Online Appendices for:

Decoding the Pricing of Uncertainty Shocks*

Management Science, accepted

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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

Keywords: macro uncertainty, micro uncertainty, expected investment growth factor, risk premium

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Online Appendices

A. A production economy with uncertainty shocks

Consider an all-equity representative firm, operating in discrete time with an infinite horizon. The firm generates output according to a constant returns to scale production function: $Y_t = X_t K_t$, where Y_t and X_t are the firm's output and total factor productivity at time t, respectively, and K_t is the productive capital at the beginning of time t.

The logarithmic productivity, lnX_t, follows an AR(1) process, with a time-varying volatility:

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

where $0 < \rho_x < 1$ and $0 < \rho_\sigma < 1$, σ^2 is the long-run average volatility, υ 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 shocks. Similar to Bansal and Yaron (2004), for analytical tractability, we assume an AR(1) process for the uncertainty.[23] Eq. (1) also captures the interplay between productivity and uncertainty shocks. Economic recessions often feature high uncertainty and low productivity contemporaneously with productivity increases in the future. This suggests that $\eta > 0$ in Eq. (1). This is similar to the leverage effect (e.g., Black, 1976; Christie, 1982; Harvey and Shephard, 1996).

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 investment at time t, δ is the depreciation rate, and a is a constant. 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 simplicity, we assume a representative household with a power utility.[24] The household consumes firm dividends to maximize her expected utility, as follows:

$$\begin{aligned} \max_{\{C_t\}_{t=0}^{\infty}} \quad & \mathbb{E}\sum_{t=0}^{\infty}\beta^t \frac{C_t^{1-\gamma}}{1-\gamma} & (3)\\ C_t \quad &= \quad Y_t - I_t - \frac{a}{2}\left(\frac{I_t}{K_t}\right)^2 K_t, \;\; \forall t = 0,1,2... & (4)\end{aligned}$$

where γ is her relative risk aversion level and C_t is her consumption at time t.

The first-order condition gives

$$1 + a\frac{I_t}{K_t} = \mathbb{E}_t\left\{\beta\left(\frac{C_{t+1}}{C_t}\right)^{-\gamma}\left[X_{t+1} + \frac{a}{2}\left(\frac{I_{t+1}}{K_{t+1}}\right)^2 + (1-\delta)\left[1 + a\left(\frac{I_{t+1}}{K_{t+1}}\right)\right]\right]\right\}. \quad (5)$$

[23] One unappealing feature of this assumption is the negative realizations of volatility. But, this assumption can be easily relaxed by assuming the logarithmic volatility satisfies an AR(1) process in a numerical model or adopting an autoregressive gamma process for volatility as in Gourieroux and Jasiak (2006).

[24] Using recursive preferences might make uncertainty shocks more important for asset prices.

The above equation says that the marginal costs of adding one additional unit of productive capital equals its marginal benefits. This defines the marginal q at time t as follows:

$$q_t \equiv 1 + a\frac{I_t}{K_t}. \tag{6}$$

The real investment return, R^I_{t+1}, is:

$$R^I_{t+1} = \frac{X_{t+1} + \frac{a}{2}\left(\frac{I_{t+1}}{K_{t+1}}\right)^2 + (1-\delta)\left[1 + a\left(\frac{I_{t+1}}{K_{t+1}}\right)\right]}{1 + a\frac{I_t}{K_t}}. \tag{7}$$

Cochrane (1991) and Restoy and Rockinger (1994) show that the stock return equals the real investment return when production is constant returns to scale. Therefore, Eq. (7) also computes the stock return R_{t+1}.

We can rewrite Eq. (5) as the standard asset pricing equation:

$$\mathbb{E}_t[M_{t+1}R_{t+1}] = 1, \tag{8}$$

with the pricing kernel $M_{t+1} = \beta\left(\frac{C_{t+1}}{C_t}\right)^{-\gamma}$.

For tractability, we consider a log-linearized version of the economy. Let $\hat{V}_t$ denote logarithmic deviations of variable V from its steady state. Given the three state variables (i.e., productivity $\hat{X}_t$, productive capital $\hat{K}_t$, and uncertainty σ^2_t), optimal investment can be approximated as:

$$\hat{I}_t = I_0 + I_x\hat{X}_t + I_k\hat{K}_t + I_\sigma\sigma^2_t, \tag{9}$$

where I_0, I_x, I_k, and I_σ are coefficients to be determined.

Log-linearizing Eq. (7) gives the expected return:

$$\begin{aligned}
\mathbb{E}_t[\hat{R}_{t+1}] \quad = \quad & \left[h(I_k-1)\delta + h - \frac{a\delta}{1+a\delta}\right] I_0 + hI_\sigma(1-\rho_\sigma)\sigma^2 \\
& + \underbrace{\left[\frac{h}{a\delta}\rho_x + h\left(I_k-1\right)\delta I_x + hI_x\rho_x - \frac{a\delta}{1+a\delta}I_x\right]\hat{X}_t}_{\text{productivity shock}} \\
& + \underbrace{\left[h\left(1-\delta+\delta I_k\right) - \frac{a\delta}{1+a\delta}\right]\left(I_k-1\right)\hat{K}_t}_{\text{capital stock}} \\
& + \underbrace{\left\{\left[h\rho_\sigma - \frac{a\delta}{1+a\delta}\right] I_\sigma + \left(\frac{h}{a\delta} + hI_x\right)\eta\right\}\sigma^2_t}_{\text{uncertainty shock}},
\end{aligned} \tag{10}$$

where $h = \frac{a\delta}{2-\frac{a}{2}\delta^2+(a-1)\delta}$. That is, uncertainty shocks affect stock returns.

Log-linearizing the resource constraint Eq. (4) gives

$$\begin{aligned}\hat{C}_t &= \left[g - \left(\frac{I}{C} + ga\delta^2\right) I_x\right] \hat{X}_t + \left[g\left(1 + \frac{a}{2}\delta^2\right) - \left(\frac{I}{C} + ga\delta^2\right) I_k\right] \hat{K}_t \\ &\quad - \left(\frac{I}{C} + ga\delta^2\right) I_\sigma \sigma_t^2 + \left(\frac{I}{C} + ga\delta^2\right) I_0, \end{aligned} \tag{11}$$

where $g = \frac{C+I}{C(1-\frac{a}{2}\delta^2)}$. C and I are the steady state values, satisfying

$$\frac{I}{C} = \frac{\delta}{1 - \frac{a}{2}\delta^2 - \delta}. \tag{12}$$

Therefore, $g = \frac{1}{1-\frac{a}{2}\delta^2 - \delta} > 0$.

Log-linearizing the first-order condition Eq. (8) gives

$$-\gamma\left(\mathbb{E}_t \hat{C}_{t+1} - \hat{C}_t\right) + \mathbb{E}_t \hat{R}_{t+1} + \frac{1}{2} Var_t\left[-\gamma \hat{C}_{t+1} + \hat{R}_{t+1}\right] = 0. \tag{13}$$

This takes into account the impacts of uncertainty on quantities and asset prices (see, e.g., Bianchi et al. (2023)).

Substituting Eq. (10) and (11) into (13) and matching coefficients, we can solve for I_0, I_x, I_k, and I_σ. I_k can be solved from the following quadratic equation:

$$\begin{aligned} 0 &= -\gamma\left[g\left(1 + \frac{a}{2}\delta^2\right) - \left(\frac{I}{C} + ga\delta^2\right) I_k\right] \delta(I_k - 1) \\ &\quad + h(I_k - 1)(1 - \delta + \delta I_k) - \frac{a\delta}{1 + a\delta}(I_k - 1). \end{aligned} \tag{14}$$

In fact, we can see that $I_k = 1$ is the solution due to the constant returns to scale technology assumption.

The other coefficients are:

$$I_x = \frac{\gamma g(\rho_x - 1) - \frac{h\rho_x}{a\delta}}{\gamma\left(\frac{I}{C} + ga\delta^2\right)(\rho_x - 1) - \gamma\delta + h\rho_x - \frac{a\delta}{1+a\delta}}, \tag{15}$$

$$I_\sigma = \frac{\frac{1}{2}\left\{\frac{h}{a\delta} + hI_x - \gamma\left[g - \left(\frac{I}{C} + ga\delta^2\right) I_x\right]\right\}^2 + \left\{-\gamma\left[g - \left(\frac{I}{c} + ga\delta^2\right) I_x\right] + \left(\frac{h}{a\delta} + hI_x\right)\right\}\eta}{\gamma\delta + \gamma\left(\frac{I}{C} + ga\delta^2\right)(1 - \rho_\sigma) + \frac{a\delta}{1-a\delta} - h\rho_\sigma}, \tag{16}$$

$$I_0 = \frac{\begin{array}{l}\frac{1}{2}\left[h + \gamma\left(\frac{I}{C} + ga\delta^2\right)\right]^2 I_\sigma^2 \upsilon^2 + \\ \left\{hI_\sigma(1 - \rho_\sigma) + \gamma\left(\frac{I}{C} + ga\delta^2\right) I_\sigma(1 - \rho_\sigma) - \left(\frac{h}{a\delta} + hI_x\right)\eta + \gamma\left[g - \left(\frac{I}{C} + ga\delta^2\right) I_x\right]\eta\right\}\sigma^2\end{array}}{h - \frac{a\delta}{1+a\delta} + \gamma\delta} \tag{17}$$

Since $0 < h < \frac{a\delta}{1+a\delta}$, we see that $I_x > 0$. That is, investment increases with productivity shocks.

If $\eta > \frac{\gamma g}{2}$,[25] then we see that $I_\sigma < 0$. That is, investment decreases with uncertainty due to risk aversion.

The optimal investment rate is

$$\widehat{\frac{I_t}{K_t}} = \hat{I}_t - \hat{K}_t = I_0 + I_x \hat{X}_t + I_\sigma \sigma_t^2. \tag{18}$$

Expected investment growth is

$$\mathbb{E}_t \left[\widehat{\frac{I_{t+1}}{K_{t+1}}} - \widehat{\frac{I_t}{K_t}} \right] = I_\sigma (1-\rho_\sigma)\sigma^2 + (\rho_x - 1)\, I_x \hat{X}_t + \left[(\rho_\sigma - 1)\, I_\sigma + I_x \eta \right] \sigma_t^2. \tag{19}$$

Since $I_x > 0$, $\eta > 0$, $I_\sigma < 0$ and $0 < \rho_\sigma < 1$, expected investment growth decreases with the productivity shock $\hat{X}_t$ but increases with the uncertainty shock σ_t^2.

The stock return can be simplified to

$$\begin{aligned} \mathbb{E}_t[\hat{R}_{t+1}] \quad = \quad & \left(h - \frac{a\delta}{1+a\delta} \right) I_0 + \left[h I_\sigma (1-\rho_\sigma) - \left(\frac{h}{a\delta} + h I_x \right) \eta \right] \sigma^2 \\ & + \underbrace{\left[\frac{h}{a\delta} \rho_x + h I_x \rho_x - \frac{a\delta}{1+a\delta} I_x \right] \hat{X}_t}_{\text{productivity shock}} + \underbrace{\left\{ \left[h\rho_\sigma - \frac{a\delta}{1+a\delta} \right] I_\sigma + \left(\frac{h}{a\delta} + h I_x \right) \eta \right\} \sigma_t^2}_{\text{uncertainty shock}} \end{aligned} \tag{20}$$

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 in the uncertainty shock.

Taking Eq. (18), (19), and (20) together, we see that the investment rate and expected investment growth capture productivity shocks and uncertainty shocks and therefore they capture expected stock returns. Also, we see that when uncertainty increases, the current investment rate decreases while both the expected investment growth rate and the expected stock return increase. This suggests that expected investment growth is positively related to stock returns, as suggested in the q^5-model (Hou et al., 2021).

B. *TFP estimation*

(1) Data

We use two main datasets to estimate the total factor productivity (TFP): Annual Compustat and CRSP files, by matching Compustat and CRSP. The sample period is from 1966 to 2016. Compustat items used include total assets (AT), net property, plant, and equipment (PPENT), sales (SALE), operating income before depreciation (OIBDP), depreciation (DP), capital expenditure (CAPX), inventory (INVT), sale of property, plant, and equipment (SPPE), depreciation, depletion and amortization (DPACT), employees (EMP), and staff expense (XLR).

[25] Since productivity variance is usually an order of magnitude smaller than its level, a large η is necessary to generate the sizeable impacts of uncertainty on productivity level in Eq. (1). As η is large, this condition is easily satisfied.

We apply several filters to select the sample firms. We include common stocks listed at NYSE/Amex/Nasdaq. We exclude the financial firms and the utility firms (four-digit SIC between 6000 - 6999 or 4900 - 4999). Also, firms with sales or total assets less than $1 millions, or with negative or missing book equity, employees, capital expenditure, and depreciation are excluded. Firms with negative value-added or material costs are excluded as well. Stock price of each firm must be greater than $5 at the end of a year. The labor expense ratio, which we will describe below, should be between 0 and 1. Following Chen and Chen (2012), we exclude firms with asset or sales growth rate exceeding 100% to avoid potential business discontinuities that might be caused by mergers and acquisitions. Finally, the sample firms should report their accounting information more than 2 years to avoid the survivorship bias.

To calculate real values, we use GDP deflator (NIPA table 1.1.9 qtr line1) and price index for nonresidential private fixed investment(NIPA table 5.3.4 qtr line2). We obtain employees' earnings data from Bureau of Labor Statistics (CES0500000030). This table reports weekly earnings for each month. We use these to compute the annual earnings.

(2) Input variables

We calculate value-added, employment, physical capital, and investment to estimate TFP.

Value-added (Y_{it}) is $\frac{Sales_{it} - Materials_{it}}{GDP\_deflator}$. Material cost ($Materials_{it}$) is total expenses minus labor expense. Total expense is sales (SALE) minus operating income before depreciation and amortization (OIBDP). Labor expense is the staff expense (XLR). However, only a small number of firms report the staff expense. We replace the missing observations with the interaction of industry average labor expense ratio and total expense. To be specific, we calculate the labor expense ratio, $\frac{xlr_{it}}{sales_{it} - oibdp_{it}}$, for each firm. Next, in each year we estimate the industry average of the labor expense ratio at 4-digit SIC code level if there are at least 3 firms. Otherwise, we estimate the industry average of the labor expense ratio at 3-digit SIC code level. In the same manner, we estimate the industry average of labor expense ratio at 2-digit and 1-digit SIC code level. Then, we back out the staff expense by multiplying the industry average labor expense ratio and total expense. If the labor expense is still missing, we interpolate those missing observations with the interaction of annual wage from the Bureau of Labor Statistics and the number of employees.

Capital stock (K_{it}) is net property, plant, and equipment divided by the capital price deflator. We calculate the capital price deflator, following İmrohoroğlu and Tüzel (2014). First, we compute the age of capital in each year. Age of capital stock is $\frac{dpact_{it}}{dp_{it}}$. We further take a 3-year moving average to smooth the capital age. Then, we match the current capital stock with the price index for private fixed investment at current year minus capital age. Finally, we take one-year lag for the capital stock to measure the available capital stock at the beginning of the period.

Investment (I_{it}) is capital expenditure (CAPX) minus sale of property, plant, and equipment (SPPE) plus a change of inventory (INVT), $INVT_{it} - INVT_{it-1}$, deflated by current fixed investment price index. We replace missing observations of SPPE with 0.

Labor (L_{it}) is the number of employees.

(3) TFP estimation

We follow Olley and Pakes (1996) to estimate the total factor productivity (TFP). Olley and

Pakes (1996) provide a robust way to measure production function parameters, solving the simultaneity problem and selection bias. Olley and Pakes (1996) estimate the labor coefficient and the capital coefficient separately to avoid the simultaneity problem. Also, they include the exit probability in TFP estimation process to avoid the selection bias. Olley and Pakes (1996) further assume that (1) TFP is a first-order Markov process; (2) physical capital is predetermined after TFP is observed; and (3) investment reflects information about TFP. İmrohoroğlu and Tüzel (2014) show how to estimate Olley and Pakes (1996) TFP using annual Compustat and share their codes.[26] We follow İmrohoroğlu and Tüzel (2014) with some modifications.

We start from the simple Cobb-Douglas production technology,

$$Y_{it} = Z_{it} L_{it}^{\beta_L} K_{it}^{\beta_K}, \tag{21}$$

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. We scale the production function by its capital stock for several reasons. First, since TFP is the residual term, it is often highly correlated with the firm size. Second, this avoids estimating the capital coefficient directly. Third, there is an upward bias in labor coefficient without scaling. After being scaled by the capital stock and transformed into logarithmic values, Eq.(21) is rewritten as

$$Log\frac{Y_{it}}{K_{it}} = \beta_L Log\frac{L_{it}}{K_{it}} + (\beta_K + \beta_L - 1)LogK_{it} + LogZ_{it}. \tag{22}$$

We define $Log\frac{Y_{it}}{K_{it}}$, $Log\frac{L_{it}}{K_{it}}$, $LogK_{it}$, and $LogZ_{it}$ as yk_{it}, lk_{it}, k_{it}, and z_{it}. Also, denote β_L and $(\beta_K + \beta_L - 1)$ as β_l and β_k. Rewrite Eq.(22) as

$$yk_{it} = \beta_l lk_{it} + \beta_k k_{it} + z_{it}. \tag{23}$$

Olley and Pakes (1996) assume a monotonic relationship between the investment and productivity (i.e., investment captures information of productivity). Hence, productivity is a function of investment, i.e., $z_{it} = h(ik_{it})$. We assume that the function $h(ik_{it})$ is 2^{nd}-order polynomials of ik_{it}.

Specifically, we estimate the following cross-sectional regression at the first stage:

$$y_{it} = \beta_l lk_{it} + \beta_k k_{it} + \beta_0 + \beta_{ik} ik_{it} + \beta_{ik^2} ik_{it}^2 + year * \eta_j + \epsilon_{it}, \tag{24}$$

where $h(ik_{it}) = \beta_0 + \beta_{ik} ik_{it} + \beta_{ik^2} ik_{it}^2$. We include the interaction between year and industry (η_j) fixed effect to capture the differences of industrial technologies over time. η_j is Fama-French 10 industry classification. From this stage, we estimate the labor coefficients, $\widehat{\beta}_l$.

Second, the conditional expectation of $y/k_{i,t+1} - \widehat{\beta}_l l/k_{i,t+1} - year * \eta_j$ on information at t and survival of the firm is

$$\begin{aligned} E_t(yk_{i,t+1} - \widehat{\beta}_l lk_{i,t+1} - year * \eta_j) &= \beta_k k_{i,t+1} + E_t(z_{i,t+1} | z_{i,t}, survival) \\ &= \beta_k k_{i,t+1} + g(z_{it}, \widehat{P}_{survival,t}), \end{aligned} \tag{25}$$

[26] Available at http://www-bcf.usc.edu/ tuzel/TFPUpload/Programs/.

where $\widehat{P}_{survival,t}$ is the probability of a firm survival from t to $t+1$. The probability is estimated with the Probit regression of a survival indicator variable on the 2^{nd} polynomials in investment rate, i/k. z_{it} is $\beta_0 + \beta_{ik} ik_{it} + \beta_{ik^2} ik_{it}^2$. The function g is the polynomials of the survival probability ($\widehat{P}_{survival,t}$) and lagged TFP (z_{it}). At this step, we estimate the coefficient of capital, $\widehat{\beta_k}$, which gives $\widehat{\beta_K}$.

From the second stage, total factor productivity (TFP) can be computed as follows:

$$TFP_{it} = exp(yk_{it} - \widehat{\beta}_l lk_{i,t} - (\widehat{\beta_K} + \widehat{\beta}_l - 1)k_{it} - year * \eta_j). \tag{26}$$

After transforming the exponential values, we estimate TFP growth (ΔTFP) as $\frac{TFP_{it} - TFP_{it-1}}{TFP_{t-1}}$. We use a 5-year rolling window to estimate TFP. TFP estimates are available from 1972 to 2016.

C. Examining principal components of TFP

Figure C1 plots the eigenvalues of principal components and proportions of TFP growth variations explained. We see that the first principal component has an eigenvalue of 0.186 and explains only 12.5% of TFP growth variations. The next five principal components are also sizable, with an eigenvalue from 0.066 to 0.114, which explains $4.5 - 7.7\%$ of TFP growth variations, respectively. This suggests that the first principal component is insufficient and additional principal components are necessary to capture the TFP growth variations. We further apply the statistical criteria suggested in Bai and Ng (2002) to determine the number of principal components, including three panel C_p criteria and three panel information criteria. Those statistical criteria suggest the number of principal components as six.

Examining the prevailing pricing factors, Chen and Kim (2020) show that (1) the first principal component is related to the momentum factor and the short-horizon behavioral factor (PEAD); (2) the second principal component is related to the size factor and the expected investment growth factor; (3) the third principal component is related to the profitability factor; (4) the fourth principal component is related to the investment factor; (5) the fifth principal component is related to the momentum factor; (6) the sixth principal component is related to the mispricing factor (MIS) and the long-horizon behavioral factor (FIN).

D. Decomposing macro uncertainty

To examine whether macro uncertainty varies due to time-varying principal components or changes in the cross-sectional distribution of firm-specific factor loadings, we decompose macro uncertainty. The cross-sectional variance of systematic TFP growth (e.g., the square of macro uncertainty) is

$$(UNC_t^{ma})^2 = \sum_{k=1}^{6} PC_{k,t}^2 Var(b_k) + 2 \sum_{k<l} PC_{k,t} PC_{l,t} Cov(b_k, b_l), \tag{27}$$

where $PC_{k,t}$ is the k^{th} principal component at t, $Var(b_k)$ is the cross-sectional variance of factor loadings on the k^{th} principal component, and $Cov(b_k, b_l)$ is the cross-sectional covariance between factor loadings on the k^{th} and l^{th} principal components.

We next construct two counterfactual measures of macro uncertainty. First, we fix the cross-sectional variance-covariance matrix of factor loadings at its time-series average, allowing only the principal components to vary over time. We denote this measure as UNC^{ma}_{PC}. Second, we allow only the cross-sectional variance-covariance matrix of factor loadings to vary over time, while replacing the time-varying principal components with constant eigenvalue-based weights.[27] We denote this measure as $UNC^{ma}_{Loadings}$. Factor loadings are estimated once on the full sample and are therefore time-invariant at the firm level, but the cross-sectional variance-covariance matrix of factor loadings still varies over time because the set of firms in the cross section changes from year to year.

Column (1) of Table D1 reports the time-series regression of ΔUNC^{ma} on ΔUNC^{ma}_{cf1} and ΔUNC^{ma}_{cf2}. The coefficient on ΔUNC^{ma}_{cf1} is 0.23 ($t = 6.07$, $R^2 = 0.70$), while the coefficient on ΔUNC^{ma}_{cf2} is -0.04 ($t = -0.16$). Columns (2) – (5) regress the band-pass-filtered counterfactual measures on either the NBER recession indicator (*Recession*) or UNC^{JLN} (Jurado et al., 2015). We see that *Recession* and UNC^{JLN} are significantly positively associated with UNC^{ma}_{PC} but are insignificantly related to $UNC^{ma}_{Loadings}$.

These findings indicate that fluctuations in the principal components drive macro uncertainty. In contrast, variations arising solely from changes in the cross-sectional distribution of factor loadings contribute little to macro uncertainty and are largely unrelated to the business cycle. Macro uncertainty therefore primarily reflects aggregate shocks embedded in common factors rather than time-variation in firm-level exposures.

E. Comparing various uncertainty measures

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 VIX, and the aggregate uncertainty (UNC^{agg}) constructed from aggregate TFP growth. Jurado et al. (2015) estimate UNC^{JLN} based on a large number of macroeconomic and financial variables. We obtain aggregate TFP growth data from the Federal Reserve Bank of San Francisco and following Bloom et al. (2018), we define aggregate uncertainty (UNC^{agg}) as the conditional standard deviation of a GARCH (1,1) on aggregate TFP growth.

Figure D1 plots the time series of UNC^{JLN}, UNC, UNC^{ma}, and UNC^{mi}. One visible difference is that our macro uncertainty UNC^{ma} measure captures high uncertainty in late 1990s, while the UNC^{JLN} measure does not. The correlations between UNC^{JLN} and UNC, UNC^{ma}, UNC^{mi} are 0.20, 0.36, and -0.09, respectively. That is, total uncertainty positively correlates with UNC^{JLN} and our macro uncertainty highly correlates with UNC^{JLN}, but not micro uncertainty.

Examining across UNC^{JLN}, UNC^{agg}, and VIX, we see that UNC^{ma} positively correlates

[27] We aggregate eigenvalues of the six principal components and normalize each eigenvalue by their sum. The eigenvalue-based weights are 0.35, 0.27, 0.14, 0.09, 0.07, and 0.07, respectively.

with the three measures, 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.

We further validate our uncertainty decomposition in three steps. First, we check if our macro uncertainty measure reasonably captures aggregate uncertainty. Panel A of Table E1 reports the time-series regressions of aggregate uncertainty UNC^{agg} on macro uncertainty (UNC^{ma}) and micro uncertainty (UNC^{mi}). Macro uncertainty positively predicts the aggregate uncertainty while micro uncertainty does not.

Second, using our TFP estimates, we investigate if total uncertainty is mainly driven by macro uncertainty. Panel B of Table E1 reports the time-series regressions of ΔUNC against ΔUNC^{ma} and ΔUNC^{mi}. The univariate regression in Column (1) shows that ΔUNC^{ma} has a coefficient of 0.60 (t-statistic=10.11) and the R^2 is 0.75. This is not surprising given the high correlation between ΔUNC and ΔUNC^{ma} reported in Panel B of Table 1. In Column (2), we add ΔUNC^{mi} to the regression. The coefficient of ΔUNC^{mi} is 0.53 (t-statistic=3.11) while that of ΔUNC^{ma} is 0.73 (t-statistic=9.62). Also, the explanatory power (R^2) increases by only 0.06 from Column (1) to Column (2). Panel B of Table E1 suggests that ΔUNC is mainly driven by ΔUNC^{ma}.

F. *Mimicking uncertainty factors*

Panel A of Table F1 present descriptive statistics for the mimicking uncertainty factors. Total uncertainty (ΔUNC) has a mean of -0.79% per month with a standard deviation of 2.23% per month. The monthly Sharpe ratio of ΔUNC is -0.35. Macro uncertainty (ΔUNC^{ma}) has a similar Sharpe ratio of -0.39 as well as a mean of -0.82% per month and a standard deviation of 2.13% per month. The monthly correlation between the mimicking portfolios of ΔUNC and ΔUNC^{ma} is 0.90. However, micro uncertainty (ΔUNC^{mi}) has a very small Sharpe ratio of -0.03. This is mainly driven by its high standard deviation of 5.52% per month and a small mean of -0.18% per month.

Using the mimicking uncertainty portfolios, we examine if the total uncertainty factor is mainly driven by the macro uncertainty factor. Panel B of Table F1 reports time-series regression results. The regression results are similar to those reported in Panel B of Table E1. First, the coefficient of ΔUNC^{ma} is 0.94 (t-statistic=32.45) in the univariate regression. ΔUNC^{ma} explains 81% of ΔUNC variations. Column (2) shows that adding ΔUNC^{mi} contributes little to ΔUNC (R^2 only increases by 0.05). Again, we see that macro uncertainty (ΔUNC^{ma}) captures most information of total uncertainty (ΔUNC) while the contribution of micro uncertainty (ΔUNC^{mi}) is negligible.

Next, we investigate whether uncertainty is a risk factor by asking if other factor models explain the mimicking uncertainty factor. Panels C through E of Table F1 report the alphas from the time-series regression of the mimicking total uncertainty (ΔUNC), macro uncertainty (ΔUNC^{ma}), and micro uncertainty (ΔUNC^{mi}), against various pricing factors, using the full sample.[28] We consider eight factor models, including the CAPM, FF3, FF4, FF5, FF6, HXZ, HMXZ, and SY.

[28]The expanding-window results are similar.

Panel C shows that except HMxZ, the alphas of total uncertainty from all models are similar and significantly negative, ranging from -0.86% to -0.51%. The alpha from the HMXZ model is smaller but remains significant, -0.13% per month (t-statistic=-3.41). We find similar results for macro uncertainty in Panel D. That is, except HMXZ, the alphas from all models are similar and significantly negative, ranging from -0.91% to -0.48%. The alpha from the HMXZ model is smaller but marginally significant, -0.03% per month (t-statistic=-1.94). Panel E shows that alphas of ΔUNC^{mi} are mostly insignificant across different factor models.

Overall, Table F1 demonstrates that macro uncertainty is the main driver of total uncertainty, which is not fully captured by the existing pricing factors, while the pricing of micro uncertainty is negligible. Therefore, we will mainly use our macro uncertainty factor (ΔUNC^{ma}) in the remaining analyses.

G. Cross-sectional regressions of factor models augmented with uncertainty factors

In this section, we first examine the factor loadings from time-series regressions. Second, we consider three variations of uncertainty augmented factor models. That is, prevailing factor models augmented by the total uncertainty factor, macro and micro uncertainty factors, and the aggregate uncertainty factor.

G.1. Factor loadings of Fama-French three-factor model augmented with macro uncertainty

Table G1 reports the loadings on UNC^{ma} of 45 test assets, estimated from the Fama-French three-factor model augmented with UNC^{ma}.[29] First, we see that UNC^{ma} is significant in most test assets. Second, we see that the loadings have correct signs in most cases, with the exception of the big and high book-to-market portfolio in Panel A. For example, stocks with low (high) investment rates, high (low) operating profitability, high (low) past cumulative returns, or high (low) expected investment growth, have low and negative (high and positive) loadings. Stocks with high operating accruals also have a high and positive loading. Together with a negative price of UNC^{ma}, macro uncertainty helps explain those asset returns. However, one must be cautious when interpreting the coefficients, as the Fama-French three factors used might confound the results.

G.2. Cross-sectional regressions of factor models augmented with total uncertainty factor

Since ΔUNC^{ma} tracks ΔUNC, we can replace ΔUNC^{ma} with ΔUNC and run the Fama-MacBeth regressions. Panel A of Table G2 reports the results with the full-sample estimation, which are qualitatively similar to those reported in Table 4. γ_0 from the augmented FF6 and SY models are insignificant. Also, γ_{UNC} are significantly negative across all models and their magnitudes are close to the average factor return. To avoid the look-ahead bias, we report Fama-MacBeth regressions using the extending-window estimation in Panel B of Table G2. The testing period is from July 1997 to June 2018. We find similar results in the extending-window cases. First,

[29] Results from other models augmented with UNC^{ma} are qualitatively similar.

γ_{UNC} is significantly negative across all augmented factor models. Second, the intercepts become smaller or insignificant after we add ΔUNC to the prevailing factor models.

G.3. Cross-sectional regressions of factor models augmented with macro and micro uncertainty factor

For another robustness check, we extend the prevailing factor models by adding both ΔUNC^{ma} and ΔUNC^{mi}, and report results in Table G3. We see that across the augmented factor models, only $\gamma_{UNC^{ma}}$ are significantly negative while $\gamma_{UNC^{mi}}$ are insignificant. The augmented FF3, FF4, FF5, FF6, HXZ, and SY models have insignificant pricing errors in the full-sample estimation reported in Panel A. Panel B shows the extending-window estimation results, which are similar to those in Panel A.

G.4. Cross-sectional regressions of factor models augmented with aggregate uncertainty factors

Table G4 reports Fama-MacBeth regressions of various factor models augmented with the mimicking aggregate uncertainty portfolio (UNC^{agg}), using full sample. Aggregate uncertainty (UNC^{agg}) is the conditional standard deviation of a GARCH (1,1) on aggregate TFP growth. Table G4 shows that the mimicking aggregate uncertainty portfolio is negatively priced, but the augmented models have significant intercepts. Overall, we see that the macro uncertainty factor (UNC^{ma}) performs better than the mimicking aggregate uncertainty factor (UNC^{agg}).

Table G5 reports Fama-MacBeth regressions of various factor models augmented with the mimicking VIX portfolio (ΔVIX), using full sample. Again, we see that the mimicking VIX portfolio is negatively priced. The augmented FF6 model has an insignificant intercept but other augmented models have significant pricing errors. Overall, we see that the macro uncertainty factor (UNC^{ma}) performs better than the mimicking VIX factor.

Results from Tables G4 and G5 suggest it is necessary to measure macro uncertainty from multiple sources (e.g., 6 principal components), instead of a single source (e.g., VIX or aggregate TFP growth).

H. Robustness tests

H.1. Different numbers of principal components

In the main results, we choose the first 6 principal components (PC) to estimate macro and micro uncertainty based on the statistical criteria in Bai and Ng (2002) and the economic reason in Chen and Kim (2020). Still, the choice of the number of PCs may be arbitrary. For the robustness check, we consider different numbers of PCs to decompose macro and micro uncertainty, and estimate their prices of risk under Hou et al. (2015) q-factor model in Table H1. Panel A presents the results from ΔUNC^{ma} augmented HXZ model. 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. Panel B shows the pricing power of ΔUNC^{mi}. 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 macro uncertainty from micro uncertainty.

H.2. 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 from the mechanical relationship. For robustness, we choose 6 size and book-to-market sorted portfolios and EG factor to construct the mimicking portfolios, and then estimate the price of uncertainty risk. Table H2 presents the price of risks for total, macro, and micro uncertainty, respectively. Again, we find that γ_{UNC} and $\gamma_{UNC^{ma}}$ are both significantly negative but $\gamma_{UNC^{mi}}$ is still insignificant. The last column shows that the results are similar when we use $\gamma_{UNC^{ma}}$ and $\gamma_{UNC^{mi}}$ simultaneously.

H.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 Table H3.

This table reports the probability that the noisy factors generate higher R^2s ("R^2" column), prices of uncertainty risk ("PRC" column), and Sharpe ratios of the uncertainty factor ("SR" column) relative to the original models. We also report two different joint probabilities. The "Joint R^2-PRC" column is the probability that the noisy factors simultaneously generate higher R^2s and prices of risk compared to the original models. The "Joint All" column is the probability that the noisy factors generate higher R^2s, prices of uncertainty risk, and Sharpe ratios of the uncertainty factor relative to the original models.

In Panel A, we test the noisy total uncertainty (ΔUNC) augmented factor models. All noisy models perform poorly. Taking the noisy total uncertainty augmented FF6 model as an example, the probability of the noisy factors performing as well as the original model is only 4.65%, 0.00%, and 0.00% in terms of the R^2, the intercept, and the price of risk, respectively. Moreover, their joint probabilities are all zero. That is, it is almost impossible for the noisy factors to achieve the same explanatory power as the original models. In Panel B, we use the macro uncertainty factor (ΔUNC^{ma}) and see very similar results. Turning to the micro uncertainty (ΔUNC^{mi}) in Panel C, we see the probabilities increase sharply. This suggests that the noisy factors might perform similarly to the original model for micro uncertainty. This is not surprising since we find that the micro uncertainty factor is not priced. Lastly, we perform similar tests with the non-tradable uncertainty factors directly and find similar results. Overall, these results suggest that the asset pricing power of macro uncertainty is not due to chance.

H.4. Using 15 latent factors

Following Giglio and Xiu (2021), we use 7 latent factors as the baseline results. For robustness, here we use 15 latent factors based on the eigenvalues. We estimate the price of risk for other pricing factors from the FF6 and HXZ models as well. Table H4 presents the estimated risk premia. First, the p-values show that all factors are not weak factors. 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, ΔUNC^{ma}'s magnitude is -4.10% per year (t=-4.14). Third, we see that micro uncertainty is insignificant, i.e., the price of risk is only 0.64% per year (t=1.42). Overall, we find that macro uncertainty is the main driver of uncertainty risk.

I. Comparing various models: Maximum squared Sharpe ratio

Table 4 uses a set of test assets as the left-hand-side variables to examine the pricing power of different models. This approach is widely used (see, e.g., Fama and French, 1996, 2015; Hou et al., 2015, 2019, 2021). However, this approach is often sensitive to the choice of test assets. Alternatively, following Barillas and Shanken (2017) and Fama and French (2018), we use the right-hand-side approach to compare various models based on the maximum squared Sharpe ratio for model factors (Barillas and Shanken, 2017).

To test a factor model i with factors f_i, consider time-series regressions of the test assets (Π_i), which include non-factor test assets and factors from other competing models, on model i's factors f_i. Suppose the vector of intercepts from the time-series regressions is a_i and the residual covariance matrix is Σ_i. The maximum squared Sharpe ratio of the intercepts is

$$Sh^2(a_i) = a_i'\Sigma_i^{-1}a_i, \tag{28}$$

where $Sh^2(\cdot)$ denotes the maximum squared Sharpe ratio. Gibbons et al. (1989) further shows that the maximum squared Sharpe ratio of the intercepts is the difference between the maximum squared Sharpe ratio constructed by Π_i and model i's factors and that constructed by model i's factors only:

$$Sh^2(a_i) = Sh^2(\Pi_i, f_i) - Sh^2(f_i). \tag{29}$$

As Π_i and f_i together include all competing factors, $Sh^2(\Pi_i, f_i)$ is independent of i. Hence, to minimize the maximum squared Sharpe ratio of the intercepts, we only need to find the maximum squared Sharpe ratio for model factors f_i, i.e., $Sh^2(f_i)$. The maximum squared Sharpe ratio can be computed from the tangent portfolio formed by model factors.

Table I1 presents the maximum squared Sharpe ratios for various factor models. Limited by data availability, we compare the FF3, FF4, FF5, FF6, HXZ, HMXZ, and macro uncertainty, micro uncertainty, or total uncertainty augmented models.[30] First, we see that adding macro uncertainty consistently improves the maximum squared Sharpe ratio across all models, suggesting the importance of macro uncertainty risk. But adding micro uncertainty only significantly improves the FF6 and the HXZ models, while adding total uncertainty only significantly improves the FF3 model. Second, we see that HXMZ has the highest maximum squared Sharpe ratio (0.30) while FF6+ΔUNC^{ma} and HXZ+ΔUNC^{ma} have a similar maximum squared Sharpe ratio (0.26 and 0.27, respectively). Again, this suggests that the EG factor and the macro uncertainty factor are very similar.

J. *Examining the pricing powers of three EG predictors*

Table J1 compares the pricing powers of three EG predictors. We augment Hou et al. (2015) q-factor model with each predictor of EG and run Fama-MacBeth regressions. We see that operating cash flows (CoP) and $dROE$ are significantly positive, but Tobin's q is insignificant. Also, HXZ+CoP has the highest R^2. This is consistent with Hou et al. (2021) that future investment growth is predicted mainly by CoP.

K. *Explaining the cross-sectional dispersions of EG predictors with total uncertainty*

Table K1 presents the univariate regression of the cross-sectional dispersion of each EG predictor against the total uncertainty (UNC). EG predictors are operating cash flows (CoP), Tobin's q (Q), and change in return on equity ($dROE$). We see that UNC explains most of the cross-sectional dispersions of EG predictors.

L. *Portfolios formed by predicted or residual component of expected investment growth: Extending window*

To avoid the look-ahead bias, we use the extending window to decompose expected investment growth into predicted and residual components. Starting from 1985, we regress the firm-level expected investment growth against the macro uncertainty to compute these two components over time. 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 the value-weighted portfolio returns and the alphas from various asset pricing models. Panel A of Table L1 shows that portfolio returns increase with predicted component of expected investment growth. The long-short portfolio (10-1) has a significantly positive alpha from all benchmark models. But Panel B of Table L1 shows that the residual component of expected investment growth doesn't provide additional information. For example, the long-short portfolio (10-1) has much smaller alphas than those reported in Panel A and its alpha is insignificant from SY model. Overall, we see that the pricing of expected investment growth is driven by the macro uncertainty risk.

[30] We cannot compute $Sh^2(f)$ for the SY model as we only have the data for the spread factors, not the corresponding portfolios.

M. *Explaining EG factor by macro or micro uncertainty factor*

In this subsection, we run a horse race between EG and uncertainty factor. Table M1 reports time-series regressions to test whether the EG factor can be captured by a factor model augmented by the uncertainty factor. In Panel A, we use the macro uncertainty factor (ΔUNC^{ma}). Unconditionally, the EG factor has an average return of 0.81% per month (t-statistic=8.77). However, the FF3, FF4, FF5, FF6, HXZ, and SY augmented with macro uncertainty can fully explain the EG factor with very small alphas. The loading of ΔUNC^{ma} is significant and close to -1. When we replace ΔUNC^{ma} with ΔUNC^{mi} in Panel B of Table M1, we see that the EG factor has a significant intercept in all regressions. Therefore, it seems that the EG factor captures a large amount of macro uncertainty risk, which contributes to its pricing power.

N. *Comparing the q^5 model with total uncertainty-augmented q-model*

For the robustness check, we compare Hou et al. (2021) q^5 model (HMXZ) with ΔUNC-augmented HXZ model (HXZ+ΔUNC) in Table N1. The results are similar to those using ΔUNC^{ma} in Table 4. Overall, the EG factor and ΔUNC have similar contribution in explaining the test portfolios in the cross section.

References

Adrian, T., Etula, E., Muir, T., 2014. Financial intermediaries and the cross-section of asset returns. Journal of Finance 69, 2557–2596.

Bai, J., Ng, S., 2002. Determining the number of factors in approximate factor models. Econometrica 70, 191–221.

Bansal, R., Yaron, A., 2004. Risks for the long run: A potential resolution of asset pricing puzzles. Journal of Finance 59, 1481–1509.

Barillas, F., Shanken, J., 2017. Which alpha? Review of Financial Studies 30, 1316–1338.

Bianchi, F., Kung, H., Tirskikh, M., 2023. The origins and effects of macroeconomic uncertainty. Quantitative Economics 14, 855–896.

Black, F., 1976. Studies of stock market volatility changes. 1976 Proceedings of the American Statistical Association, Business and Economic Statistics Section p. 177–181.

Bloom, N., Floetotto, M., Jaimovich, N., Saporta-Eksten, I., Terry, S. J., 2018. Really uncertain business cycles. Econometrica 86, 1031–1065.

Carhart, M. M., 1997. On persistence in mutual fund performance. Journal of Finance 52, 57–82.

Chen, H., Chen, S., 2012. Investment-cash flow sensitivity cannot be a good measure of financial constraints: Evidence from the time series. Journal of Financial Economics 103, 393–410.

Chen, Z., Kim, B.-C., 2020. Fundamental risk sources and pricing factors, Working Paper, Hong Kong University of Science and Technology.

Christie, A. A., 1982. The stochastic behavior of common stock variances: Value, leverage and interest rate effects. Journal of Financial Economics 10, 407–432.

Cochrane, J. H., 1991. Production-based asset pricing and the link between stock returns and economic fluctuation. Journal of Finance 46, 209–237.

Fama, E. F., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.

Fama, E. F., French, K. R., 1996. Multifactor explanations of asset pricing anomalies. Journal of Finance 51, 55–84.

Fama, E. F., French, K. R., 2015. A five-factor asset pricing model. Journal of Financial Economics 116, 1–22.

Fama, E. F., French, K. R., 2018. Choosing factors. Journal of Financial Economics 128, 234–252.

Fernández-Villaverde, J., Guerrón-Quintana, P. A., 2020. Uncertainty shocks and business cycle research. Review of Economic Dynamics 37, S118–S146.

Gibbons, M. R., Ross, S. A., Shanken, J., 1989. A test of the efficiency of a given portfolio. Econometrica 57, 1121–1152.

Gourieroux, C., Jasiak, J., 2006. Autoregressive gamma processes. Journal of Forecasting 25, 129–152.

Harvey, A. C., Shephard, N., 1996. Estimation of an asymmetric stochastic volatility model for asset returns. Journal of Business & Economic Statistics 14, 429–434.

Hou, K., Mo, H., Xue, C., Zhang, L., 2019. Which factors? Review of Finance 23, 1–35.

Hou, K., Mo, H., Xue, C., Zhang, L., 2021. An augmented q-factor model with expected growth. Review of Finance 25, 1–41.

Hou, K., Xue, C., Zhang, L., 2015. Digesting anomalies: An investment approach. Review of Financial Studies 28, 650–705.

İmrohoroğlu, A., Tüzel, Şelale., 2014. Firm-level productivity, risk, and return. Management Science 60, 1861–2109.

Jagannathan, R., Wang, Z., 1996. The conditional CAPM and the cross-section of expected returns. Journal of Finance 51, 3–53.

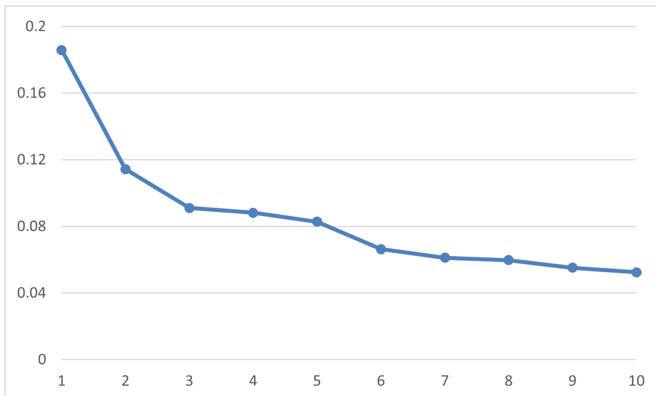
Jurado, K., Ludvigson, S. C., Ng, S., 2015. Measuring uncertainty. American Economic Review 105, 1177–1216.

Olley, G. S., Pakes, A., 1996. The dynamics of productivity in the telecommunications equipment industry. Econometrica 64, 1263–1297.

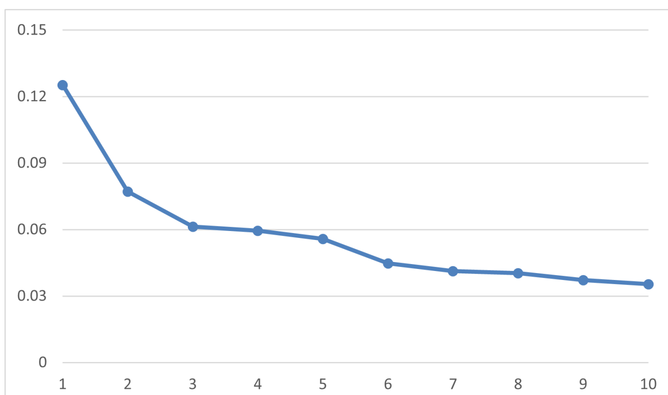
Restoy, F., Rockinger, G. M., 1994. On stock market returns and returns on investment. Journal of Finance 49, 543–556.

Shanken, J., 1992. On the estimation of beta-pricing models. Review of Financial Studies 5, 1–55.

Stambaugh, R. F., Yuan, Y., 2017. Mispricing factors. Review of Financial Studies 30, 1270–1315.



(a) Eigenvalues



(b) Proportion of variance explained by PC

Fig. C1. Eigenvalues and proportions of variance explained by principal components
These figures present the explanatory power of principal components over TFP growth. Panel (a) plots eigenvalue of each principal component. Panel (b) plots the proportions of variance explained by principal components.

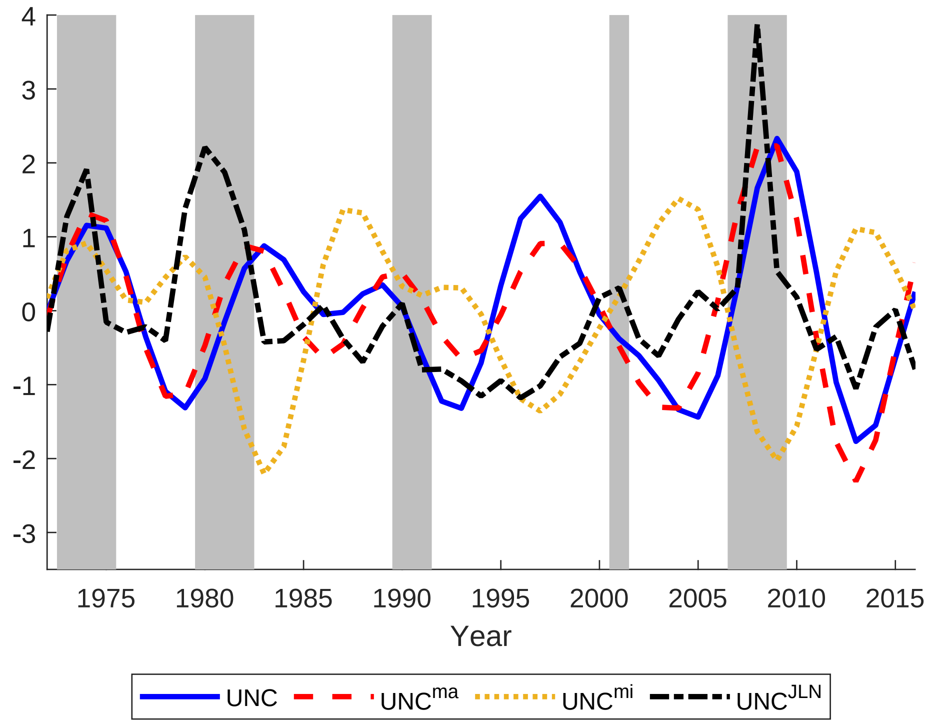


Fig. D1. TFP uncertainty and Jurado et al. (2015) uncertainty

This figure plots the time series of total uncertainty (UNC), macro uncertainty (UNC^{ma}), and micro uncertainty (UNC^{mi}) against Jurado et al. (2015) uncertainty index (UNC^{JLN}). Our uncertainty series are computed from Christiano and Fitzgerald (2003) band-pass filter and standardized. The shaded areas are NBER recession periods.

Table D1. **Decomposing macro uncertainty**

This table examines different potential drivers of macro uncertainty. We construct two counterfactual uncertainty measures, UNC^{ma}_{PC} and $UNC^{ma}_{Loadings}$. UNC^{ma}_{PC} is constructed by fixing the cross-sectional variance-covariance matrix of factor loadings at its time-series average and allowing the principal components to vary over time. $UNC^{ma}_{Loadings}$ is constructed by replacing the time-varying principal components with their eigenvalue-based weights and allowing the cross-sectional variance-covariance matrix of factor loadings to vary over time. Column (1) presents the time-series regression of macro uncertainty (ΔUNC^{ma}) on the first-differences of two counterfactual uncertainty measures (ΔUNC^{ma}_{PC} and $\Delta UNC^{ma}_{Loadings}$). Columns (2)-(5) report the time-series regressions of the counterfactual uncertainty measures on the NBER recession indicator (*Recession*) or Jurado et al. (2015) uncertainty (UNC^{JLN}). All uncertainty series are computed from Christiano and Fitzgerald (2003) band-pass filter in columns (2)-(5). Newey-West adjusted t-statistics with five-year lags are provided in parentheses. The sample period is 1972 to 2016.

	(1) ΔUNC^{ma}	(2) UNC^{ma}_{PC}	(3) UNC^{ma}_{PC}	(4) $UNC^{ma}_{Loadings}$	(5) $UNC^{ma}_{Loadings}$
ΔUNC^{ma}_{PC}	0.23				
	(6.07)				
$\Delta UNC^{ma}_{Loadings}$	-0.04				
	(-0.16)				
Recession		0.28		-0.02	
		(3.41)		(-0.37)	
UNC^{JLN}			0.08		0.00
			(1.80)		(0.27)
R^2	0.70	0.22	0.10	0.01	0.00

Table E1. **Decomposing total uncertainty into macro and micro uncertainty**

Panel A presents the time-series regression of aggregate uncertainty on macro uncertainty (UNC^{ma}) and micro uncertainty (UNC^{mi}). Aggregate uncertainty (UNC^{agg}) is the conditional standard deviation of a generalized autoregressive conditional heteroskedasticity (GARCH(1,1)) on aggregate TFP growth, obtained from the Federal Reserve Bank of San Francisco. Panel B presents the time-series regression of total uncertainty (ΔUNC) on macro uncertainty (UNC^{ma}) and micro uncertainty (UNC^{mi}). Newey-West adjusted t-statistics with 5-year lags are in parentheses. The testing period is from 1972 to 2016.

Panel A: Regression of aggregate uncertainty against macro and micro uncertainty		
	(1)	(2)
	UNC^{agg}	UNC^{agg}
UNC^{ma}	0.25	0.24
	(2.23)	(2.21)
UNC^{mi}		-0.17
		(-1.25)
R^2	0.10	0.11
Panel B: Regression of total uncertainty against macro and micro uncertainty		
	(1)	(2)
	ΔUNC	ΔUNC
ΔUNC^{ma}	0.60	0.73
	(10.11)	(9.62)
ΔUNC^{mi}		0.53
		(3.11)
R^2	0.75	0.81

Table F1. **Mimicking uncertainty factor returns and their alphas**

Panel A presents the monthly mean (% per month), standard deviation (% per month, SD), monthly Sharpe ratio (SR), and correlations for the mimicking uncertainty portfolios. Panel B reports the time-series regression of the mimicking total uncertainty portfolio on the mimicking macro uncertainty portfolio and the micro uncertainty portfolio. Panels C–E reports raw returns and alphas of the mimicking total uncertainty portfolio (ΔUNC), the mimicking macro uncertainty portfolio (ΔUNC^{ma}), and the mimicking micro uncertainty portfolio (ΔUNC^{mi}) from various factor models. Factor models include 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 (HXZ), Hou et al. (2021) q^5 model (HMXZ), and Stambaugh and Yuan (2017) model (SY). In Panels B-E, Newey-West adjusted t-statistics with 6-month lags are in parentheses. The testing period is from July 1973 to June 2018.

Panel A: Statistics of monthly mimicking uncertainty portfolios

	Mean	SD	SR	ΔUNC	ΔUNC^{ma}	ΔUNC^{mi}
ΔUNC	-0.79	2.23	-0.35			
ΔUNC^{ma}	-0.82	2.13	-0.39	0.90		
ΔUNC^{mi}	-0.18	5.52	-0.03	-0.03	-0.27	

Panel B: Regression of mimicking uncertainty portfolios

	(1)	(2)
	ΔUNC	ΔUNC
ΔUNC^{ma}	0.94	1.01
	(32.45)	(37.81)
ΔUNC^{mi}		0.09
		(9.46)
R^2	0.81	0.86

Panel C: Raw return and alpha of total uncertainty factor (ΔUNC)

	Return	CAPM	FF3	FF4	FF5	FF6	HXZ	HMXZ	SY
ΔUNC	-0.79	-0.86	-0.81	-0.77	-0.63	-0.62	-0.63	-0.13	-0.51
t-stat	-8.27	-8.84	-9.59	-8.68	-8.28	-7.82	-8.35	-3.41	-5.33

Panel D: Raw return and alpha of macro uncertainty factor (ΔUNC^{ma})

	Return	CAPM	FF3	FF4	FF5	FF6	HXZ	HMXZ	SY
ΔUNC^{ma}	-0.82	-0.91	-0.90	-0.78	-0.68	-0.61	-0.57	-0.03	-0.48
t-stat	-9.07	-10.02	-11.38	-9.94	-8.15	-7.97	-6.43	-1.94	-5.51

Panel E: Raw return and alpha of micro uncertainty factor (ΔUNC^{mi})

	Return	CAPM	FF3	FF4	FF5	FF6	HXZ	HMXZ	SY
ΔUNC^{mi}	-0.18	0.14	0.18	-0.03	0.03	-0.12	-0.41	-0.23	0.04
t-stat	-0.77	0.69	0.89	-0.13	0.12	-0.59	-1.97	-1.01	0.16

Table G1. **Examining loadings of macro uncertainty factor**

This table presents factor loadings of macro uncertainty (ΔUNC^{ma}) from the full-sample time-series regressions of 45 test assets. The factor loadings of ΔUNC^{ma} ($\hat{\beta}_{UNC^{ma},i}$) are estimated from the Fama-French three-factor model augmented with ΔUNC^{ma}. Test assets include 6 size and book-to-market sorted portfolios (Panel A), 6 size and investment sorted portfolios (Panel B), 6 size and operating profitability sorted portfolios (Panel C), 6 size and momentum sorted portfolios (Panel D), 6 size and expected investment growth sorted portfolios (Panel E),10 operating accruals sorted portfolios (Panel F), and 5 Fama-French industry portfolios (Panel G). The Newey-West t-statistics with six-month lags are provided. The sample period is from July 1973 to June 2018.

Regression: $R_{it} = \alpha_i + \beta_{MKT,i}MKT_t + \beta_{SMB,i}SMB_t + \beta_{HML,i}HML_t + \beta_{UNC^{ma},i}\Delta UNC_t^{ma} + \epsilon_{it}$							
	$\beta_{UNC^{ma},i}$				t-statistics		
Panel A: 6 size and book-to-market sorted portfolios							
	Low	Middle	High		Low	Middle	High
Small	0.09	-0.08	-0.05	Small	2.53	-1.86	-2.56
Big	-0.06	-0.09	0.07	Big	-2.21	-1.81	1.51
Panel B: 6 size and investment sorted portfolios							
	Low	Middle	High		Low	Middle	High
Small	-0.07	-0.10	0.15	Small	-1.55	-4.13	4.30
Big	-0.24	-0.08	0.10	Big	-5.26	-1.99	2.81
Panel C: 6 size and operating profitability sorted portfolios							
	Low	Middle	High		Low	Middle	High
Small	0.12	-0.08	-0.09	Small	2.33	-1.74	-1.46
Big	0.35	0.03	-0.18	Big	5.16	1.11	-4.32
Panel D: 6 size and momentum sorted portfolios							
	Low	Middle	High		Low	Middle	High
Small	0.65	0.01	-0.23	Small	5.09	0.35	-4.24
Big	0.48	-0.01	-0.38	Big	4.23	-0.33	-4.91
Panel E: 6 size and expected investment growth sorted portfolios							
	Low	Middle	High		Low	Middle	High
Small	0.57	-0.05	-0.29	Small	8.73	-1.48	-7.78
Big	0.61	-0.12	-0.52	Big	14.49	-1.77	-10.65
Panel F: 10 operating accruals sorted portfolios							
	Low	2	3		Low	2	3
	0.02	-0.11	-0.05		0.15	-1.34	-0.54
	4	5	6		4	5	6
	-0.21	-0.11	-0.16		-4.10	-1.25	-2.38
	7	8	9		7	8	9
	-0.01	0.02	0.01		-0.10	0.21	0.12
	High				High		
	0.19				4.17		
Panel G: 5 industry portfolios							
	Consumer	Manufacture	HiTec		Consumer	Manufacture	HiTec
	0.01	-0.17	0.12		0.08	-2.32	0.87
	Health	Other			Health	Other	
	-0.39	0.08			-2.55	1.31	

Table G2. **Cross-sectional regressions of factor models augmented with total uncertainty factor**

Panel A reports the coefficients (Coeff) and t-statistics (t-stat) from Fama-MacBeth regressions of various factor models and factor models augmented with total uncertainty (ΔUNC), using the full-sample estimation. Test assets are 45 portfolios and the tested 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. 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). Panel B shows similar results in the extending-window. 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 is from July 1973 to June 2018. The testing period for Panel B is from July 1997 to June 2018.

Panel A: Full-sample estimation

	FF3		FF3+ΔUNC		FF4		FF4+ΔUNC		FF5		FF5+ΔUNC		FF6		FF6+ΔUNC	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.33	6.33	0.18	3.37	0.08	3.61	0.06	2.36	0.09	3.55	0.06	2.10	0.06	2.80	0.03	1.35
γ_{MKT}	0.29	1.46	0.41	2.05	0.56	2.87	0.55	2.80	0.50	2.55	0.52	2.62	0.56	2.86	0.57	2.89
γ_{SMB}	0.19	1.47	0.24	1.80	0.23	1.74	0.25	1.90	0.27	2.10	0.28	2.12	0.27	2.09	0.28	2.12
γ_{HML}	0.21	1.57	0.25	1.81	0.36	2.67	0.33	2.42	0.13	0.95	0.20	1.49	0.25	1.88	0.29	2.23
γ_{CMA}									0.39	4.09	0.37	3.12	0.30	3.29	0.30	3.28
γ_{RMW}									0.20	1.84	0.30	2.81	0.18	1.70	0.28	2.66
γ_{UMD}					0.62	3.29	0.57	3.03					0.60	3.19	0.58	3.08
γ_{UNC}			-1.02	-8.62			-0.87	-8.30			-0.91	-8.39			-0.85	-8.04
R^2	0.19		0.82		0.51		0.88		0.51		0.86		0.64		0.91	
(5^{th}, 95^{th})	(0.02, 0.50)		(0.64, 0.88)		(0.33, 0.70)		(0.76, 0.91)		(0.29, 0.72)		(0.72, 0.91)		(0.46, 0.80)		(0.82, 0.93)	

Panel A (Continued)

	HXZ		HXZ+ΔUNC		HMXZ		SY		SY+ΔUNC	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.11	2.81	0.07	1.92	0.07	2.10	0.08	1.60	0.05	1.04
γ_{MKT}	0.50	2.50	0.52	2.61	0.54	2.72	0.51	2.48	0.52	2.54
$\gamma_{Q_{ME}}$	0.35	2.55	0.35	2.52	0.36	2.62				
$\gamma_{Q_{IA}}$	0.29	2.71	0.35	3.27	0.31	2.93				
$\gamma_{Q_{ROE}}$	0.45	3.32	0.39	2.82	0.33	2.40				
γ_{EG}					0.79	7.70				
$\gamma_{MIS_{ME}}$							0.40	3.06	0.46	3.53
γ_{MGMT}							0.53	3.57	0.52	3.47
γ_{PERF}							0.55	2.93	0.60	3.18
γ_{UNC}			-0.86	-7.85					-0.84	-7.61
R^2	0.51		0.91		0.82		0.70		0.91	
(5^{th}, 95^{th})	(0.30, 0.71)		(0.80, 0.92)		(0.66, 0.87)		(0.51, 0.82)		(0.81, 0.92)	

Panel B: Extending-window estimation

	FF3		FF3+ΔUNC		FF4		FF4+ΔUNC		FF5		FF5+ΔUNC		FF6		FF6+ΔUNC	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.22	2.89	0.01	0.21	0.09	2.38	0.06	1.61	0.12	2.93	0.05	1.15	0.09	2.89	0.07	2.04
γ_{MKT}	0.40	1.34	0.60	1.97	0.55	1.95	0.53	1.80	0.47	1.69	0.55	1.91	0.51	1.82	0.52	1.84
γ_{SMB}	0.20	0.98	0.27	1.28	0.22	1.04	0.28	1.30	0.27	1.30	0.28	1.35	0.26	1.29	0.28	1.35
γ_{HML}	0.14	0.61	0.22	0.90	0.23	0.99	0.17	0.74	0.03	0.15	0.16	0.72	0.08	0.37	0.13	0.60
γ_{CMA}									0.22	1.23	0.15	0.85	0.18	1.11	0.16	0.92
γ_{RMW}									0.13	0.59	0.19	0.88	0.16	0.76	0.20	0.91
γ_{UMD}					0.42	1.21	0.35	0.96					0.39	1.13	0.35	0.97
γ_{UNC}			-0.65	-3.04			-0.77	-3.82			-0.61	-3.17			-0.70	-4.25
R^2	0.31		0.83		0.45		0.85		0.52		0.83		0.57		0.85	
(5^{th}, 95^{th})	(0.01, 0.61)		(0.73, 0.92)		(0.30, 0.76)		(0.75, 0.93)		(0.26, 0.78)		(0.75, 0.93)		(0.43, 0.84)		(0.78, 0.94)	

Panel B (Continued)

	HXZ		HXZ+ΔUNC		HMXZ		SY		SY+ΔUNC	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.12	1.73	0.05	0.87	0.06	0.96	0.13	1.36	0.12	1.68
γ_{MKT}	0.48	1.74	0.56	1.97	0.55	1.92	0.43	1.44	0.44	1.49
$\gamma_{Q_{ME}}$	0.30	1.45	0.33	1.54	0.32	1.46				
$\gamma_{Q_{IA}}$	0.16	0.84	0.2	1.03	0.19	1.01				
$\gamma_{Q_{ROE}}$	0.19	0.72	0.14	0.57	0.14	0.53				
γ_{EG}					0.61	3.32				
$\gamma_{MIS_{ME}}$							0.37	1.71	0.39	1.80
γ_{MGMT}							0.44	1.77	0.40	1.49
γ_{PERF}							0.58	1.49	0.51	1.31
γ_{UNC}			-0.64	-3.58					-0.66	-3.95
R^2	0.44		0.83		0.74		0.61		0.80	
(5^{th}, 95^{th})	(0.25, 0.77)		(0.72, 0.92)		(0.60, 0.88)		(0.45, 0.85)		(0.73, 0.92)	

Table G3. **Cross-sectional regressions of macro- and micro- uncertainty augmented factor models**

Panel A reports Fama-MacBeth regressions of various factor models augmented with both macro and micro uncertainty factors, using the full-sample estimation. Panel B shows similar results, using the extending-window estimation. Test assets are 45 portfolios and the tested 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. 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 is from July 1973 to June 2018. The testing period for Panel B is from July 1997 to June 2018.

Panel A: Factor models augmented with macro- and micro- uncertainty, using the full-sample estimation												
	FF3+$\Delta UNC^{ma,mi}$		FF4+$\Delta UNC^{ma,mi}$		FF5+$\Delta UNC^{ma,mi}$		FF6+$\Delta UNC^{ma,mi}$		HXZ+$\Delta UNC^{ma,mi}$		SY+$\Delta UNC^{ma,mi}$	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.02	0.62	0.02	0.94	0.03	1.24	0.03	1.46	0.05	1.63	0.07	1.58
γ_{MKT}	0.58	2.91	0.57	2.93	0.57	2.89	0.57	2.90	0.55	2.80	0.51	2.48
γ_{SMB}	0.28	2.18	0.28	2.18	0.28	2.17	0.28	2.17				
γ_{HML}	0.29	2.09	0.29	2.14	0.30	2.23	0.30	2.27				
γ_{CMA}					0.28	2.97	0.28	2.98				
γ_{RMW}					0.24	2.23	0.24	2.23				
γ_{UMD}			0.57	3.04			0.57	3.02				
$\gamma_{Q_{ME}}$									0.37	2.67		
$\gamma_{Q_{IA}}$									0.35	3.38		
$\gamma_{Q_{ROE}}$									0.36	2.65		
$\gamma_{MISP_{ME}}$											0.47	3.66
γ_{MGMT}											0.45	3.07
γ_{PERF}											0.54	2.87
$\gamma_{UNC^{ma}}$	-0.82	-7.23	-0.81	-7.97	-0.83	-7.70	-0.82	-8.58	-0.81	-7.91	-0.81	-8.20
$\gamma_{UNC^{mi}}$	-0.22	-0.92	-0.23	-0.95	-0.23	-0.95	-0.23	-0.97	-0.25	-1.05	-0.26	-1.05
R^2	0.92		0.92		0.92		0.92		0.91		0.91	
(5^{th}, 95^{th})	(0.81, 0.93)		(0.82, 0.94)		(0.82, 0.94)		(0.84, 0.95)		(0.80, 0.93)		(0.81, 0.94)	

Panel B: Factor models augmneted with macro- and micro- uncertainty, using the extending window estimation

	FF3+$\Delta UNC^{ma,mi}$		FF4+$\Delta UNC^{ma,mi}$		FF5+$\Delta UNC^{ma,mi}$		FF6+$\Delta UNC^{ma,mi}$		HXZ+$\Delta UNC^{ma,mi}$		SY+$\Delta UNC^{ma,mi}$	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.02	0.39	0.05	1.44	0.05	1.12	0.06	1.89	0.10	1.73	0.14	2.39
γ_{MKT}	0.58	1.85	0.53	1.78	0.55	1.85	0.53	1.81	0.50	1.63	0.41	1.32
γ_{SMB}	0.28	1.35	0.29	1.37	0.28	1.33	0.28	1.35				
γ_{HML}	0.15	0.69	0.11	0.51	0.15	0.72	0.13	0.64				
γ_{CMA}					0.17	1.05	0.16	0.97				
γ_{RMW}					0.24	1.22	0.21	1.07				
γ_{UMD}			0.36	1.02			0.35	1.00				
$\gamma_{Q_{ME}}$									0.33	1.44		
$\gamma_{Q_{IA}}$									0.06	0.30		
$\gamma_{Q_{ROE}}$									0.05	0.18		
$\gamma_{MISP_{ME}}$											0.37	1.78
γ_{MGMT}											0.30	1.36
γ_{PERF}											0.48	1.29
$\gamma_{UNC^{ma}}$	-0.56	-2.77	-0.62	-3.38	-0.54	-2.79	-0.61	-3.47	-0.70	-3.69	-0.60	-3.35
$\gamma_{UNC^{mi}}$	-1.47	-0.69	-1.51	-0.70	-1.57	-0.74	-1.53	-0.72	-1.44	-0.67	-1.92	-0.95
R^2	0.91		0.92		0.93		0.92		0.91		0.92	
(5^{th}, 95^{th})	(0.74, 0.96)		(0.76, 0.97)		(0.77, 0.97)		(0.79, 0.97)		(0.75, 0.96)		(0.75, 0.97)	

Table G4. **Cross-sectional regressions of aggregate uncertainty-augmented factor models**

This table reports Fama-MacBeth regressions of various factor models augmented with the mimicking aggregate uncertainty portfolio (ΔUNC^{agg}), using full sample. Test assets are 45 portfolios and the tested 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. 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 is from July 1973 to June 2018.

	FF3+ΔUNC^{agg}		FF4+ΔUNC^{agg}		FF5+ΔUNC^{agg}		FF6+ΔUNC^{agg}		HXZ+ΔUNC^{agg}		SY+ΔUNC^{agg}	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.23	4.44	0.11	3.34	0.12	4.16	0.09	3.67	0.14	3.46	0.07	1.73
γ_{MKT}	0.35	1.71	0.49	2.49	0.45	2.30	0.51	2.58	0.45	2.24	0.49	2.42
γ_{SMB}	0.28	2.13	0.29	2.19	0.29	2.24	0.29	2.23				
γ_{HML}	0.23	1.69	0.32	2.36	0.20	1.47	0.31	2.38				
γ_{CMA}					0.35	3.59	0.26	2.79				
γ_{RMW}					0.20	1.89	0.19	1.74				
γ_{UMD}			0.55	2.90			0.56	2.96				
$\gamma_{Q_{ME}}$									0.39	2.82		
$\gamma_{Q_{IA}}$									0.33	3.07		
$\gamma_{Q_{ROE}}$									0.31	2.23		
$\gamma_{MIS_{ME}}$											0.49	3.80
γ_{MGMT}											0.53	3.66
γ_{PERF}											0.56	3.00
$\gamma_{UNC^{agg}}$	-1.05	-7.94	-0.93	-7.36	-0.93	-7.79	-0.90	-7.61	-0.88	-7.24	-0.79	-6.28
R^2	0.77		0.86		0.78		0.86		0.81		0.87	
(5^{th}, 95^{th})	(0.56, 0.85)		(0.74, 0.90)		(0.60, 0.87)		(0.75, 0.91)		(0.65, 0.88)		(0.74, 0.91)	

Table G5. **Cross-sectional regressions of the mimicking uncertainty augmented models: Using VIX index**

This table reports Fama-MacBeth regressions of various factor models and those augmented with the mimicking uncertainty factor using VIX index (ΔVIX), using the full-sample estimation. Test assets are 45 portfolios and the tested 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. 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), Hou et al. (2021), 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 is July 1988 to June 2018.

	FF3		FF3+ΔVIX		FF4		FF4+ΔVIX		FF5		FF5+ΔVIX		FF6		FF6+ΔVIX	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.44	5.32	0.43	5.76	0.13	3.79	0.17	4.67	0.08	2.77	0.09	2.67	0.04	1.63	0.06	2.09
γ_{MKT}	0.26	1.11	0.25	1.06	0.60	2.70	0.53	2.40	0.58	2.59	0.56	2.50	0.65	2.95	0.62	2.79
γ_{SMB}	0.06	0.36	0.06	0.35	0.09	0.55	0.08	0.52	0.15	0.95	0.14	0.89	0.15	0.96	0.14	0.87
γ_{HML}	0.08	0.47	0.12	0.69	0.24	1.45	0.25	1.50	-0.04	-0.26	-0.02	-0.10	0.08	0.47	0.11	0.69
γ_{CMA}									0.28	2.29	0.31	2.54	0.21	1.77	0.23	1.91
γ_{RMW}									0.29	2.07	0.34	2.39	0.28	1.96	0.31	2.21
γ_{UMD}					0.56	2.30	0.53	2.16					0.57	2.33	0.56	2.25
γ_{VIX}			-1.13	-7.38			-1.03	-6.86			-0.90	-5.86			-0.93	-6.15
R^2	0.03		0.58		0.38		0.81		0.52		0.80		0.66		0.91	
(5^{th}, 95^{th})	(-0.03, 0.47)		(0.33, 0.78)		(0.24, 0.67)		(0.63, 0.88)		(0.30, 0.76)		(0.60, 0.90)		(0.49, 0.83)		(0.79, 0.94)	

	HXZ		HXZ+ΔVIX		HMXZ		SY		SY+ΔVIX	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.10	1.98	0.17	2.98	0.06	1.47	0.10	1.61	0.12	1.81
γ_{MKT}	0.59	2.62	0.50	2.19	0.62	2.78	0.56	2.39	0.53	2.23
$\gamma_{Q_{ME}}$	0.24	1.43	0.19	1.10	0.26	1.51				
$\gamma_{Q_{IA}}$	0.09	0.69	0.04	0.26	0.11	0.79				
$\gamma_{Q_{ROE}}$	0.47	2.76	0.43	2.46	0.35	2.01				
γ_{EG}					0.72	5.84				
$\gamma_{MIS_{ME}}$							0.23	1.47	0.20	1.30
γ_{MGMT}							0.43	2.26	0.43	2.25
γ_{PERF}							0.60	2.33	0.68	2.64
γ_{VIX}			-0.93	-5.83					-0.89	-5.32
R^2	0.43		0.81		0.78		0.62		0.87	
(5^{th}, 95^{th})	(0.22, 0.70)		(0.61, 0.89)		(0.57, 0.86)		(0.39, 0.80)		(0.72, 0.90)	

Table H1. **Cross-sectional regressions of uncertainty factor augmented Hou et al. (2015) q-factor model: different numbers of PCs**

This table reports Fama-MacBeth regressions of Hou et al. (2015) q-factor model augmented with the annual uncertainty factor, using non-tradable uncertainty factors directly and full-sample estimation. Panel A uses macro uncertainty factor (ΔUNC^{ma}); Panel B uses micro uncertainty factor (ΔUNC^{mi}). ΔUNC^{ma} and ΔUNC^{mi} are estimated with different number (k) of principal components (PC) where k is 3, 5, 7, and 10, respectively. Test assets are 45 portfolios and the tested 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. Sample period is July 1973 to June 2018.

Panel A: Augmented factor models with macro uncertainty								
	k=3		k=5		k=7		k=10	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	1.24	1.77	1.68	2.44	1.80	3.07	1.88	3.48
γ_{MKT}	5.91	2.21	5.57	2.09	5.42	2.06	5.42	2.06
$\gamma_{Q_{ME}}$	2.55	1.29	2.35	1.20	2.38	1.23	2.45	1.27
$\gamma_{Q_{IA}}$	4.11	1.91	3.09	1.53	3.17	1.81	2.90	1.86
$\gamma_{Q_{ROE}}$	6.22	3.36	5.91	3.37	5.33	3.19	5.35	3.25
$\gamma_{UNC^{ma}}$	-10.30	-2.20	-8.38	-2.71	-4.60	-2.05	-3.76	-1.72
R^2	0.53		0.49		0.45		0.45	
(5^{th}, 95^{th})	(0.14, 0.78)		(0.13, 0.79)		(0.12, 0.78)		(0.12, 0.79)	

Panel B: Augmented factor models with micro uncertainty								
	k=3		k=5		k=7		k=10	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	1.74	3.46	1.70	3.23	1.62	2.91	1.73	3.49
γ_{MKT}	5.50	2.10	5.55	2.12	5.62	2.14	5.56	2.12
$\gamma_{Q_{ME}}$	2.59	1.35	2.64	1.37	2.64	1.37	2.61	1.36
$\gamma_{Q_{IA}}$	3.64	2.18	3.81	2.23	4.14	2.43	3.65	2.43
$\gamma_{Q_{ROE}}$	5.15	3.28	5.17	3.30	5.02	3.10	5.29	3.32
$\gamma_{UNC^{mi}}$	-0.47	-0.59	-0.25	-0.35	-0.85	-1.13	0.29	0.38
R^2	0.44		0.44		0.45		0.44	
(5^{th}, 95^{th})	(0.14, 0.78)		(0.14, 0.78)		(0.14, 0.78)		(0.13, 0.78)	

Table H2. **Cross-sectional regressions of various uncertainty-augmented factor models: alternative base assets**

This table presents the coefficients (Coeff) and t-statistics (t-stat) from Fama-MacBeth regressions of various factor models and factor models augmented with total uncertainty (ΔUNC), macro uncertainty (ΔUNC^{ma}), and micro uncertainty (ΔUNC^{mi}), using the alternative base assets including 6 size and book-to-market sorted portfolios and expected investment growth factor in the full-sample estimation. Test assets are 45 portfolios and the tested 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. 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 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 sample period for Panel A is from July 1973 to June 2018.

	HXZ+ΔUNC		HXZ+ΔUNC^{ma}		HXZ+ΔUNC^{mi}		HXZ+$\Delta UNC^{ma}+\Delta UNC^{mi}$	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.16	3.62	0.15	3.50	0.09	2.45	0.16	3.97
γ_{MKT}	0.45	2.25	0.46	2.32	0.52	2.60	0.44	2.21
$\gamma_{Q_{ME}}$	0.38	2.74	0.35	2.55	0.35	2.58	0.36	2.64
$\gamma_{Q_{IA}}$	0.19	1.68	0.21	1.90	0.29	2.71	0.18	1.59
$\gamma_{Q_{ROE}}$	0.31	2.23	0.30	2.16	0.46	3.39	0.27	1.92
γ_{UNC}	-0.85	-5.20						
$\gamma_{UNC^{ma}}$			-1.06	-5.60			-1.07	-5.64
$\gamma_{UNC^{mi}}$					-0.30	-0.89	-0.41	-1.21
R^2	0.80		0.82		0.61		0.87	
(5^{th}, 95^{th})	(0.67, 0.86)		(0.70, 0.87)		(0.38, 0.79)		(0.75, 0.91)	

Table H3. **Robustness: Noisy factors**

Panel A examines how likely "noisy" factors could generate the cross-sectional results in Table 4. Following Adrian et al. (2014), we run 100,000 simulations where we draw randomly from the empirical distribution of an uncertainty factor ($\Delta UNC, \Delta UNC^{ma}$, or ΔUNC^{mi}) with replacement. We construct the monthly mimicking uncertainty factor and rerun Fama-MacBeth two-pass regressions. For each statistic, we report the probability that noisy factors do as well as the original models (i.e., the probability that noisy factors generate R^2s as large as the original models (in "R^2" column), prices of risk of an uncertainty factor as large as original models (in "PRC" column), or Sharpe ratio of an uncertainty factor as large as original mimicking uncertainty factors (in "SR" column)). We also report the joint probabilities that noisy factors simultaneously generate higher R^2s and larger price of risk than the original models (in "Joint R^2-PRC" column) and that noisy factors simultaneously generate higher R^2, larger prices of risk, and larger Sharpe ratio than the original models (in "Joint All" column). Panel A, B, and C report results from total uncertainty (ΔUNC), macro uncertainty (ΔUNC^{ma}), and micro uncertainty (ΔUNC^{mi}), respectively. Test assets are 45 portfolios and the tested 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. 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 numbers are in percentages. The testing period is July 1973 to June 2018 except for Stambaugh and Yuan (2017) models. The testing period of Stambaugh and Yuan (2017) model is July 1973 to June 2016.

Panel A: Noisy ΔUNC-augmented factor models					
	R^2	PRC	SR	Joint R^2-PRC	Joint All
FF3+ΔUNC	5.26	0.00	0.00	0.00	0.00
FF4+ΔUNC	4.74	0.00	0.00	0.00	0.00
FF5+ΔUNC	5.45	0.00	0.00	0.00	0.00
FF6+ΔUNC	4.65	0.00	0.00	0.00	0.00
SY+ΔUNC	5.78	0.00	0.00	0.00	0.00
HXZ+ΔUNC	4.10	0.00	0.00	0.00	0.00
Panel B: Noisy ΔUNC^{ma}-augmented factor models					
	R^2	PRC	SR	Joint R^2-PRC	Joint All
FF3+ΔUNC^{ma}	3.02	0.00	0.00	0.00	0.00
FF4+ΔUNC^{ma}	3.97	0.00	0.00	0.00	0.00
FF5+ΔUNC^{ma}	3.76	0.00	0.00	0.00	0.00
FF6+ΔUNC^{ma}	4.62	0.00	0.00	0.00	0.00
SY+ΔUNC^{ma}	6.15	0.00	0.00	0.00	0.00
HXZ+ΔUNC^{ma}	4.46	0.00	0.00	0.00	0.00
Panel C: Noisy ΔUNC^{mi}-augmented factor models					
	R^2	PRC	SR	Joint R^2-PRC	Joint All
FF3+ΔUNC^{mi}	58.77	94.02	96.76	53.64	53.64
FF4+ΔUNC^{mi}	47.90	98.00	96.76	45.91	44.66
FF5+ΔUNC^{mi}	53.75	96.34	96.76	50.10	50.10
FF6+ΔUNC^{mi}	45.74	98.37	96.76	44.11	42.50
SY+ΔUNC^{mi}	32.95	97.99	96.24	30.95	29.19
HXZ+ΔUNC^{mi}	47.12	98.30	96.76	45.42	43.88

Table H4. **Giglio and Xiu (2021) Three-pass regression**

This table presents the risk premia (γ) 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 (ΔUNC), macro uncertainty (ΔUNC^{ma}), and micro uncertainty (ΔUNC^{mi}). The three-pass estimator uses 15 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	γ	SE	t-stat	R_g^2	p (g weak)
MKT	7.27	2.31	3.15	99.78	0.00
SMB	1.09	2.17	0.50	98.63	0.00
HML	2.79	1.65	1.69	97.17	0.00
CMA	3.01	1.23	2.45	90.25	0.00
RMW	2.80	1.28	2.19	92.90	0.00
UMD	5.56	2.27	2.45	66.46	0.00
Q_{ME}	1.90	2.19	0.87	97.66	0.00
Q_{IA}	3.32	1.07	3.10	86.74	0.00
Q_{ROE}	4.72	1.12	4.21	77.70	0.00
EG	6.63	1.71	3.88	76.96	0.00
ΔUNC	-2.62	0.67	-3.91	39.49	0.00
ΔUNC^{ma}	-4.10	0.99	-4.14	39.74	0.00
ΔUNC^{mi}	0.64	0.45	1.42	30.32	0.00

Table I1. **Maximum squared Sharpe ratio of factor models**

Panel A presents the maximum squared Sharpe ratio ($Sh^2(f)$) of the tangent portfolio constructed by pricing factors from prevailing factor models and macro uncertainty (ΔUNC^{ma}) augmented factor models. Panels B and C report similar results, using micro uncertainty (ΔUNC^{mi}), or total uncertainty (ΔUNC) augmented factor models, respectively. Factor models include 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). The 5^{th} and 95^{th} percentiles of the $Sh^2(f)$ distribution from a bootstrap simulation of 10,000 times are reported in brackets. The testing period is from July 1973 to June 2018.

Panel A: Prevaling factor models and ΔUNC^{ma} augmented factor models						
	FF3	FF3+ΔUNC^{ma}	FF4	FF4+ΔUNC^{ma}	FF5	FF5+ΔUNC^{ma}
Sh2(f)	0.04	0.20	0.08	0.23	0.11	0.24
(5^{th}, 95^{th})	(0.02, 0.09)	(0.14, 0.30)	(0.05, 0.15)	(0.16, 0.34)	(0.08, 0.18)	(0.18, 0.34)
	FF6	FF6+ΔUNC^{ma}	HXZ	HXZ+ΔUNC^{ma}	HMXZ	
Sh2(f)	0.14	0.26	0.16	0.27	0.30	
(5^{th}, 95^{th})	(0.10, 0.22)	(0.19, 0.38)	(0.11, 0.24)	(0.19, 0.38)	(0.23, 0.41)	
Panel B: ΔUNC^{mi} augmented factor models						
	FF3+ΔUNC^{mi}	FF4+ΔUNC^{mi}	FF5+ΔUNC^{mi}	FF6+ΔUNC^{mi}	HXZ+ΔUNC^{mi}	
Sh2(f)	0.05	0.09	0.11	0.26	0.27	
(5^{th}, 95^{th})	(0.02, 0.09)	(0.05, 0.16)	(0.08, 0.18)	(0.19, 0.37)	(020, 0.38)	
Panel C: ΔUNC augmented factor models						
	FF3+ΔUNC	FF4+ΔUNC	FF5+ΔUNC	FF6+ΔUNC	HXZ+ΔUNC	
Sh2(f)	0.18	0.09	0.12	0.15	0.19	
(5^{th}, 95^{th})	(0.12, 0.26)	(0.06, 0.16)	(0.08, 0.19)	(0.10, 0.23)	(0.13, 0.27)	

Table J1. **Cross-sectional regressions of EG predictors-augmented factor models**

This table reports Fama-MacBeth regressions of Hou et al. (2015) q-factor model (HMZ) augmented with pricing factors of three predictors of the expected investment growth, using the full-sample estimation. We construct the annual pricing factors by sorting each of three predictors, following Hou et al. (2021). Three predictors are operating cash flow (CoP), Tobin's Q (Q), and the first-difference of return on equity ($dROE$). 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 testing period is June 1973 to June 2018.

	HXZ+CoP		HXZ+Q		HXZ+$dROE$	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.96	2.17	-0.23	-0.45	0.98	1.76
γ_{MKT}	5.98	2.29	7.42	2.81	6.23	2.36
$\gamma_{Q_{ME}}$	2.83	1.46	3.14	1.62	2.76	1.43
$\gamma_{Q_{IA}}$	3.55	1.94	6.85	4.93	6.16	3.85
$\gamma_{Q_{ROE}}$	4.26	2.49	5.93	3.49	6.07	3.59
γ_{CoP}	8.70	5.02				
γ_Q			-1.92	-0.72		
γ_{dROE}					9.12	5.24
R^2	0.69		0.64		0.59	
(5^{th}, 95^{th})	(0.42, 0.83)		(0.32, 0.83)		(0.30, 0.78)	

Table K1. **Using total uncertainty to explain the cross-sectional dispersions of EG predictors**

Columns (1)–(3) report the coefficients, t-statistics (t-stat), and R^2 from the time-series regression of the cross-sectional dispersion of each EG predictor on the total uncertainty (UNC). Predictors are operating cash flows (DIS_{CoP}), Tobin's q (DIS_Q), and change in return on equity (DIS_{dROE}), respectively. Newey-West t-statistics with 5-year lags are used. The testing period is from 1972 to 2016.

	(1)	(2)	(3)
	DIS_{CoP}	DIS_Q	DIS_{dROE}
UNC	0.36	1.09	0.62
t-stat	4.00	2.82	5.46
R^2	0.61	0.36	0.65

Table L1. **Returns to portfolios sorted by the predicted and residual expected investment growth: Extending-window estimation**

All stocks are sorted into 10 portfolios, based on either the predicted expected investment growth (Panel A), or residual expected investment growth (Panel B). We decompose EG into predicted and residual expected investment growth by regressing EG against macro uncertainty (ΔUNC^{ma}) for each firm using the extending-window estimation. The decomposition starts in 1985 and extends to 2018. We compute the value-weighted portfolio returns, and the alphas from 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 (high predicted or residual expected investment growth) and Portfolio 1 (low predicted or residual expected investment growth). All returns are multiplied by 100. The testing period is from July 1986 to June 2018 except for Stambaugh and Yuan (2017) model. The testing period of Stambaugh and Yuan (2017) is July 1986 to December 2016.

Panel A: Portfolios sorted by predicted EG											
	1	2	3	4	5	6	7	8	9	10	10-1
Raw	0.05	0.17	0.49	0.63	0.67	0.77	0.59	0.68	0.86	1.14	1.09
	(0.10)	(0.51)	(1.94)	(2.49)	(2.89)	(3.70)	(3.05)	(3.03)	(3.24)	(3.30)	(4.03)
CAPM	-1.03	-0.67	-0.19	-0.09	0.05	0.21	0.03	0.09	0.16	0.30	1.34
	(-3.44)	(-4.57)	(-1.71)	(-0.97)	(0.53)	(1.90)	(0.32)	(1.06)	(1.30)	(1.74)	(5.27)
FF3	-0.79	-0.60	-0.15	-0.03	0.02	0.18	0.00	0.10	0.24	0.47	1.26
	(-3.56)	(-4.07)	(-1.37)	(-0.41)	(0.21)	(1.69)	(0.00)	(1.15)	(2.24)	(3.43)	(5.58)
FF4	-0.65	-0.47	-0.11	-0.01	0.00	0.14	0.00	0.13	0.29	0.54	1.20
	(-3.07)	(-3.05)	(-0.98)	(-0.11)	(-0.02)	(1.31)	(0.03)	(1.51)	(2.59)	(3.88)	(5.29)
FF5	-0.26	-0.43	-0.10	-0.01	-0.22	-0.05	-0.18	-0.05	0.30	0.73	0.99
	(-1.15)	(-3.19)	(-0.82)	(-0.08)	(-2.67)	(-0.59)	(-2.05)	(-0.59)	(2.78)	(4.92)	(4.29)
FF6	-0.20	-0.36	-0.08	0.01	-0.22	-0.07	-0.17	-0.01	0.33	0.76	0.96
	(-0.93)	(-2.58)	(-0.63)	(0.08)	(-2.54)	(-0.71)	(-1.97)	(-0.08)	(3.05)	(5.08)	(4.24)
HXZ	-0.21	-0.39	-0.10	0.03	-0.18	-0.03	-0.13	0.02	0.36	0.81	1.02
	(-0.80)	(-2.53)	(-0.77)	(0.36)	(-2.11)	(-0.30)	(-1.44)	(0.25)	(2.85)	(5.05)	(4.12)
SY	-0.22	-0.22	0.02	0.08	-0.12	-0.01	-0.16	-0.03	0.23	0.77	0.99
	(-0.85)	(-1.44)	(0.16)	(0.72)	(-1.23)	(-0.10)	(-1.79)	(-0.29)	(1.59)	(4.51)	(3.83)
Panel B: Portfolios sorted by residual EG											
	1	2	3	4	5	6	7	8	9	10	10-1
Raw	0.47	0.59	0.58	0.63	0.63	0.68	0.75	0.74	0.89	1.18	0.71
	(1.38)	(1.94)	(2.21)	(2.31)	(2.91)	(2.90)	(3.32)	(3.32)	(4.46)	(4.80)	(2.91)
CAPM	-0.39	-0.17	-0.09	-0.06	-0.01	0.04	0.15	0.16	0.32	0.53	0.91
	(-2.34)	(-1.56)	(-0.92)	(-0.51)	(-0.08)	(0.47)	(1.47)	(1.28)	(3.33)	(3.36)	(3.58)
FF3	-0.28	-0.10	-0.09	-0.09	0.00	0.07	0.13	0.14	0.35	0.58	0.86
	(-1.97)	(-0.98)	(-0.93)	(-0.79)	(-0.03)	(0.82)	(1.47)	(1.21)	(3.88)	(4.01)	(3.79)
FF4	-0.18	-0.03	-0.04	-0.08	0.03	0.05	0.10	0.13	0.28	0.49	0.67
	(-1.36)	(-0.22)	(-0.41)	(-0.70)	(0.31)	(0.63)	(1.07)	(1.17)	(3.07)	(3.52)	(3.19)
FF5	-0.06	-0.01	-0.15	-0.15	-0.07	-0.02	-0.03	-0.08	0.18	0.45	0.51
	(-0.39)	(-0.12)	(-1.45)	(-1.26)	(-0.81)	(-0.20)	(-0.39)	(-0.81)	(1.76)	(3.10)	(2.12)
FF6	-0.01	0.04	-0.11	-0.13	-0.04	-0.02	-0.04	-0.07	0.14	0.39	0.40
	(-0.07)	(0.31)	(-1.06)	(-1.16)	(-0.46)	(-0.28)	(-0.50)	(-0.68)	(1.46)	(2.93)	(1.88)
HXZ	0.01	0.06	-0.08	-0.13	-0.04	0.02	-0.02	-0.02	0.22	0.52	0.51
	(0.06)	(0.58)	(-0.69)	(-1.07)	(-0.44)	(0.22)	(-0.20)	(-0.16)	(1.90)	(2.97)	(1.98)
SY	0.05	0.10	-0.04	-0.12	-0.01	-0.04	-0.03	-0.11	0.03	0.21	0.15
	(0.32)	(0.84)	(-0.33)	(-0.95)	(-0.12)	(-0.49)	(-0.30)	(-0.95)	(0.30)	(1.68)	(0.72)

Table M1. **Explaining the EG factor with uncertainty-augmented factor models**

Panel A presents the mean return, alphas, and factor loadings of EG factor from various macro uncertainty (ΔUNC^{ma})-augmented factor models, using the full sample. Panel B reports the alphas and factor loadings of EG factor from various micro uncertainty (ΔUNC^{mi})-augmented factor models. Factor models include the market model (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), Stambaugh and Yuan (2017) model (SY), and Hou et al. (2015) q-factor model (HXZ). All returns are multiplied with 100. Newey-West adjusted t-statistics (t-stat) with 6-month lags are provided. R^2 denotes the explanatory power of the corresponding factor model. The testing period is from July 1973 to June 2018.

Panel A: Factor models augmented by macro uncertainty									
Return	0.81								
t-stat	8.77								
	α	MKT						ΔUNC_{ma}	R^2
CAPM	0.15	-0.06						-0.85	0.88
t-stat	3.74	-6.31						-24.77	
	α	MKT	SMB	HML				ΔUNC_{ma}	R^2
FF3	0.01	-0.08	0.19	-0.06				-1.00	0.94
t-stat	0.31	-10.83	20.27	-6.46				-51.24	
	α	MKT	SMB	HML	UMD			ΔUNC_{ma}	R^2
FF4	0.01	-0.07	0.18	-0.05	0.03			-0.97	0.94
t-stat	0.26	-11.24	18.94	-4.12	2.71			-47.55	
	α	MKT	SMB	HML	CMA	RMW		ΔUNC_{ma}	R^2
FF5	0.00	-0.09	0.22	0.01	-0.20	0.04		-1.04	0.96
t-stat	0.05	-13.89	17.5	0.79	-7.69	1.86		-54.05	
	α	MKT	SMB	HML	CMA	RMW	UMD	ΔUNC_{ma}	R^2
FF6	0.00	-0.09	0.21	0.03	-0.20	0.04	0.03	-1.01	0.96
t-stat	-0.04	-14.33	20.20	2.20	-9.26	2.26	4.47	-62.10	
	α	MKT	$MISP_{ME}$	MGMT	PERF			ΔUNC_{ma}	R^2
SY	-0.01	-0.09	0.22	-0.21	0.06			-1.05	0.98
t-stat	-0.52	-21.00	28.33	-15.85	5.77			-84.38	
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}			ΔUNC_{ma}	R^2
HXZ	0.00	-0.08	0.18	-0.06	0.05			-0.94	0.95
t-stat	-0.04	-8.93	16.16	-4.27	5.20			-54.10	

Panel B: Factor models augmented by micro uncertainty									
	α	MKT						ΔUNC^{mi}	R^2
CAPM	0.76	-0.01						0.14	0.26
t-stat	9.35	-0.24						3.70	
	α	MKT	SMB	HML				ΔUNC^{mi}	R^2
3FF	0.78	0.00	-0.13	0.03				0.13	0.30
t-stat	9.47	0.13	-3.73	0.59				3.92	
	α	MKT	SMB	HML	UMD			ΔUNC^{mi}	R^2
4FF	0.71	-0.02	-0.14	0.10	0.14			0.08	0.37
t-stat	8.93	-0.68	-5.06	2.00	4.11			2.95	
	α	MKT	SMB	HML	CMA	RMW		ΔUNC^{mi}	R^2
5FF	0.68	-0.03	-0.07	-0.08	0.29	0.29		0.05	0.38
t-stat	7.33	-0.92	-1.86	-1.57	3.14	3.41		2.43	
	α	Mktrf	SMB	HML	CMA	RMW	UMD	ΔUNC^{mi}	R^2
6FF	0.61	-0.06	-0.07	0.01	0.25	0.32	0.15	0.00	0.46
t-stat	7.43	-2.20	-2.44	-2.18	0.17	3.44	5.32	0.03	
	α	MKT	MIS_{ME}	MGMT	PERF			ΔUNC^{mi}	R^2
SY	0.44	0.03	-0.04	0.32	0.24			0.04	0.51
t-stat	5.08	1.12	-1.29	7.02	7.71			1.97	
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}			ΔUNC^{mi}	R^2
HXZ	0.58	-0.15	-0.01	0.32	0.41			-0.06	0.43
t-stat	6.10	-4.10	-0.28	3.77	7.23			-2.19	

Table N1. **Comparing the q^5 model with total uncertainty-augmented q-model**

Panel A reports the coefficients (Coeff) and t-statistics (t-stat) from Fama-MacBeth regressions of Hou et al. (2021) q^5 model (HMXZ) and total uncertainty-augmented Hou et al. (2015) q-model (HXZ+ΔUNC), using the full sample. Test assets are 45 portfolios and the tested 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. Panel B shows similar regressions for the expanding-window estimation. 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 is from July 1973 to June 2018. The testing period for Panel B is from July 1997 to June 2018.

Panel A: Full-sample estimation				
	HMXZ		HXZ+ΔUNC	
	Coeff	t-stat	Coeff	t-stat
γ_0	0.07	2.10	0.07	1.92
γ_{MKT}	0.54	2.72	0.52	2.61
$\gamma_{Q_{ME}}$	0.36	2.62	0.35	2.52
$\gamma_{Q_{IA}}$	0.31	2.93	0.35	3.27
$\gamma_{Q_{ROE}}$	0.33	2.40	0.39	2.82
γ_{EG}	0.79	7.70		
γ_{UNC}			-0.86	-7.85
R^2	0.82		0.91	
(5^{th}, 95^{th})	(0.66, 0.87)		(0.80, 0.92)	
Panel B: Expanding-window estimation				
	HMXZ		HXZ+ΔUNC	
	Coeff	t-stat	Coeff	t-stat
γ_0	0.06	0.96	0.05	0.87
γ_{MKT}	0.55	1.92	0.56	1.97
$\gamma_{Q_{ME}}$	0.32	1.46	0.33	1.54
$\gamma_{Q_{IA}}$	0.19	1.01	0.2	1.03
$\gamma_{Q_{ROE}}$	0.14	0.53	0.14	0.57
γ_{EG}	0.61	3.32		
γ_{UNC}			-0.64	-3.58
R^2	0.74		0.83	
(5^{th}, 95^{th})	(0.60, 0.88)		(0.72, 0.92)	