14) using the full sample. The normalized coefficients are [0.08, -0.35, -0.23, 0.31, 0.11, -0.91]. We find that the EG factor coefficient is significant and its magnitude is large at 0.91.[13] We further explore this relationship in Section 5. Overall, the mimicking portfolio tracks total uncertainty well. The annual correlation coefficient between the total uncertainty shock and its mimicking portfolio is about 0.32. The annual correlation coefficient between the macro (micro) uncertainty shock and the mimicking macro (micro) uncertainty portfolio is 0.24 (0.29).

To avoid look-ahead bias, we also construct the mimicking uncertainty factors in an expanding window as a robustness test. The expanding window starts from 1997 to have a sufficient number of observations. That is, the weights of the mimicking uncertainty factor are estimated from 1972 to 1997 first, then we extend the estimation period up to 2016. To estimate the weights with enough degrees of freedom for the expanding window, we use five base assets: $X_t^a$ = [SLL, BMM, SLM, BLH, EG].

Appendix F shows that total uncertainty ($\Delta UNC$) has a mean of -0.79% per month with a monthly Sharpe ratio of $-0.35$. Macro uncertainty ($\Delta UNC^{ma}$) has a similar Sharpe ratio of -

[13] Note that the negative coefficient of -0.91 is due to normalization in $\tilde{\kappa}_{x,UNC}$.

0.39 as well as a mean of -0.82% per month. The monthly correlation between the mimicking portfolios of $\Delta UNC$ and $\Delta UNC^{ma}$ is 0.90. However, micro uncertainty ($\Delta UNC^{mi}$) has a very small Sharpe ratio of -0.03 per month. We test these three uncertainty factors against eight factor models, including the CAPM, FF3, FF4, FF5, FF6, HXZ, HMXZ, and SY. We find that both total uncertainty and macro uncertainty have significantly negative alphas from these models but micro uncertainty does not (see Appendix F for more details).

### *4.2. Fama-MacBeth regressions*

Our previous results show that macro uncertainty is a significant risk factor that is not explained by many prevailing factor models while micro uncertainty is captured by many models. Next, we explore the cross-sectional pricing power of $\Delta UNC^{ma}$ by running Fama-MacBeth two-pass regressions.[14]

Panel A of Table 4 reports the price of risk for each factor across different factor models, using the full-sample estimation.[15] First, we see that $\gamma_{UNC^{ma}}$ is negatively priced with coefficient estimates ranging from -0.82% to -0.80% across the different augmented factor models. Second, we see that adding the macro uncertainty factor to the prevailing factor models improves model performance. All of the augmented models have insignificant pricing errors. For example, the pricing error ($\gamma_0$) decreases from 0.33% ($t$-statistic=6.33) of FF3 to 0.00% ($t$-statistic=0.11) of FF3+$\Delta UNC^{ma}$. The pricing error ($\gamma_0$) decreases from 0.11% ($t$-statistic=2.81) of HXZ to 0.04% ($t$-statistic=1.34) of HXZ+$\Delta UNC^{ma}$. Their adjusted $R^2$s also increase after adding $\Delta UNC^{ma}$ to the models. For example, the $R^2$ increases from 0.19 of FF3 to 0.91 of FF3+$\Delta UNC^{ma}$. The $R^2$ increases from 0.51 of HXZ to 0.89 of HXZ+$\Delta UNC^{ma}$. Bootstrap simulations further confirm that adding $\Delta UNC^{ma}$ to the factor models improves their explanatory power. This suggests that

[14] Fama-MacBeth regressions use a set of test assets, so the results may be sensitive to the choice of test assets. Alternatively, in Appendix I we follow Barillas and Shanken (2017) and Fama and French (2018) and use the right-hand-side approach to compare various models, based on the maximum squared Sharpe ratio for model factors.

[15] Appendix G.1 reports the factor loadings from the time-series regressions.

$\Delta UNC^{ma}$ plays an important role in explaining the cross-sectional return variations across the test portfolios.

To avoid a look-ahead bias, we also use the expanding-window estimation and report results in Panel B of Table 4. Again, we see that $UNC^{ma}$ is negatively priced. In particular, we see that the pricing error becomes insignificant after adding the macro uncertainty factor to the FF3, FF4, FF5, and HXZ models.

For comparison, we replace the macro uncertainty factor ($\Delta UNC^{ma}$) with the micro uncertainty factor ($\Delta UNC^{mi}$) and report the results in Panels C and D of Table 4. Clearly, $\Delta UNC^{mi}$ does not contribute to the return variation of the test portfolios. First, $\gamma_{UNC^{mi}}$ is insignificant across all augmented factor models in Panels C and D. This is consistent with Panel E of Appendix Table F1, which reports the insignificant mimicking micro uncertainty factor. Second, comparing the prevailing factor models and the $\Delta UNC^{mi}$-augmented models, we see that $\gamma_0$ does not change much and is still significant. Third, the adjusted $R^2$ also shows little improvement after adding $\Delta UNC^{mi}$ in Panels C and D.

For completeness, we also consider three variations of uncertainty augmented factor models. First, we directly use the total uncertainty ($\Delta UNC$) to augment the prevailing models. We find qualitatively similar results, i.e., $\Delta UNC$ is negatively priced and the augmented models explain various test assets (see Appendix G.2 for more details). Second, we consider adding macro and micro uncertainty factors ($\Delta UNC^{ma}$ and $\Delta UNC^{mi}$) simultaneously to the prevailing models. We find that $\Delta UNC^{ma}$ is negatively priced while $\Delta UNC^{mi}$ is not priced (see Appendix G.3 for more details). Last, we consider using the aggregate uncertainty factor derived from aggregate TFP growth data ($UNC^{agg}$) or the VIX, which assumes uncertainty from a single source. We construct the mimicking aggregate uncertainty factor in a way similar to the mimicking macro uncertainty factor. We find that the aggregate uncertainty factor is negatively priced, but it performs worse than our macro uncertainty factor (see Appendix G.4 for more details). Overall, we conclude that adding the uncertainty factor improves the explanatory power of prevailing factor models and its price of risk is significantly negative in the cross section. More importantly, this is mainly driven by macro uncertainty, not micro uncertainty and it is important to model macro uncertainty from multiple sources.

### *4.3. Robustness checks*

#### *4.3.1. Different numbers of principal components*

In the main results, we choose the first six principal components ($PC$) to estimate macro and micro uncertainty based on the statistical criteria proposed in Bai and Ng (2002) and the economic reason in Chen and Kim (2020). Still, the choice of the number of $PC$s may be arbitrary. As a robustness check, we consider different numbers of $PC$s to decompose macro and micro uncertainty, and estimate their prices of risk under the Hou et al. (2015) $q$-factor model in Appendix H.1. We gradually increase the number of principal components. In Appendix Table H1, we see that as the number of $PC$ ($k$) increases, the price of macro uncertainty, $\gamma_{UNC^{ma}}$, becomes smaller. For example, when $k$ approaches 10, $\gamma_{UNC^{ma}}$ is marginally significant only. This suggests that as the number of $PC$ increases, macro uncertainty is more likely contaminated by micro uncertainty, so the pricing power of macro uncertainty decreases. Also, we see that $\gamma_{UNC^{mi}}$ is insignificant across all specifications. Overall, this suggests that our results are robust and it is important to differentiate micro uncertainty from macro uncertainty.

#### *4.3.2. Mimicking factors with alternative base assets*

We construct the mimicking uncertainty factors by selecting base assets from Hou et al. (2015) and Hou et al. (2021). One may wonder whether the pricing power is derived mechanically. For robustness, we choose six size and book-to-market sorted portfolios and the EG factor to construct mimicking portfolios, and then estimate the price of uncertainty risk. Appendix Table H1 presents the Fama-MacBeth regression results. We find that $\gamma_{UNC}$ and $\gamma_{UNC^{ma}}$ are both significantly negative but $\gamma_{UNC^{mi}}$ is still insignificant, which are similar to those reported in Table 4 (see Appendix H.2 for details).

### *4.3.3. Examining noisy factors*

The previous sections show that the uncertainty factor, in particular the macro uncertainty factor, explains various test assets. One might wonder whether our cross-sectional results are spuriously driven by noisy factors. Here we show that the uncertainty factors do not have explanatory power by chance. Similar to Adrian et al. (2014), we randomly draw the uncertainty factor with replacement. Then, we construct mimicking uncertainty portfolios and rerun the Fama-MacBeth two-pass regressions. Because we draw factors randomly, the noisy factors should not perform as well as the original uncertainty augmented factor models. We repeat this simulation 100,000 times and estimate how likely the noisy factors could perform relative to the original model in Appendix Table H3 (see Appendix H.3 for details). Overall, these results suggest that it is almost impossible for the noisy factors to achieve the same explanatory power as the original models. That is, the asset pricing power of macro uncertainty is not due to chance.

## *4.4. Pricing of uncertainty shocks: Three pass regressions*

Estimators from the classic two-pass regressions like Fama-MacBeth regressions or the mimicking portfolio approach could be affected by an omitted variable bias, since the controlling factors or the projected space may not correctly span the return space. Therefore, our previous tests might suffer from this limitation. To address this concern, we apply the three-pass regression approach proposed in Giglio and Xiu (2021) to estimate the risk premia of uncertainty shocks.

