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THREE ESSAYS OF EMPIRICAL ASSET-PRICING

KIM BAEK-CHUN

NANYANG BUSINESS SCHOOL

2020

Three Essays of Empirical Asset Pricing

Baek-Chun Kim

Nanyang Business School

A thesis submitted to the Nanyang Technological University
in partial fulfilment of the requirement for the degree of
Doctor of Philosophy

2020

Statement of Originality

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I have reviewed the content and presentation style of this thesis and declare it is free of plagiarism and of sufficient grammatical clarity to be examined. To the best of my knowledge, the research and writing are those of the candidate with amendments, changes and improvements as suggested by me as the Supervisor. I confirm that the investigations were conducted in accord with the ethics policies and integrity standards of Nanyang Technological University and that the research data are presented honestly and without prejudice.

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Authorship Attribution Statement

This thesis contains material from two papers accepted at conferences in which I am listed as an author.

Fundamental risk sources and pricing factors (with Zhanhui Chen) is presented by Zhanhui Chen in 7th annual conference of Asian Bureau of Finance and Economic Research (ABFER).

The contributions of the co-authors are as follows:

- Prof. Zhanhui Chen provided the initial project direction and edited the draft.
- I prepared and wrote down the draft.
- I co-designed the study with Prof. Zhanhui Chen and performed all the empirical work. I also analyzed the data.

Cross-sectional dispersion of productivity and risk factor (with Zhanhui Chen and Michael Gallmeyer) is presented by Michael Gallmeyer in 2019 UBC Summer Finance Conference.

The contributions of the co-authors are as follows:

- Prof. Zhanhui Chen provided the initial project direction and edited the draft.
- I wrote the draft and the draft was revised with Prof. Zhanhui Chen and Prof. Michael Gallmeyer.
- I performed all the empirical work and analysis.

March 6th 2020

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SUMMARY

THREE ESSAYS OF EMPIRICAL ASSET PRICING

My dissertation aims at understanding the asset pricing implications of firms' fundamental productivity shock. It contains three chapters.

First chapter constructs the fundamental productivity factors to interpret prevailing factors. Neoclassical theory suggests that stocks exposed to common pricing factors must face common risk sources. We estimate firm-level productivity shocks and decompose them into six aggregate risk components via principal component analysis. We explore the fundamental risk sources of prevailing pricing factors. First, we show that the fundamental shocks capture most factors proposed in Fama-French 5-factor model (Fama and French, 2015), Fama-French 6-factor model (Fama and French, 2018), the q -factor model (Hou, Xue, and Zhang, 2015), except for the expected investment growth factor (Hou, Mo, Xue, and Zhang, 2018). Second, we find that fundamental shocks explain most mispricing factors (Stambaugh and Yuan, 2017; Daniel, Hirshleifer, and Sun, 2018), except the post-earnings-announcement-drift factor. Third, we identify an important fundamental risk, the first principal component of productivity shocks, is missed in all of these empirical factor models. We trace this missing factor to the labor risk.

In second chapter, inspired by Bloom, Floetotto, Saporta, Eksten, and Terry (2018), we estimate the cross-sectional dispersion of productivity (total uncertainty) and show that it is the risk factor. We further decompose total uncertainty into macro uncertainty and micro uncertainty. We find that macro uncertainty tracks total uncertainty and explains the cross-sectional return variations among different test portfolios. Also, we suggest income inequality risk as the economic channel. Since a productivity affects a firm's labor hiring and dividend policy, the distribution of productivity is closely linked to the distribution of labor income. That is, the cross-sectional dispersion of productivity and income inequality is

connected and then the productivity dispersion affects the pricing kernel. Further, we explore the connection between the productivity dispersion and the expected investment growth factor (EG) of Hou, Mo, Xue, and Zhang (2018b). Because the expected investment growth is estimated with Fama-MacBeth regression and the coefficients reflect the cross-sectional dispersions of regressors, EG factor share the same risk with the productivity dispersion via cross-sectional dispersions of regressors. Overall, macro uncertainty is an important macroeconomic risk factor via income inequality and EG factor captures the productivity dispersion risk.

