Decoding the Pricing of Uncertainty Shocks

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Abstract

Uncertainty affects business cycles and asset prices. We estimate firm-level productivity 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 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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Uncertainty coincides with business cycles (Bloom, 2009; Fernández-Villaverde et al., 2015; Basu and Bundick, 2017; Bloom et al., 2018; Diercks et al., 2023),¹ and affects asset prices as well (Bansal and Yaron, 2004; Segal et al., 2015; Bali et al., 2017, 2021; Bretscher et al., 2023). Uncertainty includes both macroeconomic and microeconomic components. Previous studies such as Bloom et al. (2018) use both components to match business cycle fluctuations theoretically by assuming a significant role for micro uncertainty relative to macro uncertainty under the assumption that both are driven by a common latent process. However, these two uncertainty measures seem to be distinct as discussed in Kozeniauskas et al. (2018). Given their difference is understudied, this paper aims to fill this gap by examining these two components from an asset pricing perspective. We first estimate firm-level productivity and then decompose 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 strongly countercyclical and priced among stocks, but micro uncertainty is acyclical and not priced. This challenges the importance of micro uncertainty over business cycles.

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

¹The causality is unclear, as Bloom et al. (2018) discuss. Uncertainty might lead to business fluctuations. Alternatively, uncertainty may arise endogenously from business cycles. Many papers find that the cross-sectional dispersions of firm- or establishment-level variables, like productivity, output, prices, employment, and business forecasts, appear to be countercyclical (Bloom, 2009; Bachmann and Bayer, 2013; Bachmann et al., 2013; Bachmann and Bayer, 2014; Kehrig, 2015; Bloom et al., 2018; David et al., 2022).

a higher expected stock return and a lower current investment rate,² which in turn implies higher expected investment growth in the future. Therefore, both the investment rate and expected investment growth are needed to capture these two fundamental shocks. Also, we find that expected stock returns positively covary with expected investment growth via an uncertainty channel. We test this prediction with the expected investment growth (EG) factor proposed in the q^5 -model of Hou et al. (2021). We find evidence that the pricing power of the EG factor is driven by macro uncertainty risk. This provides an alternative way to understand the success of the EG factor and the q^5 -model.

Empirically, we follow Bloom (2014) to measure uncertainty as time-varying volatilities (see, e.g., Bloom, 2009; Jurado et al., 2015; Bloom et al., 2018). Uncertainty contains two components — macro and micro uncertainty shocks. Macro uncertainty refers to the aggregate uncertainty in the economy, which is often measured over an aggregate index such as aggregate productivity or stock market volatility. Macro uncertainty is countercyclical (Bloom et al., 2018) and its asset pricing power is well accepted as it changes investors' future consumption growth and investment opportunities (Bansal and Yaron, 2004; Segal et al., 2015; Bali et al., 2017, 2021).

In contrast, micro uncertainty captures uncertainty about idiosyncratic volatility. Although idiosyncratic volatility might appear to be priced due to missing factors or a common volatility factor as discussed in Chen and Petkova (2012) and Herskovic et al. (2016), it is unclear whether micro uncertainty is priced. In particular, the empirical measure of micro uncertainty used often clouds the results. For example, Bloom et al. (2018) uses the cross-sectional dispersion of microlevel data (e.g., establishment- or firm-level productivity) to measure micro uncertainty and finds micro uncertainty is countercyclical, suggesting a pricing role for micro uncertainty. However, such a micro uncertainty measure is contaminated with macro uncertainty, since micro level productivity

²Note that investment could also decrease with uncertainty initially by adding fixed adjustment costs (see, e.g., Bloom et al. (2018)) or when capital utilization is flexible (Segal and Shaliastovich, 2022).

contains both systematic and idiosyncratic productivity.³ This calls for a clean measurement of micro uncertainty to help us understand whether micro uncertainty matters.

Guided by this observation, we use firm-level data to differentiate micro and macro economic uncertainty in two steps. First, we estimate firm-level total factor productivity (TFP) following Olley and Pakes (1996) and İmrohoroğlu and Tüzel (2014) at an annual frequency. Total uncertainty is measured as the cross-sectional standard deviation of these TFP shocks. Second, we apply an asymptotic principal component analysis as in Connor and Korajczyk (1987), Herskovic et al. (2016), and Chen et al. (2018) to estimate the systematic and idiosyncratic TFP components across all firms. We identify six principal components of productivity shocks.⁴ Macro (Micro) uncertainty is measured as the cross-sectional standard deviation of systematic (idiosyncratic) productivity shocks. Figure 1 demonstrates that macro uncertainty (total uncertainty) is countercyclical, with a correlation coefficient of -0.26 (-0.10) with industrial production growth. Micro uncertainty is almost acyclical (the correlation coefficient with the industrial production growth is 0.004). That is, uncertainty is high during recessions and this is driven mainly by macro uncertainty. This suggests that macro uncertainty and not micro uncertainty relates to business cycles.

Using the annual non-tradable uncertainty factor, we run Fama-MacBeth two-pass regressions to test its pricing power by matching stock returns with lagged uncertainty risk. We augment five cross-sectional asset pricing factor models with the total uncertainty factor, the macro uncertainty factor, or the micro uncertainty factor. The factor models include the Fama and French (1993) three-factor model (FF3), the Carhart (1997) four-factor model (FF4), the Fama and French (2015) five-factor model (FF5), the Fama and French (2018) six-factor model (FF6), and the Hou et al. (2015) q-factor model (HXZ). We find that total uncertainty risk is negatively priced, with a price

 $^{^{3}}$ Schaab (2020) illustrates that aggregate uncertainty can be transmitted to heterogeneous households via unemployment risk and wage volatilities. Therefore, household-level uncertainty also contains macro uncertainty.

 $^{^{4}}$ Chen and Kim (2020) show that this decomposition reasonably captures aggregate and idiosyncratic productivity shocks.

of -4.55% to -9.32% per year. Macro uncertainty is also negatively priced, with a price of -8.29% to -13.93% per year. Augmenting these factor models with a macro uncertainty factor improves their performances. For example, pricing errors are insignificant for the augmented FF5, FF6, and HXZ models. In particular, the price of macro uncertainty risk increases during recessions, as shown in Figure 3. However, micro uncertainty is not priced.

To allow for empirical tests at the monthly frequency, we construct mimicking factors for total uncertainty, macro uncertainty, and micro uncertainty following Adrian et al. (2014) and Chen and Yang (2019). The annual Sharpe ratios of the total uncertainty and macro uncertainty factors are sizable, -0.35 and -0.39, respectively, but micro uncertainty has a Sharpe ratio of only -0.03. Cross-sectional asset pricing tests further show that prevailing factor models, including the CAPM, the Fama-French models (FF3, FF4, FF5, FF6), the Stambaugh and Yuan (2017) mispricing factor model (SY), and the Hou et al. (2015) q-factor model (HXZ), can explain the micro uncertainty factor, but not the macro uncertainty factor. Augmenting these factor models with a mimicking macro uncertainty factor also improves their performance. For example, in the full-sample estimation, pricing errors are insignificant for the augmented FF3, FF4, FF5, FF6 and HXZ models. We further show that the pricing power is not spuriously driven by noisy factors.

We find an economic linkage between macro uncertainty and the expected investment growth factor in Hou et al. (2021). First, we show that macro uncertainty contributes to the pricing power of the expected investment growth factor. After controlling for macro uncertainty, the residual of the expected investment growth factor is not priced. Second, we find that the predictors of expected investment growth in Hou et al. (2021) capture cross-sectional productivity dispersion (e.g., macro uncertainty), especially the operating cash flow component. Finally, we show that the HXZ model augmented with the macro uncertainty factor can fully explain the expected investment growth factor. This augmented model performs similarly to the Hou et al. (2021) q^5 -factor model. Overall,

we provide evidence that the expected investment growth factor captures macro uncertainty risk.

Our paper belongs to a growing literature on economic uncertainty. Bloom (2009), Fernández-Villaverde et al. (2015), Basu and Bundick (2017), Bloom et al. (2018), and Diercks et al. (2023) study the impact of uncertainty on business cycles. Kozeniauskas et al. (2018) shows that various macro uncertainty, micro uncertainty, and higher-order uncertainty measures are distinct and some are statistically uncorrelated. Dew-Becker and Giglio (2022) shows that cross-sectional uncertainty, measured using option data, does not forecast overall economic activity as well as aggregate uncertainty.

Other works examine the asset pricing implications of aggregate uncertainty shocks. For example, Bansal and Yaron (2004) considers the equity premium implied by the conditional volatility of consumption growth. Bekaert et al. (2009) shows that economic uncertainty contributes to the term structure and countercyclical volatility of asset returns. Hartzmark (2016) shows that higher uncertainty leads to lower interest rates. Bali and Zhou (2016) shows that economic uncertainty, proxied by the variance risk premium, is significantly priced. Dew-Becker et al. (2017), Berger et al. (2019), and Dew-Becker et al. (2021) differentiate between uncertainty and realized variance using data from equity derivative markets. They show that realized variance has a negative premium, while aggregate uncertainty carries a zero or a positive premium. Segal et al. (2015) differentiate good and bad uncertainty arising from positive and negative industrial production growth. Alfaro et al. (2023) considers real and financial frictions to amplify the impacts of uncertainty shocks. Schaab (2020) considers the transmission and interaction of aggregate uncertainty and household-level uncertainty. Bretscher et al. (2023) show that uncertainty shock affects risk premium, especially when it is combined with countercyclical risk aversion. More closely related to our work, Bali et al. (2017) and Bali et al. (2021) find that macroeconomic uncertainty is priced in the cross section of stocks and corporate bonds using the Jurado et al. (2015) uncertainty index.

Herskovic et al. (2023) considers uncertainties of aggregate consumption growth and firm-specific productivity shocks, and shows that the former drives the size and the value premia while the latter contributes to the equity premium. Our paper contributes to this literature by differentiating macro and micro uncertainty and shows that micro uncertainty does not matter for asset prices.

Our paper also follows in the tradition of the production-based asset pricing literature such as Cochrane (1991), Cochrane (1996), Berk et al. (1999), Zhang (2005), and Liu et al. (2009). The neoclassical theory of investment stresses that production risks drive stock risks. Hou et al. (2015) and Hou et al. (2021) construct pricing factors based on firm investment, profitability, and expected investment growth.⁵ Our paper adds to this literature by studying the role of uncertainty shocks.

Lastly, our paper also contributes to the large literature on the empirical performance of crosssectional asset pricing factor models. For example, Fama and French (2015) constructs a five-factor model based on the dividend discount model/surplus clean accounting method, including a market factor, a size factor, a value factor, an investment factor, and a profitability factor. Fama and French (2018) further adds a momentum factor to their five-factor model. Hou et al. (2015) proposes a q-factor model motivated by the q-theory of investment, including a market factor, a size factor, an investment factor, and a profitability factor. Hou et al. (2021) further adds an expected investment growth factor to their q-factor model to create their q^5 model. Stambaugh and Yuan (2017) studies a four-factor model, which includes a market factor, a size factor, and two mispricing factors. Overall, these factor models perform well in explaining a host of anomalies. Our paper suggests that the macro uncertainty factor is missing from most models with the notable exception of the Hou et al. (2021) q^5 model as we show that macro uncertainty risk contributes to the pricing power of their expected investment growth factor in the q^5 model.

The rest of the paper proceeds as follows. Section 1 presents a production-based model to ex-

⁵Li et al. (2021) considers the impact of investment lags and show that aggregate expected investment growth negatively predicts future market returns due to firms' investment plans.

plore the linkage between uncertainty shocks, expected investment growth, and asset prices. Section 2 describes the data and the procedures used for estimating various uncertainty measures and their estimates. Section 3 presents cross-sectional asset pricing tests, using non-tradable uncertainty factors. Section 4 tests the pricing power of the uncertainty factors, using mimicking portfolios. Section 5 explores the relationship between the macro uncertainty factor and the expected investment growth factor. Finally, Section 6 concludes.

1. Uncertainty shocks, expected investment growth, and asset prices: A motivating model

We consider a simple production economy to illustrate the role of uncertainty shocks on expected investment growth and asset prices.⁶ We assume an all-equity representative firm which operates in discrete time with an infinite horizon. The firm generates output according to a constant returns to scale production function: $Y_t = X_t K_t$. Y_t and X_t are the firm's output and total factor productivity at time t, respectively. K_t is the productive capital at the beginning of time t.

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

$$\ln X_{t+1} = \rho_x \ln X_t + \eta \left(\sigma_t^2 - \sigma^2\right) + \sigma_t \varepsilon_{x,t+1}, \tag{1}$$

$$\sigma_{t+1}^2 = (1 - \rho_{\sigma}) \sigma^2 + \rho_{\sigma} \sigma_t^2 + \upsilon \varepsilon_{\sigma,t+1}, \qquad (2)$$

where $0 < \rho_x < 1$ and $0 < \rho_\sigma < 1$ are the AR(1) coefficients, σ^2 is the long-run average volatility, v is a constant, $\varepsilon_{x,t+1}$ 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

⁶For simplicity, this model is not designed to capture all empirical features. See Appendix A for a general equilibrium model.

macro uncertainty shock. Similar to Bansal and Yaron (2004), for analytic tractability, we assume an AR(1) process for uncertainty.⁷ We also assume $0 < \rho_{\sigma} < 1$, which is similar to the consecutive uncertainty shocks considered by Diercks et al. (2023).⁸ One important feature of the model is that uncertainty affects productivity growth, as captured by the second term in the right-hand side of Eq. (1). This is similar to the leverage effect (e.g. Black, 1976; Christie, 1982; Harvey and Shephard, 1996). Economic recessions often feature high uncertainty and low productivity contemporaneously with productivity increasing in the future. Therefore, high uncertainty is associated with low productivity contemporaneously and but high productivity in the future, suggesting that $\eta > 0$ in Eq. (1).

Productive capital evolves as $K_{t+1} = I_t + (1 - \delta)K_t$, with a quadratic capital adjustment cost of $\frac{a}{2} \left(\frac{I_t}{K_t}\right)^2 K_t$, where I_t is investment at time t, δ is the depreciation rate, and a is a constant.⁹ The dividend is given by $D_t = Y_t - I_t - \frac{a}{2} \left(\frac{I_t}{K_t}\right)^2 K_t$. For a given stochastic discount factor M_{t+i} , the firm chooses the optimal investment to maximize the present value of future dividends:

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

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

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

The value of an additional unit of productive capital at time t + 1 is $X_{t+1} + \frac{a}{2} \left(\frac{I_{t+1}}{K_{t+1}}\right)^2 + (1 - 1)^2 + (1 -$

⁷Admittedly, the realizations of volatility could be negative in this case. This assumption can be easily relaxed by assuming the logarithmic volatility satisfies an AR(1) process in a numerical model or adopting an autoregressive gamma process for volatility as in Gouriéroux and Jasiak (2006).

 $^{^{8}}$ Diercks et al. (2023) show that uncertainty shocks in consecutive periods are superadditive, i.e., amplifying uncertainty effects.

 $^{^{9}}$ We do not consider time-to-build. Chen (2016) and Li et al. (2021) consider investment lags.

 δ) $\left[1 + a\left(\frac{I_{t+1}}{K_{t+1}}\right)\right]$, where the first term captures the marginal productivity, the second term captures the capital adjustment costs that are saved, and the last term captures the continuation value of productive capital. Therefore, the real investment return, R_{t+1}^{I} , is

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

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

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

$$\hat{I}_{t} = I_{0} + I_{x}\hat{X}_{t} + I_{k}\hat{K}_{t} + I_{\sigma}\sigma_{t}^{2},$$
(6)

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

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

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

$$\mathbb{E}_{t}\left[\frac{\hat{I_{t+1}}}{K_{t+1}} - \frac{\hat{I}_{t}}{K_{t}}\right] = I_{\sigma}(1 - \rho_{\sigma})\sigma^{2} + (\rho_{x} - 1)I_{x}\hat{X}_{t} + \left[(\rho_{\sigma} - 1)I_{\sigma} + I_{x}\eta\right]\sigma_{t}^{2}.$$
(8)

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

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

$$\mathbb{E}_{t}[\hat{R}_{t+1}] = \left(h - \frac{a\delta}{1+a\delta}\right)I_{0} + \left[hI_{\sigma}(1-\rho_{\sigma}) - \left(\frac{h}{a\delta} + hI_{x}\right)\eta\right]\sigma^{2} + \underbrace{\left[\frac{h}{a\delta}\rho_{x} + hI_{x}\rho_{x} - \frac{a\delta}{1+a\delta}I_{x}\right]\hat{X}_{t}}_{\text{prductivity shock}} + \underbrace{\left\{\left[h\rho_{\sigma} - \frac{a\delta}{1+a\delta}\right]I_{\sigma} + \left(\frac{h}{a\delta} + hI_{x}\right)\eta\right\}\sigma_{t}^{2}, (9)}_{\text{uncertainty shock}}$$

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

In this economy, two fundamental risks drive the investment rate, expected investment growth, and the expected stock return, namely the productivity shock \hat{X}_t and the uncertainty shock $\sigma_t^{2,10}$ Taking Eq. (7), (8), and (9) together, we see that when there are productivity shocks only (i.e., no uncertainty shocks), either the investment rate or the expected investment growth rate alone is a sufficient statistic for productivity shocks. That is, either the investment rate or the expected investment growth rate is sufficient to fully capture expected stock returns. However, in the presence of uncertainty shocks, both the investment rate and expected investment growth are necessary and sufficient to fully capture these two shocks and hence expected stock returns. This suggests using firm characteristics such as the investment rate and expected investment growth rate as pricing factors. In other words, the pricing power of the investment factor and the expected

¹⁰Again, due to constant returns to scale production, the capital stock does not affect expected stock returns, i.e., no size effect. Empirically, the capital stock generally matters for asset prices providing a potential explanation of the size factor.

investment factor in the q^5 -model is due to their abilities to capture the fundamental risks, i.e., productivity shocks and uncertainty shocks. In a similar vein, other empirical factors (for example, the profitability factor), might also incorporate these two risk sources and appear to be priced.

Examining the impact of the uncertainty shock, i.e., the coefficients of σ_t^2 in Eq. (7), (8), and (9), we see that when uncertainty increases, the investment rate decreases while expected investment growth and the expected stock return increase. That is, investment and the stock return are negatively correlated while expected investment growth covaries positively with the expected stock return. This provides additional support to the investment factor and expected investment growth factor used in the q^5 -model of Hou et al. (2021), i.e., via the uncertainty channel.

2. Estimating uncertainty shocks

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

2.1. Estimating firm-level TFP and the total uncertainty

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

Assume a Cobb-Douglas production function:

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

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

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

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

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

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

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

We include all firms except for financial and utility firms (four-digit SIC codes between 6000 - 6999 and between 4900 - 4999).¹¹ We exclude firms with assets or sales below \$1 million or year-end stock price lower than \$5. Following Chen and Chen (2012), we also exclude firms with asset or sales growth rate exceeding 100% to avoid potential business discontinuities that might be caused by mergers and acquisitions. The sample period is from 1966 to 2016. The TFP estimates are from 1972 to 2016. The estimated labor coefficient β_l is 0.56 and the estimated capital coefficient β_k is 0.38. These estimates are similar to those reported in Olley and Pakes (1996), and are in line with neoclassical models. For example, Bloom et al. (2018) assume that the labor coefficient is 2/3 and the capital coefficient is 1/3. During our sample period, the production technology is slightly decreasing returns-to-scale ($\beta_l + \beta_k = 0.94$). See Appendix B for more details.

2.2. Estimating macro and micro uncertainty

Following Herskovic et al. (2016), we decompose firm-level TFP into systematic and idiosyncratic components via the asymptotic principal component analysis of Connor and Korajczyk

¹¹The results are qualitatively similar if we restrict our sample to manufacturing firms only.

(1987). This allows us to separate systematic and idiosyncratic productivity. TFP estimates for N firms over time T, denoted as TFP_{NT} , can be decomposed into k principal components:

$$TFP_{NT} = B_{Nk} \times PC_{kT} + \epsilon_{NT},\tag{13}$$

where TFP is an $N \times T$ matrix of TFP, B is an $N \times k$ matrix of the sensitivities to aggregate TFP shocks, PC is a $k \times T$ matrix of systematic TFP shocks, and ϵ is an $N \times T$ matrix of the idiosyncratic TFP shock. Next, we calculate $\Omega = \frac{1}{N}TFP^TTFP$ and estimate the eigenvector of Ω . We multiply each element of the eigenvectors with $\frac{1}{\sqrt{T}}$ to obtain unit standard deviations.

To more precisely estimate the systematic TFP components (PC), we use firms with more than 10 years of data. We choose six principal components (k = 6), following Chen and Kim (2020) as they find that (1) six principal components explain more than 50% of firm-level TFP; (2) there is a positive contemporaneous correlation between stock returns and systematic TFP growth; and (3) only the volatility of systematic productivity positively predicts expected stock returns while the idiosyncratic volatility does not. These findings suggest that six principal components reasonably approximate the systematic productivity shocks.

After we estimate systematic TFP growth and idiosyncratic TFP growth, we calculate the crosssectional standard deviations of systematic TFP growth and idiosyncratic TFP growth, which are defined as macro uncertainty and micro uncertainty here. Then, we take their first differences to compute macro and micro uncertainty shocks, denoted as ΔUNC^{ma} and ΔUNC^{mi} , respectively. Although idiosyncratic productivity is not priced, it is unclear if micro uncertainty is priced as micro uncertainty may relate to priced additional state variables.

2.3. Uncertainty estimates

Panel A of Table 1 shows that TFP growth (ΔTFP) has a mean of 0.01 and a standard deviation of 0.21. TFP growth varies over both the cross section and the time series. The next three rows present descriptive statistics for uncertainty shocks. Total uncertainty (ΔUNC) has a mean of 0.00 with a standard deviation of 0.05. Macro uncertainty (ΔUNC^{ma}) has a larger standard deviation of 0.07, while micro uncertainty (ΔUNC^{mi}) only has a standard deviation of 0.03.

Figure 1 shows the time series of the uncertainty shocks and industrial production growth (IP), including total uncertainty, macro uncertainty, and micro uncertainty. We apply the bandpass filter of Christiano and Fitzgerald (2003) to these series. Similar to findings in Bloom et al. (2018), total uncertainty (UNC) is countercyclical, with a correlation coefficient of -0.10 with IP growth.¹² Therefore, uncertainty is high during recessions. Moreover, we see that macro uncertainty (UNC^{ma}) is strongly countercyclical, with a correlation coefficient of -0.26, but micro uncertainty (UNC^{ma}) is barely correlated with IP growth, with a correlation coefficient of 0.004. Total uncertainty being countercyclical is mainly due to macro uncertainty.

Figure 2 plots the cross-sectional standard deviation of stock returns with various uncertainty measures. We decompose the stock return into systematic and idiosyncratic components by regressing annual stock returns on the Carhart (1997) four-factor model factors. We use the predicted stock return as the systematic component and the residuals as the idiosyncratic component. We calculate the cross-sectional standard deviations of stock returns and the two components in each year, denoted as RD, RD^{sys} , and RD^{idio} . Panels (a) and (b) of Figure 2 show that total uncertainty and macro uncertainty track the cross-sectional return dispersions quite well. For example,

 $^{^{12}}$ Using the detailed Census microdata of manufacturing establishments from 1972 to 2011, Bloom et al. (2018) find that TFP dispersion is negatively correlated with GDP growth with a correlation coefficient of -0.45. Our TFP dispersion measure differs from Bloom et al. (2018) in three ways. First, their TFP is establishment-level while our TFP is firm-level. Second, they only cover manufacturing establishments, while our sample includes all firms except financials and utilities. Third, they estimate TFP following Foster et al. (2001).

the correlation coefficients between UNC and RD, RD^{sys} , and RD^{idio} are 0.53, 0.56, and 0.59, respectively. The correlation coefficients between UNC^{ma} and RD, RD^{sys} , and RD^{idio} are 0.56, 0.57, and 0.55, respectively. However, Panel (c) of Figure 2 shows that UNC^{mi} is much less correlated with RD and RD^{sys} (the correlation coefficients are -0.04 and -0.12, respectively). Figure 2 shows that our uncertainty measures are reasonably estimated and comove with the stock return dispersion measures.

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

Consistent with the predictions in Section 1, Panel B shows that total uncertainty (ΔUNC) is positively related to the expected investment growth factor (EG) (a correlation coefficient of 0.29). We also see that macro uncertainty (ΔUNC^{ma}) is highly correlated with ΔUNC , with a correlation coefficient of 0.87. This suggests that total uncertainty is mainly driven by macro uncertainty. Also, ΔUNC^{ma} has a pronounced correlation coefficient with EG, 0.25. Third, micro uncertainty (ΔUNC^{mi}) has negative correlations with ΔUNC and ΔUNC^{ma} . Also, ΔUNC^{mi} does not have a strong correlation with EG. Overall, Panel B provides evidence that ΔUNC^{ma} captures most of ΔUNC and both measures have a significant relationship with the EG factor.

2.4. Inspecting the uncertainty decomposition

In this subsection, we validate our uncertainty decomposition in three steps. First, we check if our macro uncertainty measure reasonably captures aggregate uncertainty. To this end, we obtain aggregate TFP 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. Panel A of Table 2 reports the time-series regressions of aggregate uncertainty on macro uncertainty (UNC^{ma}) and micro uncertainty (UNC^{mi}) . Macro uncertainty positively predicts the aggregate uncertainty while micro uncertainty does not. This is also confirmed by the correlation between uncertainty shocks and VIX. Panel A of Table 1 shows that total uncertainty and macro uncertainty positively correlate with VIX, with a correlation coefficient of 0.38 and 0.37, respectively. But the correlation coefficient of micro uncertainty and VIX is -0.18.

Second, using our TFP estimates, we investigate if total uncertainty is mainly driven by macro uncertainty. Panel B of Table 2 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 2 suggests that ΔUNC is mainly driven by ΔUNC^{ma} .

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

We run Fama-MacBeth two-stage regressions to examine the pricing power of uncertainty shocks using annual non-tradable uncertainty factors, including total uncertainty, macro uncertainty, and micro uncertainty. We use forty-five portfolios, including six size and book-to-market sorted portfolios, six size and operating profitability sorted portfolios, six size and investment sorted portfolios, six size and momentum sorted portfolios, six size and expected investment growth sorted portfolios, ten operating accrual sorted portfolios, and five Fama-French industry portfolios.¹³ Following Lewellen et al. (2010), we add the pricing factors of tested factor models to test assets in order to restrict the price of risk to be equal to the average factor return. To ensure that uncertainty risk is strictly observable, we match the uncertainty estimates and stock returns with a six month lag.

We augment the prevailing factor models with the total uncertainty factor, macro uncertainty factor, or micro uncertainty factor, and compare those to the prevailing factor models. Seven factor models are considered, including the Fama and French (1993) three-factor model (FF3), the Carhart (1997) four-factor model (FF4), the Fama and French (2015) five-factor model (FF5), the Fama and French (2018) six-factor model (FF6), the Stambaugh and Yuan (2017) mispricing factor model (SY),¹⁴ the Hou et al. (2015) q-factor model (HXZ), and the Hou et al. (2021) q^5 model (HMXZ). We do not augment the Hou et al. (2021) q^5 model for Section 5. These macro uncertainty

 $^{^{13}}$ We download these portfolios from the following websites:

http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html; http://global-q.org/index.html

 $^{^{14}}$ For the Stambaugh and Yuan (2017) mispricing factor model, we only perform asset pricing tests on monthly mimicking portfolios for the uncertainty factors in Section 4 as we do not have the constituent portfolios available to construct annual data.

augmented factor models are as follows:

$$\begin{split} \mathrm{FF3} + \Delta UNC^{ma} \colon & R_{it} = \gamma_0 + \gamma_{MKT} \hat{\beta}_{MKT,i} + \gamma_{SMB} \hat{\beta}_{SMB,i} + \gamma_{HML} \hat{\beta}_{HML,i} \\ & + \gamma_{UNC^{ma}} \hat{\beta}_{UNC^{ma},i} + \epsilon_{it} \\ \mathrm{FF4} + \Delta UNC^{ma} \coloneqq & R_{it} = \gamma_0 + \gamma_{MKT} \hat{\beta}_{MKT,i} + \gamma_{SMB} \hat{\beta}_{SMB,i} + \gamma_{HML} \hat{\beta}_{HML,i} + \gamma_{UMD} \hat{\beta}_{UMD,i} \\ & + \gamma_{UNC^{ma}} \hat{\beta}_{UNC^{ma},i} + \epsilon_{it} \\ \mathrm{FF5} + \Delta UNC^{ma} \coloneqq & R_{it} = \gamma_0 + \gamma_{MKT} \hat{\beta}_{MKT,i} + \gamma_{SMB} \hat{\beta}_{SMB,i} + \gamma_{HML} \hat{\beta}_{HML,i} + \gamma_{CMA} \hat{\beta}_{CMA,i} + \gamma_{RMW} \hat{\beta}_{RMW,i} \\ & + \gamma_{UNC^{ma}} \hat{\beta}_{UNC^{ma},i} + \epsilon_{it} \\ \mathrm{FF6} + \Delta UNC^{ma} \coloneqq & R_{it} = \gamma_0 + \gamma_{MKT} \hat{\beta}_{MKT,i} + \gamma_{SMB} \hat{\beta}_{SMB,i} + \gamma_{HML} \hat{\beta}_{HML,i} + \gamma_{CMA} \hat{\beta}_{CMA,i} + \gamma_{RMW} \hat{\beta}_{RMW,i} \\ & + \gamma_{UNC^{ma}} \hat{\beta}_{UNC^{ma},i} + \epsilon_{it} \\ \mathrm{HXZ} + \Delta UNC^{ma} \coloneqq & R_{it} = \gamma_0 + \gamma_{MKT} \hat{\beta}_{MKT,i} + \gamma_{Q_{ME}} \hat{\beta}_{Q_{ME,i},i} + \gamma_{Q_{IA}} \hat{\beta}_{Q_{IA,i},i} + \gamma_{Q_{ROE}} \hat{\beta}_{Q_{ROE,i}} \\ & + \gamma_{UNC^{ma}} \hat{\beta}_{UNC^{ma},i} + \epsilon_{it} \\ \mathrm{SY} + \Delta UNC^{ma} \coloneqq & R_{it} = \gamma_0 + \gamma_{MKT} \hat{\beta}_{MKT,i} + \gamma_{MIS_{ME}} \hat{\beta}_{MIS_{ME},i} + \gamma_{MGMT} \hat{\beta}_{MGMT,i} + \gamma_{PERF} \hat{\beta}_{PERF,i} \\ & + \gamma_{UNC^{ma}} \hat{\beta}_{UNC^{ma},i} + \epsilon_{it} \end{split}$$

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

We report the regression results of the total uncertainty factor in Panel A of Table 3. We

find γ_{UNC} is significantly priced across different factor models. The price of total uncertainty risk ranges from -9.32% to -4.55% per year. Total uncertainty factor also improves model fit. For example, after adding the total uncertainty factor to FF6, the intercept γ_0 becomes insignificant (*t*-statistic=1.52) while the adjusted R^2 increases from 0.71 to 0.78.

Panel B of Table 3 reports the results using the macro uncertainty factor. First, we see that macro uncertainty is negatively priced in all models. The price of macro uncertainty risk $\gamma_{UNC^{ma}}$ is sizable, ranging from -13.93% to -8.29% per year across different augmented factor models. Second, we see that ΔUNC^{ma} improves model performance. For example, the pricing error is insignificant in FF5+ ΔUNC^{ma} (0.71% per year, t-statistic=1.64) and FF6+ ΔUNC^{ma} (0.58% per year, t-statistic=1.54). The results in Panels A and B of Table 3 are similar, which again suggests that the pricing power of total uncertainty is mainly from macro uncertainty risk. In Panel C of Table 3, we replace the macro uncertainty factor with the micro uncertainty factor. The price of micro uncertainty risk is negligible and insignificant.

Figure 3 plots the prices of total uncertainty risk (UNC) and macro uncertainty risk (UNC^{ma}) against industrial production growth. The prices of uncertainty risks are computed from the Fama-French three-factor model augmented with the uncertainty factor. We see that the correlation between the price of UNC (UNC^{ma}) and IP growth is 0.27 (0.25). Therefore, during recessions (when IP growth is low), uncertainty increases and the price of uncertainty risk becomes more negative. This is consistent with the explanations in Bali et al. (2017) and Alfaro et al. (2023).

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

4. Pricing of uncertainty shocks: Mimicking uncertainty factors

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

4.1. Constructing mimicking uncertainty factors

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

$$\Delta UNC = \kappa_{0,UNC} + \kappa'_{x,UNC} X^a_t + u_t, \qquad (14)$$

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

We select base assets from Hou et al. (2015) and Hou et al. (2021) to track information in productivity dispersion. As discussed in Section 1 and confirmed in Panel B of Table 1, uncertainty is highly correlated with the investment factor, the profitability factor, and the expected investment factor. Therefore, we consider eighteen size, investment, and profitability-sorted portfolios (2-by-3-by-3) from Hou et al. (2015) as well as the EG factor from Hou et al. (2021) to extract as much information as possible from ΔUNC .¹⁵ However, we can not include all eighteen portfolios as it induces a multicollinearity problem. Also, we are limited by degrees of freedom as we only have

¹⁵We further discuss the rational of using the EG factor as a base asset in Section 5. Limited by the data availability, we do not consider the mispricing portfolio as a base asset.

forty-five annual uncertainty shocks.

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

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

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

We estimate the coefficients of Eq. (14) using the full sample. The normalized coefficients are [0.08, -0.35, -0.23, 0.31, 0.11, -0.91]. We find that the EG factor coefficient is significant and its magnitude is large at 0.91.¹⁶ We further explore this relationship in Section 5. Overall, the mimicking portfolio tracks total uncertainty well. The annual correlation coefficient between the total uncertainty shock and its mimicking portfolio is about 0.32. The annual correlation coefficient between the macro (micro) uncertainty shock and the mimicking macro (micro) uncertainty

 $^{^{16}\}text{Note}$ that the negative coefficient of -0.91 is due to normalization in $\tilde{\kappa}_{x,UNC}.$

portfolio is 0.24 (0.29).

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

4.2. Mimicking uncertainty factors

Panel A of Table 4 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 4 reports time-series regression results. The regression results are similar to those reported in Panel B of Table 2. 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 4 report the alphas from the timeseries regression of the mimicking total uncertainty (ΔUNC), macro uncertainty (ΔUNC^{ma}), and micro uncertainty (ΔUNC^{mi}), against various pricing factors, using the full sample.¹⁷ We consider eight factor models, including the CAPM, FF3, FF4, FF5, FF6, HXZ, HMXZ, and SY. Panel C shows that except HXMZ, 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 HXMZ, 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 4 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.

4.3. Fama-MacBeth regressions

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

Panel A of Table 5 reports the price of risk for each factor across different factor models, using

¹⁷The expanding-window results are similar.

the full-sample estimation. First, we see that $\gamma_{UNC^{ma}}$ is negatively priced with coefficient estimates ranging from -0.82% to -0.80% across the different augmented factor models. Second, we see that adding the macro uncertainty factor to the prevailing factor models improves model performance. All of the augmented models have insignificant pricing errors. For example, the pricing error (γ_0) decreases from 0.33% (t-statistic=6.33) of FF3 to 0.00% (t-statistic=0.11) of FF3+ ΔUNC^{ma} . The pricing error (γ_0) decreases from 0.11% (t-statistic=2.81) of HXZ to 0.04% (t-statistic=1.34) of HXZ+ ΔUNC^{ma} . Their adjusted R^2 s also increase after adding ΔUNC^{ma} to the models. For example, the R^2 increases from 0.19 of FF3 to 0.91 of FF3+ ΔUNC^{ma} . The R^2 increases from 0.51 of HXZ to 0.89 of HXZ+ ΔUNC^{ma} . Bootstrap simulations further confirm that adding ΔUNC^{ma} to the factor models improves their explanatory power. This suggests that ΔUNC^{ma} plays an important role in explaining the cross-sectional return variation across the test portfolios.

To avoid a look-ahead bias, we use the expanding-window estimation and report results in Panel B. Again, we see that UNC^{ma} is negatively priced. In particular, we see that the pricing error becomes insignificant after adding the macro uncertainty factor to the FF3, FF4, FF5, FF6, HXZ, and SY models.

For comparison, we replace the macro uncertainty factor (ΔUNC^{ma}) with the micro uncertainty factor (ΔUNC^{mi}) and report the results in Panels C and D. Clearly, ΔUNC^{mi} does not contribute to the return variation of the test portfolios. First, $\gamma_{UNC^{mi}}$ is insignificant across all augmented factor models in Panels C and D. This is consistent with Panel E of Table 4, which reports the insignificant mimicking micro uncertainty factor. Second, comparing the prevailing factor models and the ΔUNC^{mi} -augmented models, we see that γ_0 does not change much and is still significant. Third, the adjusted R^2 also shows little improvement after adding ΔUNC^{mi} in Panels C and D.

For completeness, we also consider three variations of uncertainty augmented factors models. First, we directly use the total uncertainty (ΔUNC) to augment the prevailing models. We find qualitative similar results, i.e., ΔUNC is negatively priced and the augmented models explain various test assets. Second, we consider adding macro and micro uncertainty factors (ΔUNC^{ma} and ΔUNC^{mi}) simultaneously to the prevailing models. We find that ΔUNC^{ma} is negatively priced while ΔUNC^{mi} is not priced. Last, we consider using the aggregate uncertainty factor derived from aggregate TFP data (UNC^{agg}) or the VIX. We construct the mimicking aggregate uncertainty factor in a way similar to the mimicking macro uncertainty factor.

We find that the aggregate uncertainty factor is negatively priced, but its performance is weaker than the macro uncertainty factor derived from the cross-section of TFPs estimated from firm-level data. See Appendix C for more details. Overall, we conclude that adding the uncertainty factor improves the explanatory power of prevailing factor models and its price of risk is significantly positive in the cross section. More importantly, this is mainly driven by macro uncertainty, not micro uncertainty.

4.4. Robustness checks: Examining noisy factors

The previous sections shows 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 6.

This table reports the probability that the noisy factors generate higher R^2 s (" 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^2 s and prices of risk compared to the original models. The "Joint All" column is the probability that the noisy factors generate higher R^2 s, 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.¹⁸ Overall, these results suggest that the asset pricing power of macro uncertainty is not due to chance.

5. Interpreting the expected investment growth factor

Tables 1 and 4 show that total uncertainty (macro uncertainty) is highly correlated with the expected investment growth factor (EG) from Hou et al. (2021). We now explore why the EG factor might capture uncertainty risk. This helps us better understand the success of the EG factor and the q^5 -model.

¹⁸These results are available by request.

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

5.1. The expected investment growth factor

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

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

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

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

$$E_t[dI_{it+1}/K_{it+1}] = \hat{\beta}_0 + \hat{\beta}_Q \log Q_{it} + \hat{\beta}_{CoP} CoP_{it} + \hat{\beta}_{dROE} dROE_{it}.$$
(17)

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

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

5.2. Macro uncertainty and expected investment growth

Is the pricing power of EG driven by macro uncertainty risk, as suggested by Eq. (8)? We directly decompose EG into predicted and residual components by regressing EG on macro uncertainty. Following Hou et al. (2021), we match the non-tradable ΔUNC^{ma} factor to firm-level

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

EG with at least a four-month reporting gap. We regress EG on ΔUNC^{ma} for each firm, using the full sample.²⁰ We sort all stocks into decile portfolios based on either their predicted EG or residual EG. Value-weighted portfolio 10 (1) has the highest (lowest) predicted or residual EG. Table 7 computes alphas for the host of cross-sectional asset pricing model previously considered. Raw returns are also reported

Panel A presents results for the 10 portfolios sorted by predicted EG. Similar to Hou et al. (2021), the portfolio raw returns monotonically increase with predicted EG. The long-short portfolio (i.e., Portfolio 10 - Portfolio 1) has an average return of 0.89% (t-statistic = 3.59) per month. Its alpha is also significantly positive from all benchmark models. For example, the long-short portfolio has an alpha of 0.91% (t-statistic=4.79) and 0.86% (t-statistic = 4.07) for the FF6 and HXZ models, respectively. That is, we see that stocks with higher predicted EG have higher expected returns and the predicted EG is not captured by existing risk factors. However, Panel B shows that the residual EG does not generate significant alphas across all asset pricing models. Even though the long-short portfolio return is 0.77% per month (t-statistic=3.63), the alphas for the FF6, HXZ, and SY models are insignificant. That is, residual EG does not provide additional information beyond existing asset pricing factors. Therefore, we see that the pricing power of EG is driven by macro uncertainty risk.

5.3. Macro uncertainty and the predictors of expected investment growth

Next, we explore which predictors of the expected investment growth capture uncertainty risk. In each year, we calculate the cross-sectional standard deviation of each predictor in Eq. (16). Then, we run time-series regressions of the cross-sectional dispersions of the predictors against macro uncertainty (UNC^{ma}) in Panel A of Table 8. First, UNC^{ma} explains the cross-sectional dispersions

 $^{^{20}}$ To avoid look-ahead bias, we also use an expanding-window to decompose EG into predicted and residual components and find similar results. See Table D1) in Appendix D.

of three EG predictors very well. For example, UNC^{ma} explains the cross-sectional dispersion of operating cash flows (DIS_{COP}) with a coefficient of coefficient of 0.28 (t-statistic=3.21) and an R^2 of 0.42. This suggests that UNC^{ma} alone explains the cross-sectional variation of operating cash flows well. Also, UNC^{ma} explains the cross-sectional dispersions of Tobin's Q (DIS_Q) and changes in ROE (DIS_{dROE}) . The R^2 for DIS_Q and DIS_{dROE} are 0.25 and 0.38, respectively.²¹ In Panel B, we run similar regressions using micro uncertainty (UNC^{mi}) . The regression results show that UNC^{mi} explains little of the cross-sectional dispersions of the EG predictors, as UNC^{mi} is insignificant in all regressions and the highest R^2 is 0.11 only.

Turning to the asset pricing tests, we explore whether the loadings of the EG factor and the uncertainty factors are correlated in Table 9. We estimate the loadings of a set of test assets on the EG factor, the cross-sectional dispersions of its three predictors, the total uncertainty factor, the macro uncertainty factor, and the micro uncertainty factors. The test assets include 45 portfolios (used in Table 3) and the tested pricing factors. First, we see that loadings on EG are highly correlated with those of the total uncertainty factor and the macro uncertainty factor, but not the micro uncertainty factor, as shown in Columns (1) and (2). Examining loadings on the three predictors of EG, we see that operating cash flows (COP) are highly correlated with the total uncertainty factor, but Tobin's q and changes in ROE (DIS_{dROE}) have a small correlation with the uncertainty factors. This is consistent with the finding of Hou et al. (2021), i.e., operating cash flows are the strongest predictor of future investment growth.²² Therefore, the evidence from the factor loadings further strengthens the connection between the EG and uncertainty factors.

Taken together, Tables 8 and 9 suggest that macro uncertainty explains the EG factor via the cross-sectional dispersions of its predictors, especially the operating cash flow component. Also,

²¹We find similar results for total uncertainty. See Appendix E for more details.

²²Appendix F further compares the pricing power of these three EG predictors. That is, we augment the Hou et al. (2015) q-factor model with each predictor of EG. We find that COP is the strongest predictor.

micro uncertainty cannot capture the same fundamental risks of the EG factor because it does not correlate with the cross-sectional dispersions of the EG predictors.

5.4. Comparing the EG factor and the uncertainty factor: Time-series and cross-sectional regressions

Table 10 reports time-series regressions to test whether the EG factor and the uncertainty factor share the same fundamental risks. In Panel A, we present time-series regression coefficients of the EG factor on the factor models augmented with 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 10, 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.²³

We further compare the pricing power of the EG factor and the uncertainty factor by comparing the Hou et al. (2021) q^5 model (HMXZ) with the macro uncertainty-augmented HXZ model (HXZ+ ΔUNC^{ma}) and the micro uncertainty-augmented HXZ model (HXZ+ ΔUNC^{mi}). Panels A and C of Table 5 report the prices of risk and the pricing errors of the Fama-MacBeth regressions, using the full-sample estimation. First, the pricing error (γ_0) from HMXZ is 0.07% (*t*-statistic=2.10) while that of HXZ+ ΔUNC^{ma} is 0.04% (*t*-statistic=1.34) in Panel A. Again, ΔUNC^{mi} does not play a role in the regressions as ΔUNC^{mi} is insignificant throughout in Panel C. Second, γ_{EG} is 0.79% (*t*-statistic=7.70) in the HMXZ model while $\gamma_{UNC^{ma}}$ is -0.81% (*t*-statistic=-7.89) in the

²³Appendix G reports results using total uncertainty (ΔUNC) to explain the EG factor for the full-sample and expanding-window estimations. Given ΔUNC contains both macro and micro uncertainty risk, we find blended results. Under the full-sample estimation, alphas are significantly smaller than under the micro uncertainty case, but still statistically significant except for the SY model. Under the expanding-window estimation, the alphas are generally small and no longer significant except for the CAPM.

HXZ+ ΔUNC^{ma} model. That is, EG and ΔUNC^{ma} have a similar price of risk. In Panels B and D of Table 5, we estimate the price of risk using the expanding-window estimation. The main results are qualitatively similar to those in Panels A and C. The γ_0 from HMXZ is 0.06% (*t*-statistic=0.96) while that from HXZ+ ΔUNC^{ma} is 0.09% (*t*-statistic=1.50). Also, γ_{EG} and $\gamma_{UNC^{ma}}$ are 0.61% (*t*-statistic=3.32) and -0.68% (*t*-statistic=-3.75), while $\gamma_{UNC^{mi}}$ is -1.47% (*t*-statistic=-0.71).²⁴ Overall, we see that the Hou et al. (2015) *q*-factor model augmented with the macro uncertainty factor performs similarly to the Hou et al. (2021) q^5 -factor model (HMXZ).

5.5. Comparing various models: Maximum squared Sharpe ratio

Table 5 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, 2016, 2017; 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. To minimize the max squared Sharpe ratio of the intercepts for all left-hand-side portfolios, we can rank competing models 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

$$Sh^2(a_i) = a_i' \Sigma_i^{-1} a_i, \tag{18}$$

²⁴As a robustness check, we replace macro uncertainty (ΔUNC^{ma}) with total uncertainty (ΔUNC) in Appendix H and find similar results.

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:

$$Sh^{2}(a_{i}) = Sh^{2}(\Pi_{i}, f_{i}) - Sh^{2}(f_{i}).$$
(19)

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 11 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.²⁵ 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 similar maximum squared Sharpe ratio (0.26 and 0.27, respectively). Again, this suggest that the EG factor and the macro uncertainty factor are very similar.

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

 $^{^{25}}$ We cannot compute $Sh^2(f)$ for the SY model as we only have the data for the spread factors, not the corresponding portfolios.

6. Conclusions

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

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

- Adrian, T., Etula, E., Muir, T., 2014. Financial intermediaries and the cross-section of asset returns. Journal of Finance 69, 2557–2596.
- Alfaro, I., Bloom, N., Lin, X., 2023. The finance uncertainty multiplier. Journal of Political Economy forthcoming.
- Bachmann, R., Bayer, C., 2013. 'Wait-and-See' business cycles? Journal of Monetary Economics 60, 704–719.
- Bachmann, R., Bayer, C., 2014. Investment dispersion and the business cycle. American Economic Review 104, 1392–1416.
- Bachmann, R., Elstner, S., Sims, E. R., 2013. Uncertainty and economic activity: Evidence from business survey data. American Economic Journal: Macroeconomics 5, 217–49.
- Bali, T. G., Brown, S. J., Tang, Y., 2017. Is economic uncertainty priced in the cross-section of stock returns? Journal of Financial Economics 126, 471–489.
- Bali, T. G., Subrahmanyam, A., Wen, Q., 2021. The macroeconomic uncertainty premium in the corporate bond market. Journal of Financial and Quantitative Analysis 56, 1653–1678.
- Bali, T. G., Zhou, H., 2016. Risk, uncertainty, and expected returns. Journal of Financial and Quantitative Analysis 51, 707–735.
- 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.
- Basu, S., Bundick, B., 2017. Uncertainty shocks in a model of effective demand. Econometrica 85, 937–958.
- Bekaert, G., Engstrom, E., Xing, Y., 2009. Risk, uncertainty, and asset prices. Journal of Financial Economics 91, 59–82.

- Berger, D., Dew-Becker, I., Giglio, S., 2019. Uncertainty shocks as second-moment news shocks. Review of Economic Studies 87, 40–76.
- Berk, J. B., Green, R. C., Naik, V., 1999. Optimal investment, growth options, and security returns. Journal of Finance 54, 1553–1607.
- Black, F., 1976. Studies of stock market volatility changes. 1976 Proceedings of the American Statistical Association, Bisiness and Economic Statistics Section pp. 177–181.
- Bloom, N., 2009. The impact of uncertainty shocks. Econometrica 77, 623–685.
- Bloom, N., 2014. Fluctuations in uncertainty. Journal of Economic Perspectives 28, 153–76.
- Bloom, N., Floetotto, M., Jaimovich, N., Saporta-Eksten, I., Terry, S. J., 2018. Really uncertain business cycles. Econometrica 86, 1031–1065.
- Bretscher, L., Hsu, A., Tamoni, A., 2023. The real response to uncertainty shocks: The risk premium channel. Management Science 69, 119–140.
- 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., 2016. Time-to-produce, inventory, and asset prices. Journal of Financial Economics 120, 330–345.
- Chen, Z., Connor, G., Korajczyk, R. A., 2018. A performance comparison of large-n factor estimators. Review of Asset Pricing Studies 8, 153–182.
- Chen, Z., Kim, B.-C., 2020. Fundamental risk sources and pricing factors, Working Paper, Hong Kong University of Science and Technology.
- Chen, Z., Petkova, R., 2012. Does idiosyncratic volatility proxy for risk exposure? Review of Financial Studies 25, 2745–2787.
- Chen, Z., Yang, B., 2019. In search of preference shock risks: Evidence from longevity risks and

momentum profits. Journal of Financial Economics 133, 225–249.

- 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.
- Cochrane, J. H., 1996. A cross-sectional test of an investment-based asset pricing model. Journal of Political Economy 104, 572–621.
- Connor, G., Korajczyk, R. A., 1987. Estimating pervasive economic factors with missing observations, Working Paper, London School of Economics & Political Science.
- David, J., Schmid, L., Zeke, D., 2022. Risk-adjusted capital allocation and misallocation. Journal of Financial Economics 145, 684–705.
- Dew-Becker, I., Giglio, S., 2022. Cross-sectional uncertainty and the business cycle: Evidence from 40 years of options data. American Economic Journal: Macroeconomics 15, 65–96.
- Dew-Becker, I., Giglio, S., Kelly, B., 2021. Hedging macroeconomic and financial uncertainty and volatility. Journal of Financial Economics 142, 23–45.
- Dew-Becker, I., Giglio, S., Le, A., Rodriguez, M., 2017. The price of variance risk. Journal of Financial Economics 123, 225–250.
- Diercks, A. M., Hsu, A., Tamoni, A., 2023. When it rains it pours: Cascading uncertainty shocks. Journal of Political Economy forthcoming.
- 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., 2016. Dissecting anomalies with a five-factor model. Review of Financial Studies 29, 69–103.
- Fama, E. F., French, K. R., 2017. International tests of a five-factor asset pricing model. Journal of Financial Economics 123, 441–463.
- Fama, E. F., French, K. R., 2018. Choosing factors. Journal of Financial Economics 128, 234–252.
- Fernández-Villaverde, J., Guerrón-Quintana, P., Kuester, K., Rubio-Ramírez, J., 2015. Fiscal volatility shocks and economic activity. American Economic Review 105, 3352–84.
- Fernández-Villaverde, J., Guerrón-Quintana, P. A., 2020. Uncertainty shocks and business cycle research, NBER Working Paper No. 26768.
- Foster, L., Haltiwanger, J. C., Krizan, C. J., 2001. Aggregate productivity growth: Lessons from microeconomic evidence. In: New developments in productivity analysis, University of Chicago Press, pp. 303–372.
- Gibbons, M. R., Ross, S. A., Shanken, J., 1989. A test of the efficiency of a given portfolio. Econometrica 57, 1121–1152.
- Gouriéroux, C., Jasiak, J., 2006. Autoregressive gamma processes. Journal of forecasting 25, 129–152.
- Hartzmark, S. M., 2016. Economic uncertainty and interest rates. Review of Asset Pricing Studies 6, 179–220.
- Harvey, A. C., Shephard, N., 1996. Estimation of an asymmetric stochastic volatility model for asset returns. Journal of Business & Economic Statistics 14, 429–434.
- Herskovic, B., Kelly, B., Lustig, H., Nieuwerburgh, S. V., 2016. The common factor in idiosyncratic volatility: Quantitative asset pricing implications. Journal of Financial Economics 119, 249–283.
- Herskovic, B., Kind, T., Kung, H., 2023. Micro uncertainty and asset prices. Journal of Financial

Economics 149, 27–51.

- 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.
- Kehrig, M., 2015. The cyclical nature of the productivity distribution, Working Paper, Duke University.
- Kozeniauskas, N., Orlik, A., Veldkamp, L., 2018. What are uncertainty shocks? Journal of Monetary Economics 100, 1–15.
- Lewellen, J., Nagel, S., Shanken, J., 2010. A skeptical appraisal of asset-pricing tests. Journal of Financial Economics 96, 175–194.
- Li, J., Wang, H., Yu, J., 2021. Aggregate expected investment growth and stock market returns. Journal of Monetary Economics 117, 618–638.
- Liu, L. X., Whited, T. M., Zhang, L., 2009. Investment-based expected stock returns. Journal of Political Economy 117, 1105–1139.
- 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.
- Schaab, A., 2020. Micro and macro uncertainty, Working Paper, Harvard University.
- Segal, G., Shaliastovich, I., 2022. Uncertainty, risk, and capital growth, Working Paper, University of NorthCarolina at Chapel Hill.
- Segal, G., Shaliastovich, I., Yaron, A., 2015. Good and bad uncertainty: Macroeconomic and financial market implications. Journal of Financial Economics 117, 369–397.
- 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.
- Zhang, L., 2005. The value premium. Journal of Finance 60, 67–103.



Fig. 1. Uncertainty and industrial production growth

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



Fig. 2. Uncertainty and stock return dispersions

These figures plot the time series of total uncertainty (UNC), macro uncertainty (UNC^{ma}) , and micro uncertainty (UNC^{mi}) against cross-sectional return dispersions, including total stock return dispersion (RD), the systematic stock return dispersion (RD^{sys}) and the idiosyncratic return dispersion (RD^{idio}) computed from the Carhart four-factor model. All series are standardized. The shaded areas are NBER recession periods.



Fig. 3. Price of uncertainty risk and industrial production growth

This figure plots the prices of total uncertainty risk (UNC) and macro uncertainty risk (UNC^{ma}) against the annual log industrial production (IP) growth in the United States. All series are standardized. The shaded areas are NBER recession periods.

y, ΔUNC), d deviation, P growth on s the annual 16.																						
otal uncertaint mean, standau s firm-level TF Panel B report om 1972 to 20								ΔUNC^{ma}													1.00	-0.63
^{TP} growth (tc including the)). We regress [FP growth.] setimates is fr		$\rho(\Delta VIX)$		0.38	0.37	-0.18		ΔUNC												1.00	0.87	-0.36
on of TF NC^{mi}), i $\rho(\Delta VIX)$ ncratic) T neratic) T ertainty ϵ		$\rho(IP)$		-0.10	-0.26	0.00		MIS											1.00	0.11	0.07	-0.03
in deviation ΔU inty, ΔU he VIX ($_{I}$ c (idiosynce of unce		AR(1)	-0.08	-0.53	-0.60	-0.66		EG										1.00	0.68	0.29	0.25	-0.15
standar o uncerta nges in tl ystemati The samp		30%	0.22	0.04	0.07	0.04		Q_{ROE}									1.00	0.45	0.45	0.15	0.04	0.09
sectional th (micro nual cha wth as s actors. T		75%	0.09	0.02	0.03	0.02		Q_{IA}								1.00	0.17	0.28	0.34	0.06	0.00	-0.01
ie cross- , P growt) and an TFP grc pricing fi		50%	-0.01	0.01	0.01	0.00	ctors	Q_{ME}							1.00	0.18	0.05	0.16	-0.03	-0.24	-0.23	0.03
ice of th cratic TT $\alpha (\rho(IP))$ esidual) res and j		25%	-0.10	-0.01	-0.02	-0.01	ricing fa	UMD						1.00	0.26	-0.10	0.48	0.32	0.45	-0.18	-0.15	0.15
t-differer l idiosynd ?) growth dicted (r ty measu		10%	-0.21	-0.05	-0.07	-0.04	ity and p	RMW					1.00	-0.05	-0.13	0.28	0.54	0.35	0.41	0.23	0.14	-0.06
the firs m^a), and m^a), and iction (II effine pre-	easures	Max	2.03	0.14	0.19	0.07	incertair	CMA				1.00	0.24	-0.11	0.21	0.91	0.00	0.26	0.35	0.00	-0.02	0.02
(ΔTFP) , ΔUNC all prodution many and dramatical variants under the many many many many many many many many	ainty me	Min	-0.71	-0.15	-0.23	-0.05	en TFP 1	HML			1.00	0.65	0.40	-0.25	0.05	0.63	0.09	0.11	0.02	-0.05	-0.08	0.03
growth certainty, i industr r each fin etween v	ts uncert	S.D.	0.21	0.05	0.07	0.03	is betwee	SMB		1.00	0.05	0.22	-0.06	0.19	0.98	0.19	0.01	0.17	-0.02	-0.19	-0.18	0.00
al TFP acro unc tion with TFP fo ficients b	P and i	Mean	0.01	0.00	0.00	0.00	orrelation	MKT	1.00	0.10	-0.32	-0.32	-0.26	0.19	0.15	-0.27	0.01	-0.15	-0.26	0.04	-0.01	0.15
marizes annu. FP growth (m nd the correla components of orrelation coeff	Panel A: TI		$\Delta \mathrm{TFP}$	ΔUNC	ΔUNC^{ma}	ΔUNC^{mi}	Panel B: Co		MKT	SMB	HML	CMA	RMW	UMD	Q_{ME}	Q_{IA}	Q_{ROE}	EG	MIS	ΔUNC	ΔUNC^{ma}	ΔUNC^{mi}
Panel A surr systematic T percentiles, a six principal of time-series cc																						

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

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Table 2. 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, 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: Re	gression of	aggregate	uncertainty a	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: Re	gression of	total uncer	tainty agains	st mac	ro 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			

Panel A: F	actor moc	lels augr	nented w	vith total	uncertai	nty										
	E	<u>ب</u>	FF3+2	ΔUNC	FF	4	$FF4+\Delta$	UNC	FF	5	FF5+4	ΔUNC	E	95	FF6+2	NNC
	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	2.45	6.45	1.96	2.72	1.31	4.07	1.02	1.72	0.89	2.55	0.83	2.02	0.69	2.33	0.66	1.52
γ_{MKT}	4.86	1.87	4.98	1.88	6.14	2.37	6.03	2.30	5.97	2.30	5.97	2.30	6.35	2.45	6.32	2.42
γ_{SMB}	2.11	1.13	2.25	1.19	2.19	1.17	2.35	1.24	2.25	1.21	2.31	1.23	2.23	1.20	2.34	1.24
λHML	3.41	1.52	2.56	1.01	4.25	1.84	3.23	1.22	1.93	0.88	1.85	0.84	3.00	1.38	2.97	1.33
γ_{CMA}									5.23	3.93	4.96	3.68	5.23	3.88	4.70	3.29
γ_{RMW}									2.94	1.80	3.30	1.97	2.39	1.45	2.96	1.63
dMDL					9.86	4.35	9.56	4.16					9.82	4.34	9.70	4.27
γ_{UNC}			-8.35	-2.81			-9.32	-2.70			-4.55	-2.05			-7.41	-2.59
R^2	0.21		0.37		0.54		0.76		0.45		0.46		0.71		0.78	
$(5^{th}, 95^{th})$	(0.01, 0)	(59)	(0.04, (0.67)	(0.29, 0)	.76)	(0.39, 0)	(.81)	(0.17, 0)	.76)	(0.20, (0.78)	(0.47, ((.84)	(0.52, 0	(86)
	ίΗ	ΧZ	HXZ+'	ΔUNC	HM	XZ										
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat										
γ_0	1.71	3.32	1.56	2.00	1.52	2.17										
γ_{MKT}	5.57	2.13	5.48	2.03	5.33	1.68										
γ_{QME}	2.62	1.36	2.18	1.09	2.43	1.24										
$\gamma_{Q_{IA}}$	3.72	2.20	3.65	1.64	4.60	2.34										
γQ_{ROE}	5.28	3.29	5.89	3.14	5.43	2.99										
γ_{EG}					11.89	7.30										
γ_{UNC}			-7.12	-2.57												
	14		0 53		0.01											

(0.63, 0.90)0.91

(0.16, 0.80)

(0.11, 0.77)0.45

 $(5^{th}, 95^{th})$

Table 3. Cross-sectional regressions of uncertainty factor augmented models

This table reports Fama-MacBeth regressions of various factor models and those augmented with the uncertainty factor, using annual non-tradable uncertainty

factors directly and the full-sample estimation. Panel A uses the total uncertainty factor (ΔUNC) ; Panel B uses the macro uncertainty factor (ΔUNC^{ma}) ;

Panel C uses het micro uncertainty factor (ΔUNC^{mi}). Test assets are forty-five portfolios and the tested pricing factors, including six size and book-to-market sorted portfolios, six size and operating profitability sorted portfolios, six size and investment sorted portfolios, six size and momentum sorted portfolios, six size and expected investment growth sorted portfolios, ten operating accrual sorted portfolios, and five Fama-French industry portfolios. Tested factor models are

Fama and French (1993) three-factor model (FF3), Carhart (1997) four-factor model (FF4), Fama and French (2015) five-factor model (FF5), Fama and French

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	$FF3+\Delta U$	$^{1}NC^{ma}$	$FF4+\Delta U$	INC^{ma}	$FF5+\Delta i$	UNC^{ma}	$FF6+\Delta$	UNC^{ma}	$HXZ+\Delta$	UNC^{ma}
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Ű/Č	1.61	2.16	0.95	1.80	0.71	1.64	0.58	1.54	1.61	1.95
TMKT	5.43	2.04	6.25	2.39	6.17	2.37	6.50	2.50	5.52	2.04
γ_{SMB}	2.38	1.26	2.42	1.28	2.36	1.26	2.35	1.26		
λHML	2.52	0.96	3.29	1.29	2.02	0.90	3.09	1.40		
γ_{CMA}					4.97	3.63	4.91	3.54		
γ_{RMW}					3.50	2.09	2.99	1.77		
γ_{UMD}			9.45	4.12			9.67	4.27		
γQ_{ME}									2.19	1.09
γQ_{IA}									3.13	1.34
$\gamma_{Q_{ROE}}$									5.86	3.01
γ_{UNCma}	-13.93	-2.79	-12.38	-2.64	-8.29	-2.52	-8.76	-2.46	-11.23	-2.72
R^2	0.42		0.71		0.47		0.74		0.54	
$5^{th}, 95^{th}$	(0.05, 0.6	(8)	(0.36, 0.8)	(0)	(0.20, 0.	78)	(0.49, 0)	(85)	(0.15, 0.7)	(6)
anel C: Fa	ctor mode	als augm∈	inted with	micro u	ncertainty	r				
	$FF3+\Delta U$	INC^{mi}	$FF4+\Delta U$	$_{INCmi}$	$FF5+\Delta$	UNC^{mi}	$FF6+\Delta$	UNC^{mi}	$\Delta + ZXH$	UNC^{mi}
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	2.52	5.83	1.34	3.94	0.86	2.40	0.64	1.96	1.73	3.25
γ_{MKT}	4.88	1.88	6.14	2.37	5.93	2.29	6.26	2.42	5.57	2.13
γ_{SMB}	2.14	1.15	2.20	1.18	2.22	1.19	2.18	1.17		
γ_{HML}	3.24	1.42	4.18	1.81	1.99	0.90	3.14	1.44		
γ_{CMA}					5.34	4.03	5.43	4.02		
γ_{RMW}					2.81	1.73	2.11	1.28		
γ_{UMD}			9.83	4.33			9.88	4.36		
γQ_{ME}									2.62	1.36
$\gamma_{Q_{IA}}$									3.65	2.13
γQ_{ROE}									5.31	3.35
$\gamma_{UNC^{mi}} \ R^2$	$1.31 \\ 0.20$	1.46	$0.44 \\ 0.53$	0.45	-0.51	-0.55	-1.24 0 71	-1.21	$\begin{array}{c} 0.29 \\ 0.44 \end{array}$	0.32
$th_{-} 05^{th})$	(0.03, 0.6)	3)	(0.30, 0.7)	(2,	(0.21, 0.	(22)	(0.48, 0)	(85)	(0.14, 0.7)	(8)

Table 4. 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 and the micro uncertainty portfolio. Panels C - E reports alphas of the mimicking macro 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) q⁵ 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: Sta	atistics of	monthly m	imicking	uncertaint	y portfolios				
	Mean	SD	\mathbf{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: Re	gression of	f mimickin	g uncerta	inty portfo	olios				
	(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: Ab	onormal re	turn of tot	al uncert	ainty facto	r (ΔUNC)				
	Raw	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: Al	onormal re	turn of ma	cro uncer	rtainty fact	tor (ΔUNC^m)	$^{a})$			
	Raw	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: Ab	onormal re	turn of mie	ero uncer	tainty facto	or (ΔUNC^{mi}))			
	Raw	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

Panel A reporusing the full-	rts Fama- sample es	MacBetl timation	h regressio 1. Panel B	ons of vari shows sim	ous factc iilar resul	r model lts with	s and tho the expan	se augmei ding-wind	nted with ow estim	ation. Pa	nthly min nel C pre	icking me sents Fam	acro unce .a-MacBe	rtainty f th regres	actor (Δ)	UNC^{ma}), nimicking
micro uncerta	inty (ΔU)	NC^{mi}) ε	augmented	factor mc v size and	book-to-	nel D sho markat	ows simila	r results v +folios ei	vith the e	xpanding	window of a	stimation	i. Test as	sets are f	forty-five	portfolios
sorted portfol	t pricing i los, six si	actors, r. ze and n	nciuuliug si nomentum	sorted pc	rtfolios,	filiarkeu 6 size al	sorteu pu id expecte	ed investo	ant grov	t operature vth sorted	lg promai	s, 10 oper	su portio rating ac	crual sor	ted port	iolios, and
five Fama-Fre	nch indus	try port.	folios. Test	ted factor	models a	re Fama	and Fren	ch (1993)	three-fac	tor mode	(FF3), (O1E),	Carhart (1	1001 (790) I	r-factor r	nodel (F)	(4), Fama
and French (2	(15) five-	factor n	nodel (FF5,), Fama a	nd Frenc	h (2018)	six-factor	model (]	гғб), Но	u et al. (2 ii-1	(015) q-fa	ctor mode	(ZMH) 1906	, and Sta	ambaugh	and Yuan
(2017) model Jagannathan i	(SY). All and Wang	coefficie (1996).	ents are mu The 5^{th} a.	ultiplied b nd 95^{th} p	y 100. T ercentiles	ne t -stat of the z	istics are djusted <i>H</i>	adjusted 1 2 distribu	ior errors ition fron	-in-variat 1 a bootst	oles, follov trap simul	ring Shan ation of 1	ken (199: 0,000 tin	2). The a les are re	adjusted ported ir	K [≠] follows i brackets.
The testing pe	eriod for	Panel A	and C is fi	rom July	1973 to .	une 201	8. The te	sting peri	od for Pa	nel B and	l D is fro	n July 19	97 to Ju	ıe 2018.		
Panel A: $F_{\hat{\epsilon}}$	uctor mod	lels augn	nented wit	h macro u	incertain	ty, using	the full-s	ample est	imation							
	FF	33	$FF3+\Delta U$	JNC^{ma}	FF	4	$FF4+\Delta U$	INC^{ma}	FF	5	$FF5+\Delta l$	INC^{ma}	ΕF	.0	$FF6+\Delta U$	INC^{ma}
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
λ_0	0.33	6.33	0.00	0.11	0.08	3.61	0.01	0.49	0.09	3.55	0.02	0.92	0.06	2.80	0.03	1.36
γ_{MKT}	0.29	1.46	0.59	2.97	0.56	2.87	0.59	2.99	0.50	2.55	0.58	2.93	0.56	2.86	0.57	2.93
γ_{SMB}	0.19	1.47	0.29	2.19	0.23	1.74	0.29	2.19	0.27	2.10	0.28	2.17	0.27	2.09	0.28	2.17
λ_{HML}	0.21	1.57	0.29	2.12	0.36	2.67	0.29	2.13	0.13	0.95	0.30	2.26	0.25	1.88	0.30	2.27
γ_{CMA}									0.39	4.09	0.28	2.96	0.30	3.29	0.27	2.97
γ_{RMW}									0.20	1.84	0.23	2.20	0.18	1.70	0.23	2.20
γ_{UMD}					0.62	3.29	0.58	3.05					0.60	3.19	0.57	3.02
γ_{UNCma}			-0.80	-7.00			-0.80	-7.84			-0.82	-7.53			-0.82	-8.58
R^{2}	0.19		0.91		0.51		0.91		0.51		0.91		0.64		0.91	
$(5^{th}, 95^{th})$	(0.02, 0	(.50)	(0.80, 0.9)	12)	(0.33, 0)	(02)	(0.81, 0.6	3)	(0.29, 0.	72)	(0.81, 0.9)	3)	(0.46, 0.	80)	(0.83, 0.9	3)
Panel A (C	ontinued)															
	H	Z	$HXZ+\Delta I$	JNC^{ma}	HMC	ZX	S	L .	$SY+\Delta U$	NC^{ma}						
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat						
γ_0	0.11	2.81	0.04	1.34	0.07	2.10	0.08	1.60	0.06	1.46						
γ_{MKT}	0.50	2.50	0.56	2.84	0.54	2.72	0.51	2.48	0.52	2.54						
γQ_{ME}	0.35	2.55	0.36	2.63	0.36	2.62										
γQ_{IA}	0.29	2.71	0.36	3.44	0.31	2.93										
γQ_{ROE}	0.45	3.32	0.36	2.66	0.33	2.40										
γ_{EG}					0.79	7.70										
$\gamma_{MIS_{ME}}$							0.40	3.06	0.47	3.63						
γ_{MGMT}							0.53	3.57	0.45	3.00						
γ_{PERF}							0.55	2.93	0.53	2.82						
γ_{UNCma}			-0.81	-7.89					-0.80	-8.10						
R^2	0.51		0.89		0.82		0.70		0.90							
$(5^{th}, 95^{th})$	(0.30, 6	(.71)	(0.79, 0.9)	12)	(0.66, 0.	.87)	(0.51, 0.8)	32)	(0.79, 0.	92)						

Table 5. Cross-sectional regressions of mimicking uncertainty factors augmented models

Č	FF3		$FF3+\Delta U$	NC^{ma}	FF.	4	$FF4+\Delta i$	UNC^{ma}	E	F5	$FF5+\Delta i$	UNC^{ma}	FF	.9	$FF6+\Delta U$	JNC^{ma}
5	oeff t-st.	at (Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
$\gamma_0 = 0.$.22 2.8	89	0.04	0.64	0.09	2.38	0.06	1.64	0.12	2.93	0.06	1.58	0.09	2.89	0.08	2.68
$\gamma_{MKT} = 0.$.40 1.:	34	0.56	1.87	0.55	1.95	0.52	1.74	0.47	1.69	0.53	1.85	0.51	1.82	0.50	1.78
$\gamma_{SMB} = 0.$.20 0.9	98	0.29	1.33	0.22	1.04	0.29	1.37	0.27	1.30	0.28	1.34	0.26	1.29	0.28	1.34
$\gamma_{HML} = 0.$.14 0.(61	0.16	0.66	0.23	0.99	0.12	0.52	0.03	0.15	0.13	0.58	0.08	0.37	0.10	0.47
γ_{CMA}									0.22	1.23	0.13	0.76	0.18	1.11	0.13	0.75
γ_{RMW}									0.13	0.59	0.17	0.79	0.16	0.76	0.17	0.78
γ_{UMD}					0.42	1.21	0.37	1.03					0.39	1.13	0.35	0.97
γ_{UNCma}			-0.65	-3.09			-0.71	-3.43			-0.60	-3.13			-0.70	-4.15
$R^2 = 0$.31		0.81		0.45		0.82		0.51		0.80		0.56		0.81	
$(5^{th}, 95^{th})$ (0.	.01, 0.61)	(0.68, 0.91)	(1	(0.30, 0.	(92	(0.70, 0.	92)	(0.26, 0	.78)	(0.71, 0.1)	93)	(0.43, 0.	.84)	(0.74, 0.9	(3)
Panel B (Contir	nued)															
	HXZ		$HXZ + \Delta U$	$^{_{I}}NC^{ma}$	HMD	ΧZ	S	Y	$SY+\Delta l$	JNC^{ma}						
Co	beff t-st	at (Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat						
γ ₀ 0.	.12 1.	73	0.09	1.50	0.06	0.96	0.13	1.36	0.14	2.13						
$\gamma_{MKT} = 0.$.48 1.7	74	0.52	1.83	0.55	1.92	0.43	1.44	0.41	1.36						
$\gamma_{Q_{ME}} = 0.$	$.30 1.^4$	45	0.33	1.53	0.32	1.46										
$\gamma_{Q_{IA}} = 0.$.16 0.8	84	0.11	0.55	0.19	1.01										
$\gamma Q_{ROE} = 0$.19 0.7	72	0.11	0.44	0.14	0.53										
γ_{EG}					0.61	3.32										
$\gamma_{MIS_{ME}}$							0.37	1.71	0.41	1.87						
γ_{MGMT}							0.44	1.77	0.32	1.29						
γ_{PERF}							0.58	1.49	0.53	1.38						
γ_{UNCma}			-0.68	-3.75					-0.67	-3.52						
$R^{2} = 0.$.44		0.83		0.74		0.61		0.79							
$(5^{th}, 95^{th})$ (0.	.25, 0.77)	<u> </u>	(0.69, 0.91)	(1	(0.60, 0.	88)	(0.45, 0.5)	85)	(0.68, 0)	.91)						

Panel C: Fa	ctor mod	els augme	nted with	micro un	certainty	, using the	e full-sam	ple estima	ation			
	$FF3+\Delta$	UNC^{mi}	$FF4+\Delta$	UNC^{mi}	$FF5+\Delta$	UNC^{mi}	$FF6+\Delta$	UNC^{mi}	HXZ+7	ΔUNC^{mi}	$SY+\Delta l$	JNC^{mi}
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.19	5.56	0.08	3.48	0.06	2.35	0.07	2.99	0.11	2.83	0.09	1.76
γ_{MKT}	0.43	2.19	0.56	2.86	0.52	2.67	0.55	2.80	0.49	2.48	0.50	2.43
γ_{SMB}	0.20	1.51	0.23	1.73	0.27	2.11	0.27	2.09				
γ_{HML}	0.25	1.86	0.36	2.68	0.14	1.01	0.24	1.87				
γ_{CMA}					0.40	4.15	0.30	3.27				
γ_{RMW}					0.20	1.86	0.18	1.72				
ΔMDD			0.62	3.29			0.60	3.18				
$\gamma_{Q_{ME}}$									0.36	2.63		
γQ_{IA}									0.27	2.57		
γQ_{ROE}									0.45	3.28		
$\gamma_{MISP_{ME}}$											0.40	3.06
γ_{MGMT}											0.53	3.63
γ_{PERF}											0.55	2.95
$\gamma_{UNC_{mi}}$	-0.18	-0.75	-0.26	-1.09	-0.18	-0.74	-0.28	-1.17	-0.29	-1.19	-0.28	-1.11
R^2	0.33		0.60		0.59		0.70		0.61		0.76	
$(5^{th}, 95^{th})$	(0.08, 0)	.62)	(0.41, 0.	(22)	(0.35, 0)	.78)	(0.52, 0.	84)	(0.38, 0)	.78)	(0.59, 0)	(98.
Panel D: Fa	ctor mod	els augme	nted with	ı micro un	certainty	, using the	expandi	ng-windov	w estimat	tion		
	$FF3+\Delta$	UNC^{mi}	$FF4+\Delta$	UNC^{mi}	$FF5+\Delta$	UNC^{mi}	$FF6+\Delta$	UNC^{mi}	HXZ+7	ΔUNC^{mi}	$SY+\Delta l$	JNC^{mi}
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.14	1.85	0.05	1.16	0.08	1.91	0.07	2.06	0.07	1.12	0.14	1.81
γ_{MKT}	0.50	1.62	0.58	2.01	0.52	1.76	0.52	1.82	0.54	1.83	0.42	1.34
γ_{SMB}	0.21	1.02	0.22	1.08	0.28	1.34	0.27	1.32				
λ_{HML}	0.22	0.94	0.22	1.00	0.13	0.60	0.12	0.56				
γ_{CMA}					0.17	0.96	0.18	1.10				
γ_{RMW}					0.23	1.10	0.23	1.11				
γ_{UMD}			0.41	1.19			0.35	1.02				
γQ_{ME}									0.32	1.47		
γQ_{IA}									0.22	1.21		
γQ_{ROE}									0.20	0.81		
$\gamma_{MISP_{ME}}$											0.35	1.69
γ_{MGMT}											0.39	1.68
γ_{PERF}											0.50	1.37
$\gamma_{UNC_{m_{\hat{i}}}}$	-1.54	-0.76	-1.39	-0.68	-1.57	-0.75	-1.54	-0.74	-1.47	-0.71	-1.85	-0.93
R^{2}	0.82		0.83		0.91		0.91		0.86		0.91	
$(5^{th}, 95^{th})$	(0.12, 0)	.89)	(0.42, 0.	(93)	(0.39, 0)	.93)	(0.55, 0.	94)	(0.40, 0)	.93)	(0.61, 0	.95)

Table 6. Robustness: Noisy factors

Panel A examines how likely "noisy" factors could generate the cross-sectional results in Table 5. Following Adrian et al. (2014), we run 100,000 simulations where we draw randomly from the empirical distribution of an uncertainty factor $(\Delta UNC, \Delta UNC^{ma}, \text{ or } \Delta UNC^{mi})$ 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^2 s 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^2 s 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 Δb	UNC-au	gmented	factor 1	models	
	R^2	PRC	SR	Joint R^2 -PRC	Joint All
FF3+ ΔUNC	5.26	0.00	0.00	0.00	0.00
$FF4+\Delta UNC$	4.74	0.00	0.00	0.00	0.00
$FF5+\Delta UNC$	5.45	0.00	0.00	0.00	0.00
$FF6+\Delta UNC$	4.65	0.00	0.00	0.00	0.00
$SY + \Delta UNC$	5.78	0.00	0.00	0.00	0.00
$HXZ + \Delta UNC$	4.10	0.00	0.00	0.00	0.00
Panel B: Noisy Δl	UNC^{ma} -	augmen	ted facto	or models	
	R^2	PRC	\mathbf{SR}	Joint R^2 -PRC	Joint All
$FF3 + \Delta UNC^{ma}$	3.02	0.00	0.00	0.00	0.00
$FF4 + \Delta UNC^{ma}$	3.97	0.00	0.00	0.00	0.00
$FF5+\Delta UNC^{ma}$	3.76	0.00	0.00	0.00	0.00
$FF6+\Delta UNC^{ma}$	4.62	0.00	0.00	0.00	0.00
$SY + \Delta UNC^{ma}$	6.15	0.00	0.00	0.00	0.00
$HXZ + \Delta UNC^{ma}$	4.46	0.00	0.00	0.00	0.00
Panel C: Noisy Δl	UNC^{mi} -	augment	ed facto	r models	
	R^2	PRC	\mathbf{SR}	Joint R^2 -PRC	Joint All
$FF3 + \Delta UNC^{mi}$	58.77	94.02	96.76	53.64	53.64
$FF4 + \Delta UNC^{mi}$	47.90	98.00	96.76	45.91	44.66
$FF5+\Delta UNC^{mi}$	53.75	96.34	96.76	50.10	50.10
$FF6 + \Delta UNC^{mi}$	45.74	98.37	96.76	44.11	42.50
$SY + \Delta UNC^{mi}$	32.95	97.99	96.24	30.95	29.19
$HXZ + \Delta UNC^{mi}$	47.12	98.30	96.76	45.42	43.88

Table 7. Returns to portfolios sorted by the predicted and residual expected investment growth

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

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

Table 8. Using uncertainty to explain the cross-sectional dispersions of EG predictors

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

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

Table 9. Examining loadings of uncertainty factor and EG

This table presents the cross-sectional regression results of loadings of EG and its predictors against loadings of total uncertainty (ΔUNC), macro uncertainty (ΔUNC^{ma}), and micro uncertainty (ΔUNC^{mi}). β_{EG} is the factor loading of expected investment growth factor. β_{COP} is the factor loading of operating cash flow factor. β_Q is the factor loading of Tobin's q factor. β_{dROE} is the factor loading of the change in return on equity factor. We estimate all factor loadings of uncertainty, EG, and EG predictors with Hou et al. (2015) q-factors. Test assets are 45 portfolios and 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 expected investment growth sorted portfolios, 10 operating accruals sorted portfolios, and 5 Fama-French industry portfolios. The testing period is from July 1973 to June 2018.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	β_{EG}	β_{EG}	$\beta_{DIS_{COP}}$	$\beta_{DIS_{COP}}$	β_{DIS_Q}	β_{DIS_Q}	$\beta_{DIS_{dROE}}$	$\beta_{DIS_{dROE}}$
β_{UNC}	-0.91		-0.48		-0.33		-0.21	
t-stat	-4.39		-3.20		-1.53		-0.67	
$\beta_{UNC^{ma}}$		-1.08		-0.70		-0.05		0.19
t-stat		-3.60		-3.56		-0.15		0.40
$\beta_{UNC^{mi}}$		-0.03		-0.05		-0.14		-0.07
t-stat		-0.31		-0.73		-1.16		-0.44
R^2	0.29	0.37	0.18	0.41	0.05	0.06	0.01	0.00

Table 10. Explaining the EG factor with uncertainty-augmented factor models

Panel A presents the abnormal returns and the factor loadings of EG factor from various macro uncertainty (ΔUNC^{ma}) -augmented factor models, using the full sample. Panel B reports the abnormal returns and the 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 a	ugmented by	macro un	certainty				
	α								
Raw	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
HXZ	-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
SY	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	

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Panel A	: ractor	models	augmented	by micro t	incertaint	y		ATTATOMI	- D2
	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
$4 \mathrm{FF}$	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
6 FF	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 11. Maximum squared Sharpe ratio

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) and French (2015) five-factor model (FF5), Fama and French (2018) six-factor model (FF6), Hou et al. (2015) q^{-1} factor model (HXZ), and Hou et al. (2021) q^{5} model (HXZ). The 5th and 95th 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. augmented factor models, respectively. Factor models include Fama and French (1993) three-factor model (FF3), Carhart (1997) four-factor model (FF4), Fama

Panel A: P1						
	FF3	$FF3+\Delta UNC^{ma}$	FF4	$FF4+\Delta UNC^{ma}$	FF5	$FF5+\Delta UNC^{ma}$
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	$FF6+\Delta UNC^{ma}$	HXZ	$HXZ+\Delta UNC^{ma}$	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: Δi	UNC^{mi} augmented	l factor models				
	$FF3+\Delta UNC^{mi}$	$FF4+\Delta UNC^{mi}$	$FF5+\Delta UNC^{mi}$	$FF6+\Delta UNC^{mi}$	$HXZ+\Delta UNC^{mi}$	
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: Δ	UNC augmented fa	actor models				
	$FF3+\Delta UNC$	$FF4+\Delta UNC$	$FF5+\Delta UNC$	$FF6+\Delta UNC$	$HXZ+\Delta UNC$	
Sh2(f)	0.18	0.09	0.12	0.15	0.19	
$(E^{th} 0E^{th})$	(0 19 0 96)	(0.06.0.16)	(0.08 0.19)	(0 10 0 23)	(0.13 0.97)	

Online Appendices

A. A production economy with uncertainty shocks

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

$$\ln X_{t+1} = \rho_x \ln X_t + \eta (\sigma_t^2 - \sigma^2) + \sigma_t \varepsilon_{x,t+1}, \qquad (1)$$

$$\sigma_{t+1}^2 = (1 - \rho_{\sigma})\sigma^2 + \rho_{\sigma}\sigma_t^2 + \upsilon \varepsilon_{\sigma,t+1}, \qquad (2)$$

where $0 < \rho_x < 1$ and $0 < \rho_\sigma < 1$, σ^2 is the long-run average volatility, v 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.²⁶ 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 $D_t = Y_t - I_t - \frac{a}{2} \left(\frac{I_t}{K_t}\right)^2 K_t$.

 $^{^{26}}$ 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 Gouriéroux and Jasiak (2006).

For simplicity, we assume a representative household with a power utility.²⁷ The household consumes firm dividends to maximize her expected utility, as follows:

$$\max_{\{C_t\}_{t=0}^{\infty}} \qquad \mathbb{E}\sum_{t=0}^{\infty} \beta^t \frac{C_t^{1-\gamma}}{1-\gamma}$$
(3)

$$C_t = Y_t - I_t - \frac{a}{2} \left(\frac{I_t}{K_t}\right)^2 K_t, \ \forall t = 0, 1, 2...$$
(4)

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

The first-order condition gives

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

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:

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

The real investment return, R_{t+1}^I , is:

$$R_{t+1}^{I} = \frac{X_{t+1} + \frac{a}{2} \left(\frac{I_{t+1}}{K_{t+1}}\right)^{2} + (1-\delta) \left[1 + a \left(\frac{I_{t+1}}{K_{t+1}}\right)\right]}{1 + a \frac{I_{t}}{K_{t}}}.$$
(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} .

²⁷Using recursive preferences might make uncertainty shocks more important for asset prices.

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_t^2), optimal investment can be approximated as:

$$\hat{I}_{t} = I_{0} + I_{x}\hat{X}_{t} + I_{k}\hat{K}_{t} + I_{\sigma}\sigma_{t}^{2},$$
(9)

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

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

$$\mathbb{E}_{t}[\hat{R}_{t+1}] = \left[h(I_{k}-1)\delta + h - \frac{a\delta}{1+a\delta}\right]I_{0} + hI_{\sigma}(1-\rho_{\sigma})\sigma^{2} \\ + \underbrace{\left[\frac{h}{a\delta}\rho_{x} + h\left(I_{k}-1\right)\delta I_{x} + hI_{x}\rho_{x} - \frac{a\delta}{1+a\delta}I_{x}\right]\hat{X}_{t}}_{\text{prductivity shock}} \\ + \underbrace{\left[h\left(1-\delta+\delta I_{k}\right) - \frac{a\delta}{1+a\delta}\right](I_{k}-1)\hat{K}_{t}}_{\text{capital stock}} \\ + \underbrace{\left\{\left[h\rho_{\sigma} - \frac{a\delta}{1+a\delta}\right]I_{\sigma} + \left(\frac{h}{a\delta} + hI_{x}\right)\eta\right\}\sigma_{t}^{2}}_{\text{uncertainty shock}},$$
(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

$$\hat{C}_{t} = \left[g - \left(\frac{I}{C} + ga\delta^{2}\right)I_{x}\right]\hat{X}_{t} + \left[g\left(1 + \frac{a}{2}\delta^{2}\right) - \left(\frac{I}{C} + ga\delta^{2}\right)I_{k}\right]\hat{K}_{t} \\
- \left(\frac{I}{C} + ga\delta^{2}\right)I_{\sigma}\sigma_{t}^{2} + \left(\frac{I}{C} + ga\delta^{2}\right)I_{0},$$
(11)

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

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

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

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

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

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

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:

$$0 = -\gamma \left[g \left(1 + \frac{a}{2} \delta^2 \right) - \left(\frac{I}{C} + g a \delta^2 \right) I_k \right] \delta(I_k - 1) + h(I_k - 1)(1 - \delta + \delta I_k) - \frac{a\delta}{1 + a\delta} (I_k - 1).$$
(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:

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

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

$$\frac{1}{2} \left[h + \gamma \left(\frac{I}{C} + ga\delta^2 \right) \right]^2 I_{\sigma}^2 v^2 + I_{\sigma} \left\{ hI_{\sigma}(1 - \rho_{\sigma}) + \gamma \left(\frac{I}{C} + ga\delta^2 \right) I_{\sigma}(1 - \rho_{\sigma}) - \left(\frac{h}{a\delta} + hI_x \right) \eta + \gamma \left[g - \left(\frac{I}{C} + ga\delta^2 \right) I_x \right] \eta \right\}_{\sigma}^{\sigma^2} \frac{h - \frac{a\delta}{1 + a\delta} + \gamma \delta}{h - \frac{a\delta}{1 + a\delta} + \gamma \delta}$$
(17)

Since $0 < h < \frac{a\delta}{1+a\delta}$, we see that $I_x > 0$. That is, investment increase with productivity shocks. If $\eta > \frac{\gamma g}{2}$,²⁸ then we see that $I_{\sigma} < 0$. That is, investment decreases with uncertainty due to risk aversion.

The optimal investment rate is

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

Expected investment growth is

$$\mathbb{E}_{t}\left[\frac{\hat{I_{t+1}}}{K_{t+1}} - \frac{\hat{I}_{t}}{K_{t}}\right] = I_{\sigma}(1 - \rho_{\sigma})\sigma^{2} + (\rho_{x} - 1)I_{x}\hat{X}_{t} + \left[(\rho_{\sigma} - 1)I_{\sigma} + I_{x}\eta\right]\sigma_{t}^{2}.$$
(19)

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

²⁸Since 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.

The stock return can be simplified to

$$\mathbb{E}_{t}[\hat{R}_{t+1}] = \left(h - \frac{a\delta}{1+a\delta}\right)I_{0} + \left[hI_{\sigma}(1-\rho_{\sigma}) - \left(\frac{h}{a\delta} + hI_{x}\right)\eta\right]\sigma^{2} + \underbrace{\left[\frac{h}{a\delta}\rho_{x} + hI_{x}\rho_{x} - \frac{a\delta}{1+a\delta}I_{x}\right]\hat{X}_{t}}_{\text{prductivity shock}} + \underbrace{\left\{\left[h\rho_{\sigma} - \frac{a\delta}{1+a\delta}\right]I_{\sigma} + \left(\frac{h}{a\delta} + hI_{x}\right)\eta\right\}\sigma_{t}^{2}}_{\text{uncertainty shock}}(20)$$

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).

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 be-

tween 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 (CES050000030). 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. İmrohoroğlu and Tüzel (2014) show how to estimate Olley and Pakes (1996) TFP using annual Compustat and share their codes.²⁹ We follow İmrohoroğlu and Tüzel (2014) with some modifications.

We start from the simple Cobb-Douglas production technology,

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

²⁹Available at http://www-bcf.usc.edu/ tuzel/TFPUpload/Programs/

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

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

We define $Log \frac{Y_{it}}{K_{it}}$, $Log \frac{L_{it}}{K_{it}}$, $Log K_{it}$, and $Log Z_{it}$ 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

$$yk_{it} = \beta_l lk_{it} + \beta_k k_{it} + z_{it}.$$
(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 2nd-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, $\hat{\beta}_l$.

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

survival of the firm is

$$E_t(yk_{i,t+1} - \hat{\beta}_l lk_{i,t+1} - year * \eta_j) = \beta_k k_{i,t+1} + E_t(z_{i,t+1} | z_{i,t}, survival)$$

$$= \beta_k k_{i,t+1} + g(z_{it}, \hat{P}_{survival,t}),$$
(25)

where $\hat{P}_{survival,t}$ 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 2nd 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 $(\hat{P}_{survival,t})$ and lagged TFP (z_{it}) . At this step, we estimate the coefficient of capital, $\hat{\beta}_k$, which gives $\hat{\beta}_k$.

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

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

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

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

In this section, 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.

C.1. 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 C1 reports the results with the full-sample estimation, which are qualitatively similar to those reported in Table 5. 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 C1. The testing period is from July 1997 to June 2018. We find similar results in the extending-window cases. First, 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.

C.2. 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 C2. 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.

C.3. Cross-sectional regressions of factor models augmented with aggregate uncertainty factors

Table C3 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. Table C3 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 C4 reports Fama-MacBeth regressions of various factor models augmented with the mim-

icking 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.

D. Explaining the expected investment growth factor with total uncertainty-augmented factor models

To avoid the look-ahead bias, we use the extending-window to decompose EG into predicted and residual components. Starting from 1985, we regress the firm-level EG against the macro uncertainty to compute these two components over time. We sort all stocks into decile portfolios based on either their predicted EG or residual EG. Portfolio 10 (1) has the highest (lowest) predicted or residual EG. We compute the value-weighted portfolio returns and the alphas from various asset pricing models. Panel A of Table D1 shows that portfolio returns increase with predicted EG. The long-short portfolio has a significantly positive alpha from all benchmark models. But Panel B of Table D1 shows that the residual EG doesn't provide additional information. For example, the long-short portfolio 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 EG is driven by the macro uncertainty risk.

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

Table E1 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.
F. Explaining the pricing powers of three EG predictors

Table F1 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.

G. Explaining the expected investment growth factor with total uncertainty-augmented factor models

Table G1 reports the regression coefficients of using ΔUNC to explain the EG factor. The fullsample estimation results in Panel A show that ΔUNC captures the EG factor in augmented SY model, with insignificant intercepts of 0.02% (*t*-statistic=0.32). ΔUNC are significantly negative in all models.

To avoid the look-ahead bias, we presents similar regression results, using the extending-window estimation, in Panel B. The results are similar to those reported in Panel A.

H. 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 H1. The results are similar to those using ΔUNC^{ma} in Table 5. Overall, the EG factor and ΔUNC have similar contribution in explaining the test portfolios in the cross section.

References

- Bansal, R., Yaron, A., 2004. Risks for the long run: A potential resolution of asset pricing puzzles. Journal of Finance 59, 1481–1509.
- Bianchi, F., Kung, H., Tirskikh, M., 2018. The origins and effects of macroeconomic uncertainty, NBER Working Paper No. 25386.
- 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.
- 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., 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, NBER Working Paper No. 26768.
- 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.

Imrohoroğlu, 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.
- Lettau, M., Ludvigson, S., 2002. Time-varying risk premia and the cost of capital: An alternative implication of the Q theory of investment. Journal of Monetary Economics 49, 31–66.
- Malkhozov, A., 2014. Asset prices in affine real business cycle models. Journal of Economic Dynamics and Control 45, 180–193.
- 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.

Table C1. Cross-sectional regressions of factor models augmented with total uncertainty factor
Panel A reports the coefficients (Coeff) and <i>t</i> -statistics (<i>t</i> -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 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 <i>t</i> -statistics are adjusted for errors-in-variables, following Shanken (1992). The adjusted R^2 follows Jagannathan and Wang (1996). The 5^{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: Fu	ll-sample	estimat	tion													
	FI	F3	$FF3+\Delta$	ΔUNC	FF	4	FF4+2	ΔUNC	FF	15	FF5+2	ΔUNC	FΕ	9.	$FF6+\Delta$	UNC
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
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
λ_{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)	(100.01)	(0.29, 0	.72)	(0.72, 0	(101)	(0.46, 0)	(08)	(0.82, 0	.93)
Panel A (Co	ntinued															
	ΥH	ZX	HXZ+Z	ΔUNC	ΗM	XZ	S	Υ	$\Sigma + XS$	UNC						
	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										
γQ_{IA}	0.29	2.71	0.35	3.27	0.31	2.93										
γQ_{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, ((3.82)	(0.81, 0	(.92)						

$+\Delta UNC$	f t-stat	7 2.04	2 1.84	3 1.35	3 0.60	3 0.92	0.91	5 0.97) -4.25		(, 0.94)															
FF6-	Coef	0.02	0.52	0.28	0.15	0.16	0.2(0.35	-0.7(0.85	(0.78)															
F6	t-stat	2.89	1.82	1.29	0.37	1.11	0.76	1.13			0.84)															
Γ	Coeff	0.09	0.51	0.26	0.08	0.18	0.16	0.39		0.57	(0.43,															
UNC	t-stat	1.15	1.91	1.35	0.72	0.85	0.88		-3.17		(.93)															
$FF5+\Delta$	Coeff	0.05	0.55	0.28	0.16	0.15	0.19		-0.61	0.83	(0.75, 0															
ىر	t-stat	2.93	1.69	1.30	0.15	1.23	0.59				.78)		UNC	t-stat	1.68	1.49					1.80	1.49	1.31	-3.95		
ЪЪ	Coeff	0.12	0.47	0.27	0.03	0.22	0.13			0.52	(0.26, 0		$SY+\Delta$	Coeff	0.12	0.44					0.39	0.40	0.51	-0.66	0.80	0 01 0/
UNC	t-stat	1.61	1.80	1.30	0.74			0.96	-3.82		.93)		7	t-stat	1.36	1.44					1.71	1.77	1.49			10
$FF4+\Delta$	Coeff	0.06	0.53	0.28	0.17			0.35	-0.77	0.85	(0.75, 0)		S	Coeff	0.13	0.43					0.37	0.44	0.58		0.61	
4	t-stat	2.38	1.95	1.04	0.99			1.21			.76)		XZ	t-stat	0.96	1.92	1.46	1.01	0.53	3.32						~~~~
н Е	Coeff	0.09	0.55	0.22	0.23			0.42		0.45	(0.30, 0		HMC	Coeff	0.06	0.55	0.32	0.19	0.14	0.61					0.74	0 00 07
$\frac{0}{UNC}$	t-stat	0.21	1.97	1.28	0.90				-3.04		92)		UNC	t-stat	0.87	1.97	1.54	1.03	0.57					-3.58		~~~~
$\frac{\text{estimati}}{\text{FF3}+\Delta}$	Coeff	0.01	0.60	0.27	0.22				-0.65	0.83	(0.73, 0.		$\Delta + ZXH$	Coeff	0.05	0.56	0.33	0.2	0.14					-0.64	0.83	0 00 07
window 3	t-stat	2.89	1.34	0.98	0.61						61)	_	Z	t-stat	1.73	1.74	1.45	0.84	0.72							1
tending- FF	Coeff :	0.22	0.40	0.20	0.14					0.31	(0.01, 0.01)	ntinued)	HX	Coeff	0.12	0.48	0.30	0.16	0.19						0.44	
Panel B: Ext		γ_0	γ_{MKT}	γ_{SMB}	λHML	γ_{CMA}	γ_{RMW}	γ_{UMD}	γ_{UNC}	R^{2}	$(5^{th}, 95^{th})$	Panel B (Coi			γ_0	γ_{MKT}	$\gamma_{Q_{ME}}$	γQ_{IA}	γQ_{ROE}	γ_{EG}	$\gamma_{MIS_{ME}}$	γ_{MGMT}	γ_{PERF}	γ_{UNC}	R^2	Inth orth

^{anel} A: F	actor models a	ugmente	d with macro-	and mie	cro- uncertaint	y, using	the full-sam	ple estima	ation			
	$FF3+\Delta UN_{c}$	$C^{ma,mi}$	$FF4+\Delta UNC$	yma,mi	$FF5+\Delta UNC$	yma,mi	$FF6+\Delta UN$	$C^{ma,mi}$	$HXZ+\Delta UNG$	$C^{ma,mi}$	$SY+\Delta UN$	$IC^{ma,mi}$
	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				
λ_{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				
γ_{Q_ME}									0.37	2.67		
$\gamma_{Q_{I,A}}$									0.35	3.38		
γQ_{ROE}									0.36	2.65		
$\gamma_{MISP_{ME}}$											0.47	3.66
γ_{MGMT}											0.45	3.07
γ_{PERF}											0.54	2.87
γ_{UNCma}	-0.82	-7.23	-0.81	-7.97	-0.83	-7.70	-0.82	-8.58	-0.81	-7.91	-0.81	-8.20
γ_{UNCmi}	-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, 0.9)	1)

Table C2. Cross-sectional regressions of macro- and micro- uncertainty augmented factor models

market sorted portfolios, 6 size and operating profitability sorted portfolios, 6 size and investment sorted portfolios, 6 size and momentum sorted portfolios, 6 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 size and expected investment growth sorted portfolios, 10 operating accrual sorted portfolios, and 5 Fama-French industry portfolios. Tested factor models are (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 une 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-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 of the 2018

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	$FF3+\Delta UN$	$C^{ma,mi}$	$FF4+\Delta UNC$	yma,mi	$FF5+\Delta UNC$	yma,mi	$FF6+\Delta UNC$	yma,mi	$HXZ+\Delta UNC$	yma,mi	$SY+\Delta UN$	$C^{ma,mi}$
	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
$_{IKT}$	0.58	1.85	0.53	1.78	0.55	1.85	0.53	1.81	0.50	1.63	0.41	1.32
SMB	0.28	1.35	0.29	1.37	0.28	1.33	0.28	1.35				
ML	0.15	0.69	0.11	0.51	0.15	0.72	0.13	0.64				
CMA					0.17	1.05	0.16	0.97				
MM					0.24	1.22	0.21	1.07				
DMD			0.36	1.02			0.35	1.00				
2_{ME}									0.33	1.44		
QIA									0.06	0.30		
RO E									0.05	0.18		
P_{ME}											0.37	1.78
TMT											0.30	1.36
ERF											0.48	1.29
Cma	-0.56	-2.77	-0.62	-3.38	-0.54	-2.79	-0.61	-3.47	-0.70	-3.69	-0.60	-3.35
$_{VCmi}$	-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	
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)	

	$FF3+\Delta($	UNC^{agg}	$FF4+\Delta l$	UNC^{abb}	$FF5+\Delta U$	JNC^{agg}	$FF6+\Delta$	UNC^{agg}	$\Delta + ZXH$	UNC^{agg}	$SY+\Delta U$	JNC^{agg}
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
λ_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				
γ_{OME}									0.39	2.82		
γ_{OIA}									0.33	3.07		
$\gamma_{Q_{ROE}}$									0.31	2.23		
YMISME											0.49	3.80
YMGMT											0.53	3.66
γ_{PERF}											0.56	3.00
$UNC^{a}dd$	-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	
h orth	0 200/	(10	0 11 0/	(00	0000000	1	0 14 0/	(00 2001			(10

Table C3. Cross-sectional regressions of aggregate uncertainty-augmented factor models

lation of This table reports Fama-MacBeth regressions of various factor models augmented with the mimicking aggregate uncertainty portfolio (ΔUNC^{agg}), using full portfolios, 6 size and investment sorted portfolios, 6 size and momentum sorted portfolios, 6 size and expected investment growth sorted portfolios, 10 operating 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 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 accrual sorted portfolios, and 5 Fama-French industry portfolios. Tested factor models are Fama and French (1993) three-factor model (FF3), Carhart (1997) (1992). The 10,000 time

					(00)	0.87	(00	0.62	86)	0.78	(08 (0.81	(02 (0.43
					-5.32	-0.89					-5.83	-0.93		
					2.64	0.68	2.33	0.60						
					2.25	0.43	2.26	0.43						
					1.30	0.20	1.47	0.23						
									5.84	0.72				
									2.01	0.35	2.46	0.43	2.76	0.47
									0.79	0.11	0.26	0.04	0.69	0.09
									1.51	0.26	1.10	0.19	1.43	0.24
					2.23	0.53	2.39	0.56	2.78	0.62	2.19	0.50	2.62	0.59
					1.81	0.12	1.61	0.10	1.47	0.06	2.98	0.17	1.98	0.10
					t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff
					XIX	$\Sigma Y + \Delta$	2	S	XZ	HM	ΔVIX	HXZ+.	ZZ	KΗ
(0.79, 0.94)	83)	(0.49, 0.	(06)	(0.60, C	(.76)	(0.30, 0	.88)	(0.63, 0)	.67)	(0.24, 0)	.78)	(0.33, 0	0.47)	(-0.03,
0.91		0.66		0.80		0.52		0.81		0.38		0.58		0.03
-0.93 -6.15			-5.86	-0.90			-6.86	-1.03			-7.38	-1.13		
0.56 2.25	2.33	0.57					2.16	0.53	2.30	0.56				
0.31 2.21	1.96	0.28	2.39	0.34	2.07	0.29								
0.23 1.91	1.77	0.21	2.54	0.31	2.29	0.28								
0.11 0.69	0.47	0.08	-0.10	-0.02	-0.26	-0.04	1.50	0.25	1.45	0.24	0.69	0.12	0.47	0.08
0.14 0.87	0.96	0.15	0.89	0.14	0.95	0.15	0.52	0.08	0.55	0.09	0.35	0.06	0.36	0.06
0.62 2.79	2.95	0.65	2.50	0.56	2.59	0.58	2.40	0.53	2.70	0.60	1.06	0.25	1.11	0.26
0.06 2.09	1.63	0.04	2.67	0.09	2.77	0.08	4.67	0.17	3.79	0.13	5.76	0.43	5.32	0.44
Coeff t-stat	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff
		FF(V115	FF5+2	15 15	Ŧ	XIN	$FF4+\Delta$	4	FF	ΔVIX	FF3+1	13	Ţ

Table C4. Cross-sectional regressions of the mimicking uncertainty augmented models: Using VIX index

sorted portfolios, 10 operating accrual sorted portfolios, and 5 Fama-French industry portfolios. Tested factor models are Fama and French (1993) three-factor

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

This table reports Fama-MacBeth regressions of various factor models and those augmented with the mimicking uncertainty factor using VIX index (ΔVIX) ,

Table D1. 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:	Portfolic	s sorted b	y predicte	ed 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:	Portfolio	s sorted b	y residual	l 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 E1. 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 crosssectional 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 F1. 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 5th and 95th 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	Z+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)	0.83)	(0.32,	0.83)	(0.30, 0	0.78)

Table G1. Explaining EG factor with total uncertainty-augmented factor models

Panel A presents the average return and the factor loadings of EG factor from various total uncertainty (ΔUNC)augmented factor models, using the full sample. Panel B shows similar results from the expanding-window estimation. 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 by 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 for Panel A is from July 1973 to June 2018.

Panel A	: Full-sa	ample est	timation						
	α								
Raw	0.81								
t-stat	8.77								
	α	MKT						ΔUNC	R^2
CAPM	0.37	-0.10						-0.63	0.61
t-stat	5.31	-4.86						-9.64	
	α	MKT	SMB	HML				ΔUNC	R^2
3FF	0.30	-0.12	0.12	-0.11				-0.76	0.65
t-stat	4.22	-6.71	3.59	-3.53				-10.11	
	α	MKT	SMB	HML	UMD			ΔUNC	R^2
4FF	0.21	-0.10	0.10	-0.05	0.14			-0.72	0.73
t-stat	3.85	-7.66	4.32	-1.89	6.19			-13.15	
	α	MKT	SMB	HML	CMA	RMW		ΔUNC	R^2
5FF	0.22	-0.11	0.19	-0.08	-0.12	0.25		-0.77	0.72
t-stat	3.25	-6.14	5.55	-1.77	-1.61	3.8		-17.84	
	α	MKT	SMB	HML	CMA	RMW	UMD	ΔUNC	R^2
6 FF	0.15	-0.10	0.18	0.00	-0.17	0.22	0.13	-0.75	0.79
t-stat	2.90	-7.36	7.36	-0.11	-3.33	4.88	10.05	-23.97	
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}			ΔUNC	R^2
HXZ	0.12	-6.05	12.79	2.60	19.95			-0.65	0.77
t-stat	2.25	-4.03	6.26	0.85	11.09			-17.21	
	α	MKT	MIS_{ME}	MGMT	PERF			ΔUNC	R^2
SY	0.02	-0.12	0.28	-0.30	0.35			-0.90	0.87
t-stat	0.32	-9.71	9.31	-7.29	14.20			-28.65	

Panel B:	Expan	ding-win	dow estima	tion					
	α								
Raw	0.61								
t-stat	3.85								
	α	MKT						ΔUNC	R^2
CAPM	0.15	-0.09						-0.79	0.89
t-stat	2.53	-4.76						-25.67	
	α	MKT	SMB	HML				ΔUNC	R^2
3FF	0.11	-0.09	0.08	0.00				-0.82	0.90
t-stat	1.91	-4.75	2.43	-0.14				-28.49	
	α	MKT	SMB	HML	UMD			ΔUNC	R^2
$4 \mathrm{FF}$	0.11	-0.09	0.07	0.00	0.01			-0.82	0.90
t-stat	1.88	-4.56	2.40	0.02	0.75			-29.79	
	α	MKT	SMB	HML	CMA	RMW		ΔUNC	R^2
5FF	0.10	-0.08	0.10	0.00	-0.06	0.07		-0.81	0.90
t-stat	1.74	-4.44	5.16	-0.03	-1.58	2.37		-25.67	
	α	Mktrf	SMB	HML	CMA	RMW	UMD	ΔUNC	R^2
6 FF	0.10	-0.08	0.10	0.00	-0.06	0.07	0.01	-0.81	0.90
t-stat	1.72	-4.25	5.08	0.11	-1.60	2.37	0.77	-27.69	
	α	MKT	MIS_{ME}	MGMT	PERF			ΔUNC	R^2
HXZ	0.11	-0.09	0.08	-0.02	0.04			-0.81	0.90
t-stat	1.86	-4.17	2.87	-0.76	1.43			-24.45	
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}			ΔUNC	R^2
SY	0.06	-0.08	0.09	0.02	0.02			-0.79	0.91
t-stat	1.14	-4.02	3.12	0.68	1.96			-24.78	

Table H1. 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 5th and 95th 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.

Panel A: Full-sample betas									
	HM	[XZ	$HXZ + \Delta UNC$						
	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)	0.87)	(0.80, 0)	0.92)					
Panel B: Expanding-window betas									
Panel B: Ex	panding	-window	betas						
Panel B: Ex	panding HM	-window IXZ	betas HXZ+	ΔUNC					
Panel B: Ex	Epanding HM Coeff	-window IXZ t-stat	HXZ+. Coeff	ΔUNC t-stat					
γ_0	Epanding HM Coeff 0.06	-window IXZ t-stat 0.96	betas HXZ+ Coeff 0.05	$\frac{\Delta UNC}{\text{t-stat}}$					
$\begin{array}{c} \text{Panel B: Ex} \\ \hline \\ \gamma_0 \\ \gamma_{MKT} \end{array}$	Epanding HM Coeff 0.06 0.55	-window IXZ t-stat 0.96 1.92	HXZ+ Coeff 0.05 0.56	$\frac{\Delta UNC}{\text{t-stat}}$ 0.87 1.97					
$\begin{array}{c} \begin{array}{c} \text{Panel B: Ex} \\ \hline \\ \gamma_0 \\ \gamma_{MKT} \\ \gamma_{Q_{ME}} \end{array}$	Epanding HN Coeff 0.06 0.55 0.32	-window IXZ t-stat 0.96 1.92 1.46	betas HXZ+ Coeff 0.05 0.56 0.33	$\begin{array}{r} \underline{\Delta UNC} \\ \hline \text{t-stat} \\ 0.87 \\ 1.97 \\ 1.54 \end{array}$					
$\begin{array}{c} \begin{array}{c} \gamma_{0} \\ \gamma_{0} \\ \gamma_{MKT} \\ \gamma_{Q_{ME}} \\ \gamma_{Q_{IA}} \end{array}$	Epanding HM Coeff 0.06 0.55 0.32 0.19	-window IXZ t-stat 0.96 1.92 1.46 1.01	betas HXZ+. Coeff 0.05 0.56 0.33 0.2	ΔUNC t-stat 0.87 1.97 1.54 1.03					
Panel B: Ex γ_0 γ_{MKT} $\gamma_{Q_{ME}}$ $\gamma_{Q_{IA}}$ $\gamma_{Q_{ROE}}$	HM Coeff 0.06 0.55 0.32 0.19 0.14	-window IXZ t-stat 0.96 1.92 1.46 1.01 0.53	betas HXZ+. Coeff 0.05 0.56 0.33 0.2 0.14	ΔUNC t-stat 0.87 1.97 1.54 1.03 0.57					
$\begin{array}{c} \gamma_{0} \\ \gamma_{0} \\ \gamma_{MKT} \\ \gamma_{Q_{ME}} \\ \gamma_{Q_{IA}} \\ \gamma_{Q_{ROE}} \\ \gamma_{EG} \end{array}$	HM Coeff 0.06 0.55 0.32 0.19 0.14 0.61	-window IXZ t-stat 0.96 1.92 1.46 1.01 0.53 3.32	betas HXZ+. Coeff 0.05 0.56 0.33 0.2 0.14	$\frac{\Delta UNC}{\text{t-stat}} \\ 0.87 \\ 1.97 \\ 1.54 \\ 1.03 \\ 0.57 \\ \end{array}$					
$\begin{array}{c} \gamma_{0} \\ \gamma_{0} \\ \gamma_{MKT} \\ \gamma_{Q_{ME}} \\ \gamma_{Q_{IA}} \\ \gamma_{Q_{ROE}} \\ \gamma_{EG} \\ \gamma_{UNC} \end{array}$	$\frac{\text{Fpanding}}{\text{HM}}$ $\frac{\text{HM}}{\text{Coeff}}$ 0.06 0.55 0.32 0.19 0.14 0.61	-window IXZ t-stat 0.96 1.92 1.46 1.01 0.53 3.32	betas HXZ+. Coeff 0.05 0.56 0.33 0.2 0.14 -0.64	$\frac{\Delta UNC}{\text{t-stat}}$ 0.87 1.97 1.54 1.03 0.57 -3.58					
$\begin{array}{c} \gamma_{0} \\ \gamma_{0} \\ \gamma_{MKT} \\ \gamma_{Q_{ME}} \\ \gamma_{Q_{IA}} \\ \gamma_{Q_{ROE}} \\ \gamma_{EG} \\ \gamma_{UNC} \\ R^{2} \end{array}$	$\frac{\text{Fpanding}}{\text{HM}}$ $\frac{\text{HM}}{\text{Coeff}}$ 0.06 0.55 0.32 0.19 0.14 0.61 0.74	-window IXZ t-stat 0.96 1.92 1.46 1.01 0.53 3.32	betas HXZ+, Coeff 0.05 0.56 0.33 0.2 0.14 -0.64 0.83	$\begin{array}{c} \underline{\Delta UNC} \\ \hline \text{t-stat} \\ 0.87 \\ 1.97 \\ 1.54 \\ 1.03 \\ 0.57 \\ -3.58 \end{array}$					