Giglio and Xiu (2021) use a large set of test assets to recover the entire factor space, which allows us to estimate risk premium of any factor even when other factors are omitted. We follow their three-step approach. First, we apply the principal component analysis (PCA) to a large panel of test asset returns to extract the principal components (PCs). Second, we run a cross-sectional regression of these PCs against test asset returns to find their risk premia. Third, we run a time series regression of our uncertainty measure on the PCs. Then, the price of uncertainty risk is the product of the PCs' risk premia in the second step and the loadings of uncertainty shock on PCs in the third step. We construct a large set of test assets as close to Giglio and Xiu (2021) as possible, which has 198 test assets.[16] Following Giglio and Xiu (2021), we use 7 latent factors.[17]

As a comparison, we estimate the price of risk for other pricing factors from the FF6 and HMXZ models as well. Table 5 presents the estimated risk premia. First, the $p$-values show that all factors are not weak factors, except the micro uncertainty factor. Second, we find that total and macro uncertainty are negatively priced, though their magnitudes are smaller than those reported in Panel B of Table 2. For example, $\Delta UNC^{ma}$ has a premium of -3.57% per year ($t$=-3.28). Third, we see that micro uncertainty is insignificant, i.e., the price of risk is only 0.26% per year ($t$=0.67). Overall, the results suggest that macro uncertainty is the main driver of uncertainty risk.

## 5. Interpreting the expected investment growth factor

Section 1 theoretically establishes the connection between uncertainty risk and the expected investment growth factor. Table 1 and Appendix Table F1 show that total uncertainty (macro uncertainty) is highly correlated with the expected investment growth factor (EG) from Hou et al. (2021). We now further explore empirically why the EG factor might capture uncertainty risk.

[16] These include (1) 25 investment and operating profitability sorted portfolios (downloaded from Kenneth French's library); (2) 10 book-to-market sorted portfolios, 10 expected investment growth sorted portfolios, 10 discretionary accruals sorted portfolios, 10 organizational capital sorted portfolios, 10 operating cash flow sorted portfolios, 10 changes in ROE sorted portfolios, and 10 sales-to-price sorted portfolios (downloaded from the q-data library: http://global-q.org/index.html); (3) 10 coskewness sorted portfolios, 10 inventory growth sorted portfolios, 10 cash-based operating profitability sorted portfolios, 10 intangible return sorted portfolios, 10 past trading volume sorted portfolios, 5 Dimson beta sorted portfolios, 5 quarterly cashflow-to-market sorted portfolios, 5 changes in financial liabilities sorted portfolios, 5 changes in net operating assets sorted portfolio, 5 net external financing sorted portfolios, 5 zero trades sorted portfolios, 5 firm age sorted portfolios, 5 book leverage sorted portfolios, and 3 one-year share issuance sorted portfolios (downloaded from Open Source Asset Pricing data library: http://www.openassetpricing.com/); (4) 10 abnormal returns sorted portfolios, following Chan et al. (1996).

[17] See Appendix H.4 for the robustness check, using 15 latent factors.

This helps us better understand the success of the EG factor and the $q^5$-model.

We first discuss the economic linkage between the EG factor and uncertainty risk. Then, we relate the cross-sectional dispersion of EG predictors to the uncertainty factor. Lastly, we compare the pricing power of the EG factor and the uncertainty factor.

### *5.1. The expected investment growth factor*

Hou et al. (2015) introduce the $q$-factor model which includes the market portfolio (MKT), the size factor ($Q_{ME}$), the investment factor ($Q_{IA}$), and the profitability factor ($Q_{ROE}$). Motivated by Eq. (5), Hou et al. (2021) further separate the numerator of Eq. (5) into the dividend yield, $[X_{it+1} + (a/2)(I_{it+1}/K_{it+1})^2]/[1+a(I_{it}/K_{it})]$, and the capital gain, $(1-\delta)[1+a(I_{it+1}/K_{it+1})]/[1+a(I_{it}/K_{it})]$, and suggest that the second part captures expected investment growth (EG). They propose the $q^5$ model by adding the EG factor to their $q$-factor model and demonstrate its empirical success by explaining many test portfolios and other pricing factors.

We replicate the EG factor by following Hou et al. (2021). To predict expected future investment growth, Hou et al. (2021) run Fama-MacBeth regressions, using weighted least squares with market capitalization, as follows:

$$d\left(\frac{I_{it}}{K_{it}}\right) = \beta_0 + \beta_Q \, log \, Q_{it-1} + \beta_{CoP} \, CoP_{it-1} + \beta_{dROE} \, dROE_{it-1} + \epsilon_{it}, \tag{16}$$

where $d\left(\frac{I_{it}}{K_{it}}\right)$ is the first difference of the investment-to-assets of firm $i$ at time $t$, $Q$ is Tobin's $q$, $CoP$ is the operating cashflow, $dROE$ is the first difference between current $ROE$ and the four-quarter-lagged $ROE$. They estimate the regression coefficients using a 120-month rolling window and estimate the predicted future investment growth as follows:

$$E_t[dI_{it+1}/K_{it+1}] = \hat{\beta}_0 + \hat{\beta}_Q \, logQ_{it} + \hat{\beta}_{CoP} \, CoP_{it} + \hat{\beta}_{dROE} \, dROE_{it}. \tag{17}$$

After estimating Eq. (17), they sort stocks on size and $E_t[dI_{it+1}/K_{it+1}]$ into 2-by-3 portfolios. They then construct the expected investment growth factor (EG) as the difference between the average returns of two high $E_t[dI_{it+1}/K_{it+1}]$ portfolios and the average returns of two low $E_t[dI_{it+1}/K_{it+1}]$ portfolios, following Fama and French (1993). During our sample period, the EG factor has a mean of 0.81% per month, a standard deviation of 2.02%, and an annual Sharpe ratio of 0.40. Also, untabulated results show that the prevailing factor models cannot explain the EG factor.[18]

Why is the EG factor highly correlated with the uncertainty factor? First, we see from Eq. (8) that uncertainty contributes to expected investment growth. In fact, after controlling for other pricing factors, the EG factor mainly captures uncertainty risk. Second, the empirical measure of expected investment growth captures the cross-sectional dispersion of productivity. When predicting the future investment growth in Eq. (17), the coefficients of the Fama-MacBeth regressions depend on the cross-sectional variation of each predictor and these cross-sectional variations embed productivity dispersion. For example, productivity dispersion clearly affects the cross-sectional variations of Tobin's $q$, operating cash flows, and ROE. Therefore, the EG factor constructed from running Fama-MacBeth regressions can capture productivity dispersion.[19] That is, we expect that productivity dispersion is significantly correlated with the cross-sectional dispersions of the three predictors in Eq. (16). We next empirically verify these two reasons.

### *5.2. Macro uncertainty and expected investment growth*

Although high uncertainty accompanies low TFP contemporaneously, high uncertainty leads to higher TFP growth in the future, as captured in Eq. (1). Meanwhile, Eq. (8) suggests that expected investment growth increases with uncertainty. Taken together, this suggests that firms

[18] Appendix J examines the pricing power of each EG predictor.

[19] Bachmann and Bayer (2014) show that shocks to productivity dispersion can generate procyclical cross-sectional investment rate dispersion. This implies that expected investment growth can be driven by productivity dispersion shocks.

with higher expected investment growth are more exposed to uncertainty shocks. We test these predictions by running a panel regression as follows,

$$\Delta TFP_{i,t} = \beta_0 + \beta_1 \Delta UNC_{t-1} + \beta_2 \Delta UNC_{t-1} \times HighEG_{i,t-1} + \beta_3 HighEG_{i,t-1} + \mathbf{Z}_{t-1} + \epsilon_{i,t} \quad (18)$$

where $\Delta TFP_{it}$ is the productivity growth of firm $i$ in year $t$, $\Delta UNC_{t-1}$ is uncertainty shock (total uncertainty, macro uncertainty, or micro uncertainty) in year $t-1$, $HighEG$ is an indicator variable which equals one if its expected investment growth is in the top tercile and 0 otherwise, and $\mathbf{Z}_{t-1}$ is a vector of control variables, including the logarithmic market capitalization (Size), Tobin's $q$, investment-to-assets ratio (I/A), and operating cashflow (CoP). We also include the firm and year fixed effects, and the standard errors are clustered by firms.

Table 6 presents the regression results. First, we find that lagged uncertainty is positively related to high productivity in the next period. This is consistent with Eq. (1). For example, in Column (1), where we use total uncertainty ($\Delta UNC$), it has a statistically significant positive coefficient on $\Delta TFP$. In Columns (2)–(4), we find that macro uncertainty ($\Delta UNC^{ma}$) is positive and statistically significant while micro uncertainty ($\Delta UNC^{mi}$) is insignificant. Second, high expected investment growth, $HighEG$, is also positively related to future productivity, as shown in Eqs. (1) and (8). Lastly, we find that the interaction term is positive and significant. For example, in Column (2), the interaction term between $\Delta UNC^{ma}$ and $HighEG$ has a coefficient of 0.05 ($t$=2.15), suggesting that stocks with high expected investment growth are more exposed to macro uncertainty shocks.

Next, we explore which expected investment growth predictors capture uncertainty risk. In each year, we calculate the cross-sectional standard deviation of each predictor in Eq. (16). Then, we run time-series regressions of the cross-sectional dispersions of the three predictors against macro uncertainty ($UNC^{ma}$) in Panel A of Table 7. First, $UNC^{ma}$ explains the cross-sectional dispersions of the three EG predictors quite well. For example, $UNC^{ma}$ explains the cross-sectional dispersion of operating cash flows ($DIS_{CoP}$) with a coefficient of 0.28 ($t$-statistic=3.21) and an $R^2$ of 0.42.

This suggests that $UNC^{ma}$ alone explains the cross-sectional variation of operating cash flows well. Also, $UNC^{ma}$ explains the cross-sectional dispersions of Tobin's Q ($DIS_Q$) and changes in ROE ($DIS_{dROE}$). The $R^2$ for $DIS_Q$ and $DIS_{dROE}$ are 0.25 and 0.38, respectively.[20]

In Panel B, we run similar regressions using micro uncertainty ($UNC^{mi}$). The regression results show that $UNC^{mi}$ explains little of the cross-sectional dispersion of the EG predictors, as $UNC^{mi}$ is insignificant in all regressions and the highest $R^2$ is only 0.11. Therefore, micro uncertainty cannot capture the same fundamental risks of the EG factor since it is not correlated with the cross-sectional dispersion of the EG predictors.

### *5.3. Comparing the EG factor and the uncertainty factor*

We now directly test whether expected investment growth contains information other than uncertainty risk. We decompose expected investment growth into predicted and residual components by regressing expected investment growth on macro uncertainty. Following Hou et al. (2021), we match the non-tradable $\Delta UNC^{ma}$ factor to firm-level expected investment growth with at least a four-month reporting gap. We regress expected investment growth on $\Delta UNC^{ma}$ for each firm, using the full sample.[21] We sort all stocks into decile portfolios based on either their predicted or residual component of expected investment growth. Portfolio 10 (1) has the highest (lowest) predicted or residual component of expected investment growth. We compute value-weighted portfolio returns and their alphas for the host of cross-sectional asset pricing models previously considered.

Panel A of Table 8 presents results for the ten portfolios sorted by the predicted component of expected investment growth. Similar to Hou et al. (2021), the portfolio raw returns monotonically increase with the predicted component of expected investment growth. The long-short portfolio (i.e., Portfolio 10 - Portfolio 1) has an average return of 0.89% ($t$-statistic = 3.59) per month. Its alpha is also significantly positive from all benchmark models. For example, the long-short

[20] We find similar results for total uncertainty. See Appendix K for more details.

[21] To avoid look-ahead bias, we also use an expanding-window to decompose expected investment growth into predicted and residual components and find similar results. See Table L1 in Appendix L.

portfolio has an alpha of 0.91% ($t$-statistic=4.79) and 0.86% ($t$-statistic = 4.07) for the FF6 and HXZ models, respectively. That is, we see that stocks with higher predicted component of expected investment growth have higher expected returns and the predicted component is not captured by existing pricing factors.

Panel B shows that the residual component of expected investment growth does not generate significant alphas relative to the FF6, HXZ, and SY models. While the long-short portfolio has a significant average return of 0.77% per month ($t$-statistic=3.63), its risk-adjusted alphas for the FF6, HXZ, and SY models are insignificant. That is, the residual component of expected investment growth does not provide additional information beyond existing asset pricing factors. Therefore, we see that the pricing power of EG is driven by macro uncertainty risk. Appendix M further shows that the FF3, FF4, FF5, FF6, HXZ, and SY augmented with macro uncertainty can fully explain the EG factor.

We further compare the pricing power of the EG factor and the uncertainty factor by comparing the Hou et al. (2021) $q^5$ model (HMXZ) with the macro uncertainty-augmented HXZ model (HXZ+$\Delta UNC^{ma}$) and the micro uncertainty-augmented HXZ model (HXZ+$\Delta UNC^{mi}$). Panels A and C of Table 4 report the prices of risk and the pricing errors of the Fama-MacBeth regressions, using the full-sample estimation. First, the pricing error ($\gamma_0$) from HMXZ is 0.07% ($t$-statistic=2.10) while that of HXZ+$\Delta UNC^{ma}$ is 0.04% ($t$-statistic=1.34) in Panel A. Again, $\Delta UNC^{mi}$ does not play a role in the regressions as $\Delta UNC^{mi}$ is insignificant in Panel C. Second, $\gamma_{EG}$ is 0.79% ($t$-statistic=7.70) in the HMXZ model while $\gamma_{UNC^{ma}}$ is -0.81% ($t$-statistic=-7.89) in the HXZ+$\Delta UNC^{ma}$ model. That is, EG and $\Delta UNC^{ma}$ have similar magnitudes in the price of risk but with opposite signs, consistent with the negative correlation between the two factors.

In Panels B and D of Table 4, we estimate the price of risk using the expanding-window estimation. The main results are qualitatively similar to those in Panels A and C. The $\gamma_0$ from HMXZ is 0.06% ($t$-statistic=0.96) while that from HXZ+$\Delta UNC^{ma}$ is 0.09% ($t$-statistic=1.50).

Also, $\gamma_{EG}$ and $\gamma_{UNC^{ma}}$ are 0.61% ($t$-statistic=3.32) and -0.68% ($t$-statistic=-3.75), while $\gamma_{UNC^{mi}}$ is -1.47% ($t$-statistic=-0.71).[22] Overall, we see that the Hou et al. (2015) $q$-factor model augmented with the macro uncertainty factor performs similarly to the Hou et al. (2021) $q^5$-factor model (HMXZ).

We close this section by concluding that the expected investment growth factor captures macro uncertainty risk. This contributes to the pricing power of the expected investment growth factor and the success of the $q^5$-model.

## 6. Conclusions

Both macro and micro uncertainty affect real economic activities. To match business cycle statistics, the macroeconomic literature often assumes a prominent role for micro uncertainty which is measured from the firm-level data, without acknowledging that micro uncertainty might be proxying for macro uncertainty in this measurement. In this paper, we use firm-level productivity estimates to decompose total uncertainty into macro and micro uncertainty. We find that macro uncertainty is strongly countercyclical and priced among a cross section of stocks, but micro uncertainty is almost acyclical and not priced. During recessions, both macro uncertainty and the price of macro uncertainty risk increase. Overall, our results from financial markets cast doubt on the importance of micro uncertainty on the business cycle.

Macro uncertainty appears to be a missing factor in prevailing factor models. Moreover, we find that macro uncertainty risk drives the pricing power of the expected investment growth factor proposed in Hou et al. (2021), because uncertainty affects both expected returns and expected investment growth. Empirically, both uncertainty and EG predictors, in particular operating cash flows, capture cross-sectional productivity dispersion. This suggests an alternative way to understand the success of the EG factor and the $q^5$-model.

[22] As a robustness check, we replace macro uncertainty ($\Delta UNC^{ma}$) with total uncertainty ($\Delta UNC$) in Appendix N and find similar results.

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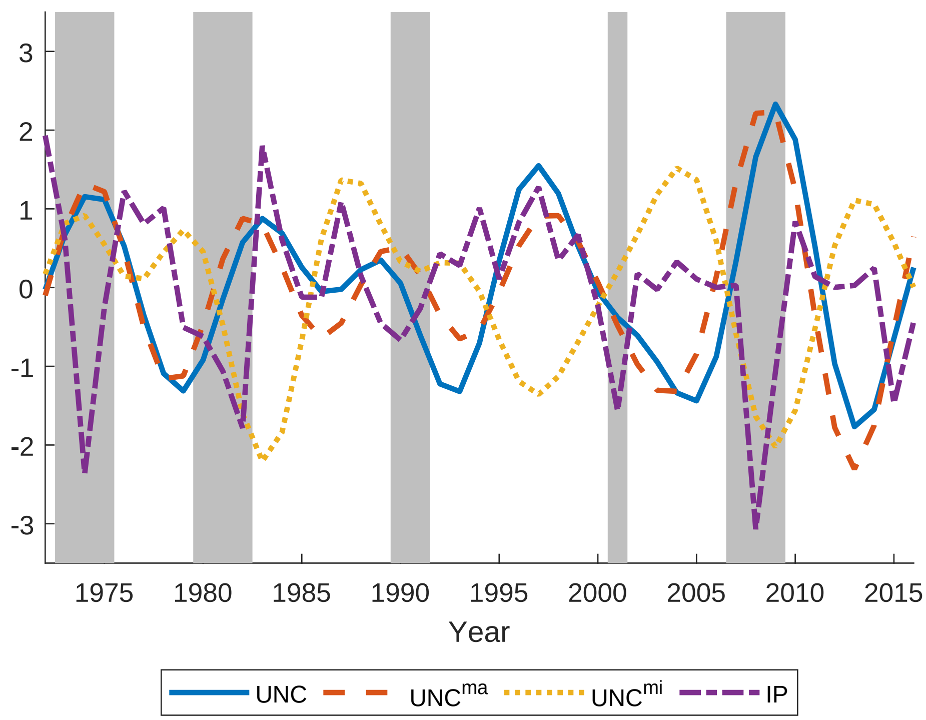


Fig. 1. Uncertainty and industrial production growth

This figure plots the time series of total uncertainty ($UNC$), macro uncertainty ($UNC^{ma}$), and micro uncertainty ($UNC^{mi}$) against the annual log industrial production (IP) growth in the United States. Series are computed from Christiano and Fitzgerald (2003) band-pass filter and standardized. The shaded areas are NBER recession periods.

Table 1. **Uncertainty factors: Descriptive statistics and relations with other pricing factors**

Panel A summarizes annual TFP growth ($\Delta$TFP), the first-difference of the cross-sectional standard deviation of TFP growth (total uncertainty, $\Delta UNC$), systematic TFP growth (macro uncertainty, $\Delta UNC^{ma}$), and idiosyncratic TFP growth (micro uncertainty, $\Delta UNC^{mi}$), including the mean, standard deviation, percentiles, and the correlation with industrial production (IP) growth ($\rho(IP)$), Jurado et al. (2015) uncertainty ($\rho(UNC^{JLN})$), the aggregate uncertainty ($\rho(UNC^{agg})$) as in Bloom et al. (2018), and the VIX ($\rho(VIX)$). We regress firm-level TFP growth on six principal components of TFP growth for each firm and define predicted (residual) TFP growth as systematic (idiosyncratic) TFP growth. Panel B reports the annual time-series correlation coefficients between various uncertainty measures and pricing factors. The sample of uncertainty estimates is from 1972 to 2016.

Panel A: TFP growth and its uncertainty measures

| | Mean | S.D. | Min | Max | 10% | 25% | 50% | 75% | 90% | AR(1) | $\rho(IP)$ | $\rho(UNC^{JLN})$ | $\rho(UNC^{agg})$ | $\rho(VIX)$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\Delta$TFP | 0.01 | 0.21 | -0.71 | 2.03 | -0.21 | -0.10 | -0.01 | 0.09 | 0.22 | -0.08 | | | | |
| $\Delta UNC$ | 0.00 | 0.05 | -0.15 | 0.14 | -0.05 | -0.01 | 0.01 | 0.02 | 0.04 | -0.53 | -0.10 | 0.20 | 0.29 | 0.38 |
| $\Delta UNC^{ma}$ | 0.00 | 0.07 | -0.23 | 0.19 | -0.07 | -0.02 | 0.01 | 0.03 | 0.07 | -0.60 | -0.26 | 0.36 | 0.32 | 0.37 |
| $\Delta UNC^{mi}$ | 0.00 | 0.03 | -0.05 | 0.07 | -0.04 | -0.01 | 0.00 | 0.02 | 0.04 | -0.66 | 0.00 | -0.09 | -0.13 | -0.18 |

Panel B: Correlations between TFP uncertainty and pricing factors

| | MKT | SMB | HML | CMA | RMW | UMD | $Q_{ME}$ | $Q_{IA}$ | $Q_{ROE}$ | EG | MIS | $\Delta UNC$ | $\Delta UNC^{ma}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| MKT | 1.00 | | | | | | | | | | | | |
| SMB | 0.10 | 1.00 | | | | | | | | | | | |
| HML | -0.32 | 0.05 | 1.00 | | | | | | | | | | |
| CMA | -0.32 | 0.22 | 0.65 | 1.00 | | | | | | | | | |
| RMW | -0.26 | -0.06 | 0.40 | 0.24 | 1.00 | | | | | | | | |
| UMD | 0.19 | 0.19 | -0.25 | -0.11 | -0.05 | 1.00 | | | | | | | |
| $Q_{ME}$ | 0.15 | 0.98 | 0.05 | 0.21 | -0.13 | 0.26 | 1.00 | | | | | | |
| $Q_{IA}$ | -0.27 | 0.19 | 0.63 | 0.91 | 0.28 | -0.10 | 0.18 | 1.00 | | | | | |
| $Q_{ROE}$ | 0.01 | 0.01 | 0.09 | 0.00 | 0.54 | 0.48 | 0.05 | 0.17 | 1.00 | | | | |
| EG | -0.15 | 0.17 | 0.11 | 0.26 | 0.35 | 0.32 | 0.16 | 0.28 | 0.45 | 1.00 | | | |
| MIS | -0.26 | -0.02 | 0.02 | 0.35 | 0.41 | 0.45 | -0.03 | 0.34 | 0.45 | 0.68 | 1.00 | | |
| $\Delta UNC$ | 0.04 | -0.19 | -0.05 | 0.00 | 0.23 | -0.18 | -0.24 | 0.06 | 0.15 | 0.29 | 0.11 | 1.00 | |
| $\Delta UNC^{ma}$ | -0.01 | -0.18 | -0.08 | -0.02 | 0.14 | -0.15 | -0.23 | 0.00 | 0.04 | 0.25 | 0.07 | 0.87 | 1.00 |
| $\Delta UNC^{mi}$ | 0.15 | 0.00 | 0.03 | 0.02 | -0.06 | 0.15 | 0.03 | -0.01 | 0.09 | -0.15 | -0.03 | -0.36 | -0.63 |

Table 2. **Cross-sectional regressions of uncertainty factor augmented models**

This table reports Fama-MacBeth regressions of various factor models and those augmented with the uncertainty factor, using annual non-tradable uncertainty factors directly and the full-sample estimation. Panel A uses the total uncertainty factor ($\Delta UNC$); Panel B uses the macro uncertainty factor ($\Delta UNC^{ma}$); Panel C uses the micro uncertainty factor ($\Delta UNC^{mi}$). Test assets are 45 portfolios and the tested pricing factors, including six size and book-to-market sorted portfolios, six size and operating profitability sorted portfolios, six size and investment sorted portfolios, six size and momentum sorted portfolios, six size and expected investment growth sorted portfolios, ten operating accrual sorted portfolios, and five Fama-French industry portfolios. Tested factor models are Fama and French (1993) three-factor model (FF3), Carhart (1997) four-factor model (FF4), Fama and French (2015) five-factor model (FF5), Fama and French (2018) six-factor model (FF6), Hou et al. (2015) $q$-factor model (HXZ), and Hou et al. (2021) $q^5$ model (HMXZ). All coefficients are multiplied by 100. The $t$-statistics are adjusted for errors-in-variables, following Shanken (1992). The adjusted $R^2$ follows Jagannathan and Wang (1996). The $5^{th}$ and $95^{th}$ percentiles of the adjusted $R^2$ distribution from a bootstrap simulation of 10,000 times are reported in brackets. The testing period is July 1973 to June 2018.

Panel A: Factor models augmented with total uncertainty

| | FF3 | | FF3+$\Delta UNC$ | | FF4 | | FF4+$\Delta UNC$ | | FF5 | | FF5+$\Delta UNC$ | | FF6 | | FF6+$\Delta UNC$ | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat |
| $\gamma_0$ | 2.45 | 6.45 | 1.96 | 2.72 | 1.31 | 4.07 | 1.02 | 1.72 | 0.89 | 2.55 | 0.83 | 2.02 | 0.69 | 2.33 | 0.66 | 1.52 |
| $\gamma_{MKT}$ | 4.86 | 1.87 | 4.98 | 1.88 | 6.14 | 2.37 | 6.03 | 2.30 | 5.97 | 2.30 | 5.97 | 2.30 | 6.35 | 2.45 | 6.32 | 2.42 |
| $\gamma_{SMB}$ | 2.11 | 1.13 | 2.25 | 1.19 | 2.19 | 1.17 | 2.35 | 1.24 | 2.25 | 1.21 | 2.31 | 1.23 | 2.23 | 1.20 | 2.34 | 1.24 |
| $\gamma_{HML}$ | 3.41 | 1.52 | 2.56 | 1.01 | 4.25 | 1.84 | 3.23 | 1.22 | 1.93 | 0.88 | 1.85 | 0.84 | 3.00 | 1.38 | 2.97 | 1.33 |
| $\gamma_{CMA}$ | | | | | | | | | 5.23 | 3.93 | 4.96 | 3.68 | 5.23 | 3.88 | 4.70 | 3.29 |
| $\gamma_{RMW}$ | | | | | | | | | 2.94 | 1.80 | 3.30 | 1.97 | 2.39 | 1.45 | 2.96 | 1.63 |
| $\gamma_{UMD}$ | | | | | 9.86 | 4.35 | 9.56 | 4.16 | | | | | 9.82 | 4.34 | 9.70 | 4.27 |
| $\gamma_{UNC}$ | | | -8.35 | -2.81 | | | -9.32 | -2.70 | | | -4.55 | -2.05 | | | -7.41 | -2.59 |
| $R^2$ | 0.21 | | 0.37 | | 0.54 | | 0.76 | | 0.45 | | 0.46 | | 0.71 | | 0.78 | |
| ($5^{th}$, $95^{th}$) | (0.01, 0.59) | | (0.04, 0.67) | | (0.29, 0.76) | | (0.39, 0.81) | | (0.17, 0.76) | | (0.20, 0.78) | | (0.47, 0.84) | | (0.52, 0.86) | |

| | HXZ | | HXZ+$\Delta UNC$ | | HMXZ | |
|---|---|---|---|---|---|---|
| | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat |
| $\gamma_0$ | 1.71 | 3.32 | 1.56 | 2.00 | 1.52 | 2.17 |
| $\gamma_{MKT}$ | 5.57 | 2.13 | 5.48 | 2.03 | 5.33 | 1.68 |
| $\gamma_{Q_{ME}}$ | 2.62 | 1.36 | 2.18 | 1.09 | 2.43 | 1.24 |
| $\gamma_{Q_{IA}}$ | 3.72 | 2.20 | 3.65 | 1.64 | 4.60 | 2.34 |
| $\gamma_{Q_{ROE}}$ | 5.28 | 3.29 | 5.89 | 3.14 | 5.43 | 2.99 |
| $\gamma_{EG}$ | | | | | 11.89 | 7.30 |
| $\gamma_{UNC}$ | | | -7.12 | -2.57 | | |
| $R^2$ | 0.45 | | 0.53 | | 0.91 | |
| ($5^{th}$, $95^{th}$) | (0.11, 0.77) | | (0.16, 0.80) | | (0.63, 0.90) | |

Panel B: Factor models augmented with macro uncertainty

| | FF3+$\Delta UNC^{ma}$ | | FF4+$\Delta UNC^{ma}$ | | FF5+$\Delta UNC^{ma}$ | | FF6+$\Delta UNC^{ma}$ | | HXZ+$\Delta UNC^{ma}$ | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat |
| $\gamma_0$ | 1.61 | 2.16 | 0.95 | 1.80 | 0.71 | 1.64 | 0.58 | 1.54 | 1.61 | 1.95 |
| $\gamma_{MKT}$ | 5.43 | 2.04 | 6.25 | 2.39 | 6.17 | 2.37 | 6.50 | 2.50 | 5.52 | 2.04 |
| $\gamma_{SMB}$ | 2.38 | 1.26 | 2.42 | 1.28 | 2.36 | 1.26 | 2.35 | 1.26 | | |
| $\gamma_{HML}$ | 2.52 | 0.96 | 3.29 | 1.29 | 2.02 | 0.90 | 3.09 | 1.40 | | |
| $\gamma_{CMA}$ | | | | | 4.97 | 3.63 | 4.91 | 3.54 | | |
| $\gamma_{RMW}$ | | | | | 3.50 | 2.09 | 2.99 | 1.77 | | |
| $\gamma_{UMD}$ | | | 9.45 | 4.12 | | | 9.67 | 4.27 | | |
| $\gamma_{Q_{ME}}$ | | | | | | | | | 2.19 | 1.09 |
| $\gamma_{Q_{IA}}$ | | | | | | | | | 3.13 | 1.34 |
| $\gamma_{Q_{ROE}}$ | | | | | | | | | 5.86 | 3.01 |
| $\gamma_{UNC^{ma}}$ | -13.93 | -2.79 | -12.38 | -2.64 | -8.29 | -2.52 | -8.76 | -2.46 | -11.23 | -2.72 |
| $R^2$ | 0.42 | | 0.71 | | 0.47 | | 0.74 | | 0.54 | |
| ($5^{th}$, $95^{th}$) | (0.05, 0.68) | | (0.36, 0.80) | | (0.20, 0.78) | | (0.49, 0.85) | | (0.15, 0.79) | |

Panel C: Factor models augmented with micro uncertainty

| | FF3+$\Delta UNC^{mi}$ | | FF4+$\Delta UNC^{mi}$ | | FF5+$\Delta UNC^{mi}$ | | FF6+$\Delta UNC^{mi}$ | | HXZ+$\Delta UNC^{mi}$ | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat |
| $\gamma_0$ | 2.52 | 5.83 | 1.34 | 3.94 | 0.86 | 2.40 | 0.64 | 1.96 | 1.73 | 3.25 |
| $\gamma_{MKT}$ | 4.88 | 1.88 | 6.14 | 2.37 | 5.93 | 2.29 | 6.26 | 2.42 | 5.57 | 2.13 |
| $\gamma_{SMB}$ | 2.14 | 1.15 | 2.20 | 1.18 | 2.22 | 1.19 | 2.18 | 1.17 | | |
| $\gamma_{HML}$ | 3.24 | 1.42 | 4.18 | 1.81 | 1.99 | 0.90 | 3.14 | 1.44 | | |
| $\gamma_{CMA}$ | | | | | 5.34 | 4.03 | 5.43 | 4.02 | | |
| $\gamma_{RMW}$ | | | | | 2.81 | 1.73 | 2.11 | 1.28 | | |
| $\gamma_{UMD}$ | | | 9.83 | 4.33 | | | 9.88 | 4.36 | | |
| $\gamma_{Q_{ME}}$ | | | | | | | | | 2.62 | 1.36 |
| $\gamma_{Q_{IA}}$ | | | | | | | | | 3.65 | 2.13 |
| $\gamma_{Q_{ROE}}$ | | | | | | | | | 5.31 | 3.35 |
| $\gamma_{UNC^{mi}}$ | 1.31 | 1.46 | 0.44 | 0.45 | -0.51 | -0.55 | -1.24 | -1.21 | 0.29 | 0.32 |
| $R^2$ | 0.20 | | 0.53 | | 0.44 | | 0.71 | | 0.44 | |
| ($5^{th}$, $95^{th}$) | (0.03, 0.63) | | (0.30, 0.77) | | (0.21, 0.77) | | (0.48, 0.85) | | (0.14, 0.78) | |

Table 3. **Comparing various uncertainty measures: Cross-sectional evidence**

This table compares the pricing power of different uncertainty measures via Fama-MacBeth regressions, using the full-sample estimation. we augment Hou et al. (2015) $q$-factor model (HXZ) with uncertainty factors. In Panel A, we compare Jurado et al. (2015) uncertainty ($UNC^{JLN}$) with total uncertainty ($\Delta UNC$), macro uncertainty ($\Delta UNC^{ma}$), or micro uncertainty ($\Delta UNC^{mi}$). In Panel B, we compare total uncertainty ($\Delta UNC$) and macro uncertainty ($\Delta UNC^{ma}$). We first regress total uncertainty on macro uncertainty and take the residual ($UNC_{res}$). Similarly, we regress macro uncertainty on total uncertainty and take the residual ($UNC^{ma}_{res}$). We use the first-differences of uncertainty residual measures ($\Delta UNC_{res}$ and $\Delta UNC^{ma}_{res}$), respectively. Column (1) reports the pricing of macro uncertainty and the residual; Column (2) reports the pricing of total uncertainty and the residual. Test assets are 45 portfolios and the tested tradable pricing factors, including 6 size and book-to-market sorted portfolios, 6 size and operating profitability sorted portfolios, 6 size and investment sorted portfolios, 6 size and momentum sorted portfolios, 6 size and expected investment growth sorted portfolios, 10 operating accrual sorted portfolios, and 5 Fama-French industry portfolios. All coefficients are multiplied by 100. The $t$-statistics are adjusted for errors-in-variables, following Shanken (1992). The adjusted $R^2$ follows Jagannathan and Wang (1996). The $5^{th}$ and $95^{th}$ percentiles of the adjusted $R^2$ distribution from a bootstrap simulation of 10,000 times are reported in brackets. The sample period is July 1973 to June 2018.

| Panel A: Comparing $UNC^{JLN}$ with TFP-based uncertainty measures | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) HXZ+$UNC^{JLN}$ | | (2) HXZ+$\Delta UNC$ | | (3) HXZ+$\Delta UNC^{ma}$ | | (4) HXZ+$\Delta UNC^{mi}$ | |
| | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat |
| $\gamma_0$ | 1.31 | 2.16 | 1.18 | 1.36 | 0.96 | 1.18 | 1.31 | 2.20 |
| $\gamma_{MKT}$ | 5.68 | 2.14 | 5.67 | 2.06 | 5.92 | 2.17 | 5.69 | 2.15 |
| $\gamma_{Q_{ME}}$ | 2.75 | 1.42 | 2.28 | 1.14 | 2.37 | 1.19 | 2.75 | 1.42 |
| $\gamma_{Q_{IA}}$ | 3.79 | 2.13 | 3.74 | 1.64 | 3.33 | 1.45 | 3.78 | 2.09 |
| $\gamma_{Q_{ROE}}$ | 5.40 | 3.27 | 5.99 | 3.16 | 5.99 | 3.13 | 5.41 | 3.32 |
| $\gamma_{UNC^{JLN}}$ | -2.97 | -2.40 | -2.83 | -1.77 | -2.00 | -1.39 | -2.96 | -2.58 |
| $\gamma_{UNC}$ | | | -7.18 | -2.55 | | | | |
| $\gamma_{UNC^{ma}}$ | | | | | -10.18 | -2.69 | | |
| $\gamma_{UNC^{mi}}$ | | | | | | | -0.30 | -0.34 |
| $R^2$ | 0.54 | | 0.61 | | 0.61 | | 0.53 | |
| ($5^{th}$, $95^{th}$) | (0.21, 0.81) | | (0.25, 0.82) | | (0.25, 0.82) | | (0.24, 0.82) | |

| Panel B: Comparing total uncertainty and macro uncertainty measures | | | | |
|---|---|---|---|---|
| | HXZ+$\Delta UNC_{res}$, $\Delta UNC^{ma}$ | | HXZ+$\Delta UNC$, $\Delta UNC^{ma}_{res}$ | |
| | Coeff | t-stat | Coeff | t-stat |
| $\gamma_0$ | 1.58 | 1.93 | 1.58 | 1.92 |
| $\gamma_{MKT}$ | 5.50 | 2.03 | 5.50 | 2.03 |
| $\gamma_{Q_{ME}}$ | 2.15 | 1.07 | 2.15 | 1.07 |
| $\gamma_{Q_{IA}}$ | 3.32 | 1.44 | 3.32 | 1.44 |
| $\gamma_{Q_{ROE}}$ | 5.92 | 3.07 | 5.92 | 3.07 |
| $\gamma_{UNC_{res}}$ | 1.94 | 1.16 | | |
| $\gamma_{UNC^{ma}}$ | -11.15 | -2.68 | | |
| $\gamma_{UNC}$ | | | -7.35 | -2.54 |
| $\gamma_{UNC^{ma}_{res}}$ | | | -3.95 | -1.83 |
| $R^2$ | 0.53 | | 0.53 | |
| ($5^{th}$, $95^{th}$) | (0.19, 0.80) | | (0.19, 0.80) | |

Table 4. **Cross-sectional regressions of mimicking uncertainty factors augmented models**

Panel A reports Fama-MacBeth regressions of various factor models and those augmented with the monthly mimicking macro uncertainty factor ($\Delta UNC^{ma}$), using the full-sample estimation. Panel B shows similar results with the expanding-window estimation. Panel C presents Fama-MacBeth regressions of mimicking micro uncertainty ($\Delta UNC^{mi}$) augmented factor models. Panel D shows similar results with the expanding window estimation. Test assets are 45 portfolios and the tested pricing factors, including six size and book-to-market sorted portfolios, six size and operating profitability sorted portfolios, six size and investment sorted portfolios, six size and momentum sorted portfolios, 6 size and expected investment growth sorted portfolios, 10 operating accrual sorted portfolios, and five Fama-French industry portfolios. Tested factor models are Fama and French (1993) three-factor model (FF3), Carhart (1997) four-factor model (FF4), Fama and French (2015) five-factor model (FF5), Fama and French (2018) six-factor model (FF6), Hou et al. (2015) $q$-factor model (HMZ), and Stambaugh and Yuan (2017) model (SY). All coefficients are multiplied by 100. The $t$-statistics are adjusted for errors-in-variables, following Shanken (1992). The adjusted $R^2$ follows Jagannathan and Wang (1996). The $5^{th}$ and $95^{th}$ percentiles of the adjusted $R^2$ distribution from a bootstrap simulation of 10,000 times are reported in brackets. The testing period for Panel A and C is from July 1973 to June 2018. The testing period for Panel B and D is from July 1997 to June 2018.

Panel A: Factor models augmented with macro uncertainty, using the full-sample estimation

| | FF3 | | FF3+$\Delta UNC^{ma}$ | | FF4 | | FF4+$\Delta UNC^{ma}$ | | FF5 | | FF5+$\Delta UNC^{ma}$ | | FF6 | | FF6+$\Delta UNC^{ma}$ | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat |
| $\gamma_0$ | 0.33 | 6.33 | 0.00 | 0.11 | 0.08 | 3.61 | 0.01 | 0.49 | 0.09 | 3.55 | 0.02 | 0.92 | 0.06 | 2.80 | 0.03 | 1.36 |
| $\gamma_{MKT}$ | 0.29 | 1.46 | 0.59 | 2.97 | 0.56 | 2.87 | 0.59 | 2.99 | 0.50 | 2.55 | 0.58 | 2.93 | 0.56 | 2.86 | 0.57 | 2.93 |
| $\gamma_{SMB}$ | 0.19 | 1.47 | 0.29 | 2.19 | 0.23 | 1.74 | 0.29 | 2.19 | 0.27 | 2.10 | 0.28 | 2.17 | 0.27 | 2.09 | 0.28 | 2.17 |
| $\gamma_{HML}$ | 0.21 | 1.57 | 0.29 | 2.12 | 0.36 | 2.67 | 0.29 | 2.13 | 0.13 | 0.95 | 0.30 | 2.26 | 0.25 | 1.88 | 0.30 | 2.27 |
| $\gamma_{CMA}$ | | | | | | | | | 0.39 | 4.09 | 0.28 | 2.96 | 0.30 | 3.29 | 0.27 | 2.97 |
| $\gamma_{RMW}$ | | | | | | | | | 0.20 | 1.84 | 0.23 | 2.20 | 0.18 | 1.70 | 0.23 | 2.20 |
| $\gamma_{UMD}$ | | | | | 0.62 | 3.29 | 0.58 | 3.05 | | | | | 0.60 | 3.19 | 0.57 | 3.02 |
| $\gamma_{UNC^{ma}}$ | | | -0.80 | -7.00 | | | -0.80 | -7.84 | | | -0.82 | -7.53 | | | -0.82 | -8.58 |
| $R^2$ | 0.19 | | 0.91 | | 0.51 | | 0.91 | | 0.51 | | 0.91 | | 0.64 | | 0.91 | |
| ($5^{th}$, $95^{th}$) | (0.02, 0.50) | | (0.80, 0.92) | | (0.33, 0.70) | | (0.81, 0.93) | | (0.29, 0.72) | | (0.81, 0.93) | | (0.46, 0.80) | | (0.83, 0.93) | |

Panel A (Continued)

| | HXZ | | HXZ+$\Delta UNC^{ma}$ | | HMXZ | | SY | | SY+$\Delta UNC^{ma}$ | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat |
| $\gamma_0$ | 0.11 | 2.81 | 0.04 | 1.34 | 0.07 | 2.10 | 0.08 | 1.60 | 0.06 | 1.46 |
| $\gamma_{MKT}$ | 0.50 | 2.50 | 0.56 | 2.84 | 0.54 | 2.72 | 0.51 | 2.48 | 0.52 | 2.54 |
| $\gamma_{Q_{ME}}$ | 0.35 | 2.55 | 0.36 | 2.63 | 0.36 | 2.62 | | | | |
| $\gamma_{Q_{IA}}$ | 0.29 | 2.71 | 0.36 | 3.44 | 0.31 | 2.93 | | | | |
| $\gamma_{Q_{ROE}}$ | 0.45 | 3.32 | 0.36 | 2.66 | 0.33 | 2.40 | | | | |
| $\gamma_{EG}$ | | | | | 0.79 | 7.70 | | | | |
| $\gamma_{MIS_{ME}}$ | | | | | | | 0.40 | 3.06 | 0.47 | 3.63 |
| $\gamma_{MGMT}$ | | | | | | | 0.53 | 3.57 | 0.45 | 3.00 |
| $\gamma_{PERF}$ | | | | | | | 0.55 | 2.93 | 0.53 | 2.82 |
| $\gamma_{UNC^{ma}}$ | | | -0.81 | -7.89 | | | | | -0.80 | -8.10 |
| $R^2$ | 0.51 | | 0.89 | | 0.82 | | 0.70 | | 0.90 | |
| ($5^{th}$, $95^{th}$) | (0.30, 0.71) | | (0.79, 0.92) | | (0.66, 0.87) | | (0.51, 0.82) | | (0.79, 0.92) | |

Panel B: Factor models augmented with macro uncertainty, using the expanding-window estimation

| | FF3 | | FF3+$\Delta UNC^{ma}$ | | FF4 | | FF4+$\Delta UNC^{ma}$ | | FF5 | | FF5+$\Delta UNC^{ma}$ | | FF6 | | FF6+$\Delta UNC^{ma}$ | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat |
| $\gamma_0$ | 0.22 | 2.89 | 0.04 | 0.64 | 0.09 | 2.38 | 0.06 | 1.64 | 0.12 | 2.93 | 0.06 | 1.58 | 0.09 | 2.89 | 0.08 | 2.68 |
| $\gamma_{MKT}$ | 0.40 | 1.34 | 0.56 | 1.87 | 0.55 | 1.95 | 0.52 | 1.74 | 0.47 | 1.69 | 0.53 | 1.85 | 0.51 | 1.82 | 0.50 | 1.78 |
| $\gamma_{SMB}$ | 0.20 | 0.98 | 0.29 | 1.33 | 0.22 | 1.04 | 0.29 | 1.37 | 0.27 | 1.30 | 0.28 | 1.34 | 0.26 | 1.29 | 0.28 | 1.34 |
| $\gamma_{HML}$ | 0.14 | 0.61 | 0.16 | 0.66 | 0.23 | 0.99 | 0.12 | 0.52 | 0.03 | 0.15 | 0.13 | 0.58 | 0.08 | 0.37 | 0.10 | 0.47 |
| $\gamma_{CMA}$ | | | | | | | | | 0.22 | 1.23 | 0.13 | 0.76 | 0.18 | 1.11 | 0.13 | 0.75 |
| $\gamma_{RMW}$ | | | | | | | | | 0.13 | 0.59 | 0.17 | 0.79 | 0.16 | 0.76 | 0.17 | 0.78 |
| $\gamma_{UMD}$ | | | | | 0.42 | 1.21 | 0.37 | 1.03 | | | | | 0.39 | 1.13 | 0.35 | 0.97 |
| $\gamma_{UNC^{ma}}$ | | | -0.65 | -3.09 | | | -0.71 | -3.43 | | | -0.60 | -3.13 | | | -0.70 | -4.15 |
| $R^2$ | 0.31 | | 0.81 | | 0.45 | | 0.82 | | 0.51 | | 0.80 | | 0.56 | | 0.81 | |
| ($5^{th}$, $95^{th}$) | (0.01, 0.61) | | (0.68, 0.91) | | (0.30, 0.76) | | (0.70, 0.92) | | (0.26, 0.78) | | (0.71, 0.93) | | (0.43, 0.84) | | (0.74, 0.93) | |

Panel B (Continued)

| | HXZ | | HXZ+$\Delta UNC^{ma}$ | | HMXZ | | SY | | SY+$\Delta UNC^{ma}$ | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat |
| $\gamma_0$ | 0.12 | 1.73 | 0.09 | 1.50 | 0.06 | 0.96 | 0.13 | 1.36 | 0.14 | 2.13 |
| $\gamma_{MKT}$ | 0.48 | 1.74 | 0.52 | 1.83 | 0.55 | 1.92 | 0.43 | 1.44 | 0.41 | 1.36 |
| $\gamma_{Q_{ME}}$ | 0.30 | 1.45 | 0.33 | 1.53 | 0.32 | 1.46 | | | | |
| $\gamma_{Q_{IA}}$ | 0.16 | 0.84 | 0.11 | 0.55 | 0.19 | 1.01 | | | | |
| $\gamma_{Q_{ROE}}$ | 0.19 | 0.72 | 0.11 | 0.44 | 0.14 | 0.53 | | | | |
| $\gamma_{EG}$ | | | | | 0.61 | 3.32 | | | | |
| $\gamma_{MIS_{ME}}$ | | | | | | | 0.37 | 1.71 | 0.41 | 1.87 |
| $\gamma_{MGMT}$ | | | | | | | 0.44 | 1.77 | 0.32 | 1.29 |
| $\gamma_{PERF}$ | | | | | | | 0.58 | 1.49 | 0.53 | 1.38 |
| $\gamma_{UNC^{ma}}$ | | | -0.68 | -3.75 | | | | | -0.67 | -3.52 |
| $R^2$ | 0.44 | | 0.83 | | 0.74 | | 0.61 | | 0.79 | |
| ($5^{th}$, $95^{th}$) | (0.25, 0.77) | | (0.69, 0.91) | | (0.60, 0.88) | | (0.45, 0.85) | | (0.68, 0.91) | |

Panel C: Factor models augmented with micro uncertainty, using the full-sample estimation

| | FF3+$\Delta UNC^{mi}$ | | FF4+$\Delta UNC^{mi}$ | | FF5+$\Delta UNC^{mi}$ | | FF6+$\Delta UNC^{mi}$ | | HXZ+$\Delta UNC^{mi}$ | | SY+$\Delta UNC^{mi}$ | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat |
| $\gamma_0$ | 0.19 | 5.56 | 0.08 | 3.48 | 0.06 | 2.35 | 0.07 | 2.99 | 0.11 | 2.83 | 0.09 | 1.76 |
| $\gamma_{MKT}$ | 0.43 | 2.19 | 0.56 | 2.86 | 0.52 | 2.67 | 0.55 | 2.80 | 0.49 | 2.48 | 0.50 | 2.43 |
| $\gamma_{SMB}$ | 0.20 | 1.51 | 0.23 | 1.73 | 0.27 | 2.11 | 0.27 | 2.09 | | | | |
| $\gamma_{HML}$ | 0.25 | 1.86 | 0.36 | 2.68 | 0.14 | 1.01 | 0.24 | 1.87 | | | | |
| $\gamma_{CMA}$ | | | | | 0.40 | 4.15 | 0.30 | 3.27 | | | | |
| $\gamma_{RMW}$ | | | | | 0.20 | 1.86 | 0.18 | 1.72 | | | | |
| $\gamma_{UMD}$ | | | 0.62 | 3.29 | | | 0.60 | 3.18 | | | | |
| $\gamma_{Q_{ME}}$ | | | | | | | | | 0.36 | 2.63 | | |
| $\gamma_{Q_{IA}}$ | | | | | | | | | 0.27 | 2.57 | | |
| $\gamma_{Q_{ROE}}$ | | | | | | | | | 0.45 | 3.28 | | |
| $\gamma_{MISP_{ME}}$ | | | | | | | | | | | 0.40 | 3.06 |
| $\gamma_{MGMT}$ | | | | | | | | | | | 0.53 | 3.63 |
| $\gamma_{PERF}$ | | | | | | | | | | | 0.55 | 2.95 |
| $\gamma_{UNC_{mi}}$ | -0.18 | -0.75 | -0.26 | -1.09 | -0.18 | -0.74 | -0.28 | -1.17 | -0.29 | -1.19 | -0.28 | -1.11 |
| $R^2$ | 0.33 | | 0.60 | | 0.59 | | 0.70 | | 0.61 | | 0.76 | |
| ($5^{th}$, $95^{th}$) | (0.08, 0.62) | | (0.41, 0.77) | | (0.35, 0.78) | | (0.52, 0.84) | | (0.38, 0.78) | | (0.59, 0.86) | |

Panel D: Factor models augmented with micro uncertainty, using the expanding-window estimation

| | FF3+$\Delta UNC^{mi}$ | | FF4+$\Delta UNC^{mi}$ | | FF5+$\Delta UNC^{mi}$ | | FF6+$\Delta UNC^{mi}$ | | HXZ+$\Delta UNC^{mi}$ | | SY+$\Delta UNC^{mi}$ | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat |
| $\gamma_0$ | 0.14 | 1.85 | 0.05 | 1.16 | 0.08 | 1.91 | 0.07 | 2.06 | 0.07 | 1.12 | 0.14 | 1.81 |
| $\gamma_{MKT}$ | 0.50 | 1.62 | 0.58 | 2.01 | 0.52 | 1.76 | 0.52 | 1.82 | 0.54 | 1.83 | 0.42 | 1.34 |
| $\gamma_{SMB}$ | 0.21 | 1.02 | 0.22 | 1.08 | 0.28 | 1.34 | 0.27 | 1.32 | | | | |
| $\gamma_{HML}$ | 0.22 | 0.94 | 0.22 | 1.00 | 0.13 | 0.60 | 0.12 | 0.56 | | | | |
| $\gamma_{CMA}$ | | | | | 0.17 | 0.96 | 0.18 | 1.10 | | | | |
| $\gamma_{RMW}$ | | | | | 0.23 | 1.10 | 0.23 | 1.11 | | | | |
| $\gamma_{UMD}$ | | | 0.41 | 1.19 | | | 0.35 | 1.02 | | | | |
| $\gamma_{Q_{ME}}$ | | | | | | | | | 0.32 | 1.47 | | |
| $\gamma_{Q_{IA}}$ | | | | | | | | | 0.22 | 1.21 | | |
| $\gamma_{Q_{ROE}}$ | | | | | | | | | 0.20 | 0.81 | | |
| $\gamma_{MISP_{ME}}$ | | | | | | | | | | | 0.35 | 1.69 |
| $\gamma_{MGMT}$ | | | | | | | | | | | 0.39 | 1.68 |
| $\gamma_{PERF}$ | | | | | | | | | | | 0.50 | 1.37 |
| $\gamma_{UNC_{mi}}$ | -1.54 | -0.76 | -1.39 | -0.68 | -1.57 | -0.75 | -1.54 | -0.74 | -1.47 | -0.71 | -1.85 | -0.93 |
| $R^2$ | 0.82 | | 0.83 | | 0.91 | | 0.91 | | 0.86 | | 0.91 | |
| ($5^{th}$, $95^{th}$) | (0.12, 0.89) | | (0.42, 0.93) | | (0.39, 0.93) | | (0.55, 0.94) | | (0.40, 0.93) | | (0.61, 0.95) | |

Table 5. **Giglio and Xiu (2021) Three-pass regression**

This table presents the risk premia ($\gamma$) of various factors using the three-pass regression of Giglio and Xiu (2021). The factors include the market (MKT), size (SMB), value (HML), investment (CMA), profitability (RMW), and momentum (UMD) factors of Fama and French (2018) six-factor model, size ($Q_{ME}$), investment ($Q_{IA}$), profitability ($Q_{ROE}$), and expected investment growth (EG) of Hou et al. (2021) $q^5$ model (HMXZ), total uncertainty ($\Delta UNC$), macro uncertainty ($\Delta UNC^{ma}$), and micro uncertainty ($\Delta UNC^{mi}$). The three-pass estimator uses 7 latent factors from 198 test assets. All returns are multiplied with 100. Newey-West adjusted standard error (SE) and $t$-statistics (t-stat) with five-year lags are provided. $R_g^2$ denotes the explanatory power of the projection of each factor onto the latent factors, as a percentage. $p$ ($g$ weak) denotes the $p$-value of the test that a factor $g$ is weak. The sample period is from July 1973 to June 2018.

| Factors | $\gamma$ | SE | t-stat | $R_g^2$ | $p$ ($g$ weak) |
|---:|---:|---:|---:|---:|---:|
| MKT | 6.81 | 2.38 | 2.86 | 99.14 | 0.00 |
| SMB | 1.82 | 2.39 | 0.76 | 90.38 | 0.00 |
| HML | 2.91 | 1.16 | 2.51 | 84.21 | 0.00 |
| CMA | 5.43 | 1.51 | 3.60 | 78.09 | 0.00 |
| RMW | 3.64 | 1.60 | 2.28 | 76.02 | 0.00 |
| UMD | 4.74 | 2.35 | 2.02 | 21.12 | 0.00 |
| $Q_{ME}$ | 2.12 | 2.40 | 0.88 | 89.36 | 0.00 |
| $Q_{IA}$ | 5.33 | 1.03 | 5.17 | 74.55 | 0.00 |
| $Q_{ROE}$ | 3.66 | 1.07 | 3.42 | 44.00 | 0.00 |
| EG | 7.83 | 1.40 | 5.59 | 62.62 | 0.00 |
| $\Delta UNC$ | -2.64 | 0.81 | -3.26 | 29.53 | 0.00 |
| $\Delta UNC^{ma}$ | -3.57 | 1.09 | -3.28 | 23.59 | 0.00 |
| $\Delta UNC^{mi}$ | 0.26 | 0.39 | 0.67 | 8.43 | 0.05 |

Table 6. **Productivity response to uncertainty shocks**

This table presents the results from regressing TFP growth ($\Delta TFP$) against uncertainty shocks and expected investment growth (EG). The independent variables include the uncertainty, EG, and the interaction term between the uncertainty and EG. The uncertainty shock is measured as total uncertainty ($\Delta UNC$), macro uncertainty ($\Delta UNC^{ma}$), or micro uncertainty ($\Delta UNC^{mi}$), respectively. The dummy variable ($HighEG$) equals one if the expected investment growth is in the top tercile and 0 otherwise. Control variables $\mathbf{Z}$ include the logrithmic market capitalization (Size), Tobin's $q$, investment-to-assets ratio (I/A), and operating cashflow (CoP). We use the firm and year fixed effects. The standard errors are clustered by firms, and $t$-statistics are reported in parentheses. The sample period is from July 1973 to June 2018.

| Regression: $\Delta TFP_{i,t} = \beta_0 + \beta_1 \Delta UNC_{t-1} + \beta_2 \Delta UNC_{t-1} \times HighEG_{i,t-1} + \beta_3 HighEG_{i,t-1} + \mathbf{Z}_{t-1} + \epsilon_{i,t}$ | | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\Delta UNC$ | 0.05 | | | |
| | (2.09) | | | |
| $\Delta UNC\times$HighEG | 0.07 | | | |
| | (1.89) | | | |
| $\Delta UNC^{ma}$ | | 0.04 | | 0.06 |
| | | (2.73) | | (2.91) |
| $\Delta UNC^{ma}\times$HighEG | | 0.05 | | 0.07 |
| | | (2.15) | | (2.31) |
| $\Delta UNC^{mi}$ | | | -0.06 | 0.07 |
| | | | (-1.55) | (1.40) |
| $\Delta UNC^{mi}\times$HighEG | | | -0.06 | 0.09 |
| | | | (-0.90) | (1.09) |
| HighEG | 0.05 | 0.05 | 0.05 | 0.05 |
| | (13.97) | (13.95) | (14.00) | (13.93) |
| Size | 0.03 | 0.03 | 0.03 | 0.03 |
| | (8.72) | (8.76) | (8.82) | (8.73) |
| Tobin's $q$ | 0.06 | 0.06 | 0.06 | 0.06 |
| | (9.19) | (9.14) | (9.12) | (9.17) |
| I/A | -0.18 | -0.18 | -0.18 | -0.18 |
| | (-15.43) | (-15.43) | (-15.45) | (-15.42) |
| CoP | -0.80 | -0.80 | -0.80 | -0.80 |
| | (-20.44) | (-20.43) | (-20.42) | (-20.43) |
| Firm-fixed | Yes | Yes | Yes | Yes |
| Year-Fixed | Yes | Yes | Yes | Yes |
| adj $R^2$ | 0.200 | 0.200 | 0.199 | 0.200 |
| Observations | 322,300 | 322,300 | 322,300 | 322,300 |

Table 7. **Using uncertainty to explain the cross-sectional dispersions of EG predictors**

Panel A reports the coefficients, $t$-statistics (t-stat), and $R^2$ from the time-series regression of the cross-sectional dispersion of each EG predictor against the macro uncertainty ($UNC^{ma}$). The dependent variables, EG predictors, include operating cash flows ($DIS_{CoP}$), Tobin's q ($DIS_Q$), and change in return on equity ($DIS_{dROE}$). Panel B runs similar regressions, using the micro uncertainty ($UNC^{mi}$). Newey-West $t$-statistics with 5-year lags are used. The testing period is from 1972 to 2016.

| Panel A: Using macro uncertainty | | | |
|---|---|---|---|
| | $DIS_{CoP}$ | $DIS_Q$ | $DIS_{dROE}$ |
| $UNC^{ma}$ | 0.28 | 0.85 | 0.44 |
| t-stat | 3.21 | 2.34 | 3.50 |
| $R^2$ | 0.42 | 0.25 | 0.38 |
| **Panel B: Using micro uncertainty** | | | |
| | $DIS_{CoP}$ | $DIS_Q$ | $DIS_{dROE}$ |
| $UNC^{mi}$ | 0.37 | 1.05 | 0.64 |
| t-stat | 1.62 | 1.29 | 1.52 |
| $R^2$ | 0.11 | 0.06 | 0.11 |

Table 8. **Returns to portfolios sorted by the predicted and residual components of expected investment growth**

All stocks are sorted into 10 portfolios, based on the predicted component of expected investment growth (Panel A) or residual component of expected investment growth (Panel B). We decompose the expected investment growth into predicted and residual components by regressing expected investment growth against macro uncertainty ($\Delta UNC^{ma}$) for each firm using the full sample. We compute the value-weighted portfolio returns, and the alphas from the CAPM, Fama and French (1993) three-factor model (FF3), Carhart (1997) four-factor model (FF4), Fama and French (2015) five-factor model (FF5), Fama and French (2018) six-factor model (FF6), Hou et al. (2015) $q$-factor model (HMZ), and Stambaugh and Yuan (2017) model (SY). Newey-West $t$-statistics with six-month lags are in parenthesis. 10-1 indicates the difference between Portfolio 10 (highest predicted or residual component of expected investment growth) and Portfolio 1 (lowest predicted or residual component of expected investment growth). All returns are multiplied by 100. The testing period is from July 1973 to June 2018 except for Stambaugh and Yuan (2017) model. The testing period of Stambaugh and Yuan (2017) is July 1973 to December 2016.

| Panel A: Portfolios sorted by predicted component of expected investment growth | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 10-1 |
| Return | -0.16 | 0.34 | 0.47 | 0.65 | 0.70 | 0.62 | 0.70 | 0.61 | 0.72 | 0.73 | 0.89 |
| | (-0.39) | (1.05) | (1.99) | (2.91) | (3.22) | (2.92) | (3.59) | (3.23) | (3.32) | (2.91) | (3.59) |
| $\alpha_{CAPM}$ | -1.05 | -0.47 | -0.17 | 0.01 | 0.10 | 0.03 | 0.16 | 0.04 | 0.14 | 0.06 | 1.11 |
| | (-4.33) | (-3.21) | (-1.92) | (0.14) | (1.05) | (0.36) | (1.92) | (0.50) | (1.51) | (0.53) | (4.91) |
| $\alpha_{FF3}$ | -0.94 | -0.49 | -0.13 | -0.01 | 0.04 | 0.01 | 0.14 | 0.06 | 0.23 | 0.26 | 1.20 |
| | (-4.83) | (-3.43) | (-1.55) | (-0.12) | (0.41) | (0.17) | (1.82) | (0.80) | (2.87) | (2.37) | (6.14) |
| $\alpha_{FF4}$ | -0.80 | -0.44 | -0.09 | 0.02 | 0.03 | 0.03 | 0.09 | 0.09 | 0.23 | 0.35 | 1.15 |
| | (-4.43) | (-3.27) | (-1.05) | (0.25) | (0.35) | (0.44) | (1.14) | (1.16) | (2.97) | (2.73) | (6.02) |
| $\alpha_{FF5}$ | -0.44 | -0.24 | -0.08 | -0.05 | -0.13 | -0.09 | -0.06 | -0.01 | 0.20 | 0.48 | 0.92 |
| | (-2.23) | (-1.98) | (-0.79) | (-0.61) | (-1.45) | (-1.23) | (-0.77) | (-0.18) | (2.45) | (3.79) | (4.76) |
| $\alpha_{FF6}$ | -0.38 | -0.22 | -0.06 | -0.02 | -0.12 | -0.07 | -0.08 | 0.02 | 0.21 | 0.53 | 0.91 |
| | (-2.04) | (-1.85) | (-0.55) | (-0.30) | (-1.40) | (-0.95) | (-1.18) | (0.21) | (2.56) | (3.87) | (4.79) |
| $\alpha_{HXZ}$ | -0.31 | -0.17 | -0.05 | -0.02 | -0.13 | -0.06 | -0.05 | 0.00 | 0.25 | 0.55 | 0.86 |
| | (-1.34) | (-1.18) | (-0.48) | (-0.21) | (-1.30) | (-0.76) | (-0.59) | (0.05) | (2.45) | (3.65) | (4.07) |
| $\alpha_{SY}$ | -0.39 | -0.19 | 0.01 | -0.03 | -0.08 | 0.03 | -0.03 | 0.01 | 0.13 | 0.40 | 0.79 |
| | (-1.68) | (-1.57) | (0.11) | (-0.40) | (-0.95) | (0.33) | (-0.34) | (0.17) | (1.66) | (2.31) | (3.38) |
| Panel B: Portfolios sorted by residual component of expected investment growth | | | | | | | | | | | |
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 10-1 |
| Return | 0.28 | 0.18 | 0.45 | 0.53 | 0.65 | 0.71 | 0.79 | 0.79 | 0.97 | 1.06 | 0.77 |
| | (0.99) | (0.68) | (2.05) | (2.49) | (3.06) | (3.57) | (3.82) | (3.83) | (4.57) | (4.44) | (3.63) |
| $\alpha_{CAPM}$ | -0.46 | -0.52 | -0.18 | -0.07 | 0.05 | 0.18 | 0.21 | 0.21 | 0.39 | 0.42 | 0.88 |
| | (-3.05) | (-4.48) | (-2.50) | (-1.01) | (0.70) | (2.24) | (2.60) | (2.61) | (3.79) | (2.95) | (3.79) |
| $\alpha_{FF3}$ | -0.32 | -0.44 | -0.15 | -0.06 | 0.06 | 0.15 | 0.20 | 0.19 | 0.43 | 0.43 | 0.75 |
| | (-2.42) | (-3.42) | (-2.06) | (-0.77) | (0.74) | (1.84) | (2.72) | (2.55) | (4.25) | (3.42) | (3.68) |
| $\alpha_{FF4}$ | -0.16 | -0.30 | -0.08 | -0.02 | 0.01 | 0.11 | 0.16 | 0.16 | 0.29 | 0.32 | 0.48 |
| | (-1.26) | (-2.25) | (-1.08) | (-0.31) | (0.07) | (1.36) | (2.17) | (2.20) | (2.98) | (2.52) | (2.43) |
| $\alpha_{FF5}$ | -0.08 | -0.27 | -0.16 | -0.14 | 0.01 | -0.03 | 0.04 | 0.06 | 0.28 | 0.35 | 0.43 |
| | (-0.57) | (-2.28) | (-2.07) | (-1.89) | (0.08) | (-0.40) | (0.63) | (0.71) | (2.14) | (2.67) | (1.96) |
| $\alpha_{FF6}$ | 0.02 | -0.17 | -0.10 | -0.11 | -0.03 | -0.04 | 0.03 | 0.05 | 0.19 | 0.28 | 0.25 |
| | (0.17) | (-1.43) | (-1.35) | (-1.49) | (-0.35) | (-0.55) | (0.41) | (0.60) | (1.66) | (2.16) | (1.22) |
| $\alpha_{HXZ}$ | 0.07 | -0.19 | -0.10 | -0.11 | 0.00 | -0.03 | 0.04 | 0.06 | 0.26 | 0.33 | 0.26 |
| | (0.52) | (-1.57) | (-1.30) | (-1.30) | (-0.01) | (-0.34) | (0.54) | (0.64) | (1.62) | (2.23) | (1.14) |
| $\alpha_{SY}$ | 0.08 | -0.12 | -0.05 | -0.12 | -0.08 | -0.03 | 0.07 | -0.02 | 0.01 | 0.11 | 0.03 |
| | (0.49) | (-0.92) | (-0.67) | (-1.61) | (-1.05) | (-0.37) | (0.93) | (–0.17) | (0.13) | (0.90) | (0.15) |