Third chapter estimates cross-sectional skewness of productivity. Further, we decompose the skewness shock into the right-tail skewness and left-tail skewness. First, we find that the fundamental skewness is procyclical and is significantly priced. Also, the right-tail skewness drives the asset pricing power of the skewness while the left-tail skewness is insignificant. Second, we explore the economic link between the skewness factors and post-earnings-announcement-drift (PEAD) measures, ABR and SUE. We show that the skewness and the right-tail skewness factor fully explain the abnormal returns of PEAD measures. This suggests that strong abnormal returns of PEAD may reflect the higher-moment macroeconomic risk.

Chapter 1

Fundamental Risk Sources and Pricing Factors

WITH ZHANHUI CHEN

1.1 Introduction

Motivated from the risk or behavioral perspective, several new factor models have been proposed recently (Fama and French (2015, 2018); Hou et al. (2015, 2018d); Stambaugh and Yuan (2017); Daniel et al. (2018)), and they successfully account for more anomalies.¹ Given the 15 pricing factors suggested in these models, e.g., a factor zoo (Feng et al. (2019)), one might wonder how to differentiate and interpret them. Meanwhile, the neoclassical theory of investment (see, e.g. Cochrane (1991, 1996); Berk et al. (1999); Zhang (2005); Liu et al. (2009); Hou et al. (2015)) suggests that under some regularities, stock returns are equivalent to the real investment returns, which can be derived from producers' first-order conditions, e.g., firms' optimal investment decisions. This implies that we can construct the pricing kernel from productivity shocks. Motivated by these, we start with the common productivity shocks in firm productions to understand the systematic risks which might be captured or missed by the prevailing pricing factors. Empirically, we identify six principal

¹See Hou et al. (2018d) for a comprehensive evaluation of 452 anomalies.

components of productivity shocks, which capture 13 of 15 prevailing factors. That is, these 13 factors represent various aspects of fundamental risks. We show that the size factor, profitability factor, and investment factor used in Fama and French (2015), Fama and French (2018), Hou et al. (2015), and Hou et al. (2018b) represent the same set of fundamental risks, though they are motivated differently from the valuation model and q -theory of investment. We also find that the momentum factor, the mispricing factor in Stambaugh and Yuan (2017) and the long-horizon behavioral factor in Daniel et al. (2018) actually capture fundamental risks. However, the productivity factors fail to capture the expected investment growth factor in Hou et al. (2018b) and the short-horizon behavioral factor in Daniel et al. (2018). Moreover, we find that an important productivity factor, the first principal component contains information not captured by the existing factors, i.e., a missing factor. We show that this missing factor largely captures the labor risks. Overall, the productivity shocks are priced and the productivity-based model explains various test assets similarly well to the existing models.

Why should we care about fundamental risk sources? For example, given the large literature on empirical asset pricing models, which typically computes factors from asset prices, one might suggest that we bypass fundamental risks and use those factor returns directly. The reasons build on the promising of the neoclassical theory of investment. Investment-based asset pricing models link real investment returns to the stock returns and suggest that production shocks drive the stock return volatilities. That is, asset price risks arise endogenously from the fundamental risks. That means we can construct the pricing kernel from the productivity shocks. First, this can reveal the fundamental risks behind the prevailing factors, which are mainly constructed in a reduced form. For example, the investment or profitability factors capture corporate responses to the fundamental shocks, so they only indirectly measure the underlying risk sources. Second, the risk sources tell us the difference among return-based factors, which are often hard to differentiate.² For example, do different

²Current literature mainly differentiates factors from the statistical perspective. For example, Barillas and Shanken (2018) use Bayesian tests to select factors. Kozak et al. (2020), Kelly et al. (2018), and Feng et al. (2019) propose econometric methodologies to reduce dimensionality for a large number of characteristics. Hou et al. (2018c) provide thoughtful discussion on the traditional covariance view, behavioral view, and

pricing factors represent different or similar fundamental risks? Third, this provides a direct way to understand why stocks with similar characteristics such as investment or profitability comove. Hou et al. (2015) point out that "the factor models require that returns of stocks with similar investment (and returns of stocks with similar profitability) comove together", but the direct mechanism of comovement is often lack in a factor model. Clearly, if stocks with similar characteristics are expected to common productivity shocks, then their returns comove. Last, on the other hand, this can serve as tests of investment-based asset pricing models as well. If the fundamental shocks are priced, then they are likely to be found in the prevailing factors.

Empirically, we identify the fundamental risk sources and test their pricing power in four steps. We first estimate firm-level total factor productivity (TFP), closely following Olley and Pakes (1996) and Imrohoroglu and Tuzel (2014). Second, we apply the asymptotic principal component analysis (e.g. Connor and Korajczyk (1987); Herskovic et al. (2016); Chen et al. (2018)) to estimate the systematic TFP components across all firms. We identify six principal components of productivity shocks. Third, modeling through the pricing kernel, we show the pricing power of these principal components via GMM estimation, using 155 test assets. Fourth, to increase the statistical power, we construct the mimicking productivity factors for these six components and perform asset pricing tests at the monthly frequency, following Adrian et al. (2014) and Chen and Yang (2019). We test whether the productivity factors can capture the prevailing 15 pricing factors and identify fundamental risks behind them. The 15 pricing factors are (1) six factors used in Fama and French (2018), including the market factor (MKT), the size factor (SMB), the value factor (HML), the investment factor (CMA), the profitability factor (RMW), and the momentum factor (MOM); (2) four factors used in Hou et al. (2018b), including the size factor (Q_{ME}), the investment factor (Q_{IA}), the profitability factor (Q_{ROE}), and the expected investment growth factor (EG); (3) three mispricing factors used in Stambaugh and Yuan (2017), including the univariate mispricing measure (MIS), a component related to firms' management ($MGMT$), and a

investment CAPM view of factors.

component related to firms' performance (*PERF*); (4) two behavioral factors used in Daniel et al. (2018), including a factor related to long-horizon behavioral bias (*FIN*) and a factor related to short-horizon behavioral bias (*PEAD*).

We find that 13 out of 15 pricing factors can be explained by the productivity factors. The exceptions are the expected investment growth factor (*EG*) and the short-horizon behavioral bias factor (*PEAD*). That is, these 13 pricing factors indeed capture the fundamental risks. The size factor, profitability factor, and investment factor used in Fama and French (2015), Fama and French (2018), Hou et al. (2015), and Hou et al. (2018b) correspond to the second, third, and fourth productivity factor, respectively. We find that the momentum factor is captured by the fifth productivity factor, while the sixth productivity factor captures the mispricing factor in Stambaugh and Yuan (2017) and the long-horizon behavioral factor in Daniel et al. (2018).

On the other hand, we find that these prevailing 15 pricing factors can explain the second to sixth productivity factors. That is, these productivity shocks are priced and captured by the prevailing factors. However, the prevailing factors can not explain the first productivity component. We dig deep to understand this missing factor. Empirically, we first show that labor productivity is an important part of total factor productivity and is captured by the first productivity component. Then we construct the labor share portfolios, following Donangelo et al. (Forthcoming). We find that these labor share sorted portfolios are not explained by the prevailing pricing factors, as they capture mainly returns to installed capital. However, the first productivity component does fully explain the labor share sorted portfolios. Therefore, returns to installed labor appear to be missing from existing factor models, while the first productivity component tracks such labor risks. Although our main goal is not to propose an alternative factor model, using various test assets, we show that the productivity-based model performs similarly to the existing factor models. In fact, the productivity-based model provides the highest maximum squared Sharpe ratio among competing models.

This paper follows the tradition of production-based asset pricing literature, e.g., Cochrane

(1991), Restoy and Rockinger (1994), Cochrane (1996), Berk et al. (1999), Zhang (2005), and Liu et al. (2009). Neoclassical theory of investment relates real investment returns to the stock returns and suggests that production risks are behind asset price risks. Hou et al. (2015) and Hou et al. (2018b) construct pricing factors based on firm investment and profitability, which are the consequences of production shocks. Closely related to our work, Imrohoroglu and Tuzel (2014) is the first paper comprehensively showing that firm-level productivity is correlated with lots of firm characteristics and affects stock returns. For example, they show that TFP is related to firm size, book-to-market equity, investment, asset growth, labor hiring, inventory growth, organization capital, capital leases, profitability, net stock issues, and leverage. We build on their results and make progress in three ways. First, Imrohoroglu and Tuzel (2014) use the total firm-level TFP, while we decompose it into six systematic components and link them with the firm characteristics and pricing factors. Second, besides the pricing factors based on firm characteristics, we also explore the behavioral factors. Last, while Imrohoroglu and Tuzel (2014) mainly perform correlation analyses, we explicitly estimate the productivity factors and show that the productivity-based factor model performs similarly to the prevailing factor models. In a similar vein, Belo et al. (2019) show that factors other than installed physical capital are important determinants of firm values, suggesting the importance of recognizing the multiple risk sources in firm production.

Recently, several asset pricing models have been proposed in the empirical literature. Some models use rational risk factors. For example, based on the dividend discount model/surplus clean accounting, Fama and French (2015) construct a five-factor model, including a market factor, a size factor, a value factor, an investment factor, and a profitability factor. Fama and French (2018) further add the momentum factor to the five-factor model to create a six-factor model. Motivated by the neoclassical q -theory of investment, Hou et al. (2015) propose a q -factor model, including a market factor, a size factor, an investment factor, and a profitability factor, where the investment and profitability factors are constructed differently from those in Fama and French (2015). Hou et al. (2018b) add the expected investment growth factor to the q -factor model to create q^5 model. The other models use mispricing or

behavioral factors. For example, Stambaugh and Yuan (2017) suggest a four-factor model, which includes a market factor, a size factor, and two mispricing factors. They construct two mispricing factors by aggregating over six anomalies that are related to firms’ management and five anomalies that are related to firms’ performance. Daniel et al. (2018) propose a three-factor model, including a market factor, a factor related to managerial responses to long-horizon behavioral bias (which is based on security issuance and repurchase), and a factor related to short-horizon behavioral bias (which captures limited attention and underreaction to earnings information, e.g., post-earnings-announcement drift). Overall, these factor models enjoy some success in explaining more anomalies, but it is often difficult to evaluate these factors.³ Our paper explores the fundamental risks possibly embedded or missed in these pricing models to understand these pricing factors.

This paper also adds to the recent asset pricing literature on labor risks. Like installed capital, installed labor affects firm value when labor market frictions are present. Important labor frictions include labor adjustment costs (Merz and Yashiv (2007); Belo et al. (2014)), wage rigidity (Favilukis and Lin (2016b,a)), and search frictions in labor markets (Petrosky-Nadeau et al. (2018)). For asset pricing purposes, labor can increase equity risks through the labor leverage channel (Danthine and Donaldson (2002); Donangelo (2014); Donangelo et al. (Forthcoming)) or through the insurance provided by the shareholders to workers (Marfè (2016, 2017); Hartman-Glaser et al. (2019); Lettau et al. (2019)). Unlike the literature, our paper considers the labor risk embedded in the productivity shocks and estimates the labor factor without directly considering the labor market frictions.

The rest of the paper proceeds as follows. Section 1.2 describes the data and procedures of estimating systematic productivity factors and presents the estimates. Section 1.3 tests the pricing power of productivity factors over other prevailing pricing factors and test assets. Section 1.4 examines the explanatory power of productivity factors over mispricing portfolios in detail. Section 1.5 identifies a productivity factor missed by the prevailing models and

³Empirically, Hou et al. (2018c) show that many seemingly different factor models are closely related. For example, they find that the q -factor and q^5 models subsume the Fama-French five- and six-factor premium and the mispricing factors in Stambaugh and Yuan (2017), but not the PEAD factor in Daniel et al. (2018).

relates it to the labor risk. Finally, Section 1.6 concludes.

1.2 Estimating systematic productivity shocks

Production-based asset pricing models relate stock returns with real investment returns (see, e.g. Cochrane (1991)). For example, if production is a constant return to scale, then the producers' first-order conditions suggest that stock returns equal real investment returns state-by-state. Cochrane (1996) and Liu et al. (2009) empirically confirmed this prediction among a cross-section of stocks. This suggests that stock return risks are inherited from production risks. If stock returns relate to multiple rational pricing factors, firms' production must be subject to multiple systematic productivity shocks, and *vice versa* (see Appendix 1.7.1 for illustrations via a motivating model). Therefore, we can model the pricing kernel from the productivity shocks, suggesting a productivity-based model, which is equivalent to a standard factor model. In this section, we first estimate firm-level productivity. Then we identify systematic productivity shocks across firms.

1.2.1 Estimating firm-level total factor productivity

We closely follow Olley and Pakes (1996) and Imrohoroglu and Tuzel (2014) to estimate TFP. Olley and Pakes (1996) address two issues during TFP estimation. First, there is an endogeneity problem in the estimation of TFP because input factors such as labor and capital stock are contemporaneously correlated with TFP. They estimate the production function parameters separately to avoid the simultaneity problem. Second, there is a selection issue. Firms with very low (high) TFP exit (enter) the markets. Olley and Pakes (1996) mitigate this issue by specifying TFP as a function of the survival probability. Olley and Pakes (1996) assume that (1) productivity is a first-order Markov process; (2) capital is predetermined after productivity is observed; (3) investment contains information on productivity. Imrohoroglu and Tuzel (2014) apply Olley and Pakes (1996) to estimate firm-level

TFP. We follow their approach with some modifications.⁴

Assume the simple Cobb-Douglas production function:

$$Y_{it} = Z_{it} L_{it}^{\beta_L} K_{it}^{\beta_K}, \quad (1.1)$$

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 , respectively. The productivity shocks include both some systematic productivity shocks and an idiosyncratic component. Next, we scale the production function by its capital stock and take the logarithm at both sides. We scale the production function by the capital stock for several reasons. First, since TFP is the residual term, it is highly correlated with the firm size. Second, this avoids estimating the capital coefficient directly. Third, there is an upward bias in the labor coefficient, without scaling. Eq.(1.1) can be rewritten as

$$\text{Log} \frac{Y_{it}}{K_{it}} = \beta_L \text{Log} \frac{L_{it}}{K_{it}} + (\beta_K + \beta_L - 1) \text{Log} K_{it} + \text{Log} Z_{it} \quad (1.2)$$

Denote $\text{Log} \frac{Y_{it}}{K_{it}}$, $\text{Log} \frac{L_{it}}{K_{it}}$, $\text{Log} K_{it}$, and $\text{Log} Z_{it}$ 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 . Rewriting the above equation as follows:

$$yk_{it} = \beta_l lk_{it} + \beta_k k_{it} + z_{it}, \quad (1.3)$$

we can estimate the labor coefficient (β_l) and capital coefficient (β_k) using linear regressions. Then, the logarithmic TFP (z_{it}) can be computed as $y/k_{it} - \beta_l l/k_{it} - \beta_k k_{it}$. We estimate TFP with a 5-year rolling window. TFP shocks can be computed as first-order autoregressive residuals by running a regression of TFP in year t against TFP in year $t - 1$.

We use annual Compustat data to estimate TFP for common stocks from NYSE/Amex/Nasdaq,

⁴Levinsohn and Petrin (2003) suggest another widely used approach to estimate TFP. Both Olley and Pakes (1996) and Levinsohn and Petrin (2003) address the endogeneity concern of the correlation between the unobserved productivity and factor inputs. Unlike Olley and Pakes (1996) use investment to proxy for productivity, Levinsohn and Petrin (2003) assume that intermediate inputs (like materials and electricity) contain information on productivity. Intermediate inputs could be a better proxy for productivity than investment because an investment is often lumpy. However, the firm-level data of intermediate inputs (e.g. in Compustat) are often missing.

with a fiscal year ending in December. We exclude firms with assets or sales below \$1 million, or stock price lower than \$1 at the end of each year. Our main results are based on firms with a four-digit SIC code lower than 4900. These firms are in agriculture, mining, manufacturing, construction, and transportation industries, which fit well the Cobb-Douglas production function. To obtain stable estimates, following Bloom et al. (2018), we assume all firms follow the same production function. Admittedly, this neglects the fact that production function may vary across industries and over time, which might add noise to our estimates. However, we expect this has little impact on our results because we focus on the systematic components of productivity shocks, not the cross-sectional TFP variations. Empirically, we show later that such TFP estimates well capture the aggregate risks across different industries. As a robustness check, we also consider an expanded sample to estimate TFP, by further adding firms in wholesale trade and retail trade (SIC codes between 5000 and 5999), and services (SIC codes between 7000 and 8999), and find qualitatively similar results, reported in Appendix 1.7.5.

We calculate value-added, employment, physical capital, and investment to estimate TFP. Value-added (Y_{it}) is $\frac{SALE_{it}-Materials_{it}}{GDP_deflator}$. 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 staff expense (XLR). However, only a small number of firms report their staff expense. We replace the missing observations with the interaction of the industry average labor expense ratio and total expense. To be specific, we calculate the labor expense ratio, $\frac{XLR_{it}}{SALE_{it}-OIBDP_{it}}$, for each firm. Next, 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 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 wages 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 by following Imrohoroglu and Tuzel (2014). First, we compute the age of capital each year. Age of capital stock is $\frac{DPACT_{it}}{DP_{it}}$. We take a 3-year moving average to smooth the capital age. Then, we match capital stock with the price index for private fixed investment at the current year minus capital age. Finally, we take a 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 deflated by the current fixed investment price index. Labor (L_{it}) is the number of employees. The sample starts from 1966, and the rolling-window estimates are available from 1972 to 2015. See Appendix 1.7.2 for more details about TFP estimation.

1.2.2 Estimating systematic productivity factors

Next, we estimate the systematic TFP components across all firms to identify common risk sources. Similar to Herskovic et al. (2016), we estimate common risk sources via asymptotic principal component analysis, following Connor and Korajczyk (1987). The time-series estimates of TFP for N firms over time T , denoted as TFP_{NT} , are decomposed into k principal components, as follows:

$$TFP_{NT} = B_{Nk} * PC_{kT} + \epsilon_{NT} \quad (1.4)$$

where TFP is $N \times T$ matrix, PC is $k \times T$ matrix of aggregate TFP shocks, B is an $N \times k$ matrix of the sensitivities to aggregate TFP shocks, and ϵ is an $N \times T$ matrix of the idiosyncratic TFP shocks.⁵ We calculate $\Omega = \frac{1}{N}TFP^T TFP$ and estimate the eigenvector of Ω . Then we multiply each element of the eigenvectors by $\frac{1}{\sqrt{T}}$ to obtain the unit standard deviation. The largest k eigenvectors of Ω are the asymptotic principal component estimators.

Two issues remain as we apply the asymptotic principal component over the TFP matrix. First, the TFP matrix is unbalanced due to missing observations. Connor and Korajczyk

⁵Note that it is possible to aggregate these K principal components into a single factor

(1987) address this issue by replacing the missing observations with zero. They prove that if the missing observations follow the same approximate factor structure, the estimated principal components are close to the true factors. Chen et al. (2018) document that the main finding of Connor and Korajczyk (1987) is robust by using the simulations. We require the sample firms to have at least 11 years of TFP estimates to be included in the principal component analysis. This is similar to the requirement in Chen et al. (2018). Second, we need to decide the number of principal components. In this paper, we choose six principal components based on the model fit and empirical implications.⁶ We validate our choice in Section 1.2.4.

1.2.3 Productivity estimates

We first describe our TFP estimates and their principal components in Table 1.1.⁷ The labor coefficient, β_L , is 0.62, and the capital coefficient, β_K , is 0.34. These numbers are very similar to those reported in Olley and Pakes (1996). Also, these estimates are consistent with the neoclassical models. For example, Zhang (2005) uses 0.30 as the capital coefficient. The production function is slightly decreasing return to scale over the sample period.

Panel A of Table 1.1 shows that log TFP growth (ΔTFP) has a mean of 0.01 and a standard deviation of 0.19. There are large variations of TFP growth in both time-series and cross-section. The average first-order autocorrelation coefficient is only 0.07. Panel A presents the summary statistics for six principal components (PC1 to PC6). By construction, the standard deviations are normalized as one. R^2 shows to what degree principal components explain TFP growth. For each firm, we run the time-series regression of log TFP growth on principal components. We estimate the fitted value of log TFP growth and its explanatory power. We report the average R^2 in Panel A. For example, the first principal component (PC1) explains 15% of log TFP growth on average. When we add the second principal component (PC2), the average R^2 increases to 24%. The first six principal com-

⁶Bai and Ng (2002) suggest statistical criteria to determine the optimal number of factors. However, their criteria are inapplicable to the unbalanced panel data.

⁷Table 1.21 in Appendix 1.7.5 reports similar results using the expanded sample.

ponents explain 52% of log TFP growth, and the marginal increment of R^2 decreases when we add more principal components.

It is difficult to interpret the principal components from the principal component analysis. We attempt to understand these principal components by linking them with the prevailing factors. Panel B of Table 1.1 reports the annual correlation coefficients between productivity components and other pricing factors. In the main context, we consider 15 prevailing pricing factors that are either risk-based or behavioral-based: (1) Six factors used in Fama and French (2018), including 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). We download these factors and the corresponding portfolios from Kenneth French’s website. (2) Five factors used in Hou et al. (2018b), including 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). We follow Hou et al. (2018b) to construct these factors. (3) Three mispricing factors used in Stambaugh and Yuan (2017). Stambaugh and Yuan (2017) construct the mispricing factors from 11 mispricing anomalies. They categorize these anomalies into two types of mispricing. One mispricing is related to firm management, MGMT. Another mispricing is related to firm performance, PERF. They also construct a univariate mispricing factor (MIS), including both MGMT and PERF information. We download two mispricing factors (MGMT and PERF) from Robert Stambaugh’s website and construct the univariate mispricing factor (MIS) by using their mispricing scores.⁸ (4) Two behavioral factors used in Daniel et al. (2018). Daniel et al. (2018) suggest two different behavioral factors, i.e., the short-horizon behavioral factor (post-earnings-announcement drift, PEAD), and the long-horizon behavioral factor (financing, FIN).⁹ PEAD captures limited attention and underreaction to earnings information. FIN is based on security issuance and repurchase, which measures managerial response to the long-horizon behavioral bias.

First, we note that none of the pricing factors have a strong correlation with the first

⁸<http://finance.wharton.upenn.edu/stambaugh/>

⁹We thank them for providing the factor data. The sample period is from July 1972 to December 2014.

productivity components (PC1) except for the momentum factor (UMD) and the short-horizon behavioral factor (PEAD). The correlation between PC1 and UMD is -0.28, while the correlation between PC1 and PEAD is -0.22. However, these two correlations are driven by one extreme observation in 2009.¹⁰ When we exclude the 2009 observation, the correlations become 0.17 and 0.16.¹¹ Since the first productivity component is the most important factor of the aggregate productivity shocks, it is surprising to see that none of the pricing factors captures this component. Second, we see that PC2 to PC6 have strong correlations with these prevailing pricing factors. The second productivity component (PC2) is negatively correlated with the size factor (SMB and Q_{ME}), with a correlation coefficient of -0.24 and -0.25, respectively. It also has a similar relationship with the expected investment growth factor (EG). The third productivity component (PC3) has a pronounced correlation with the profitability factors (RMW and Q_{ROE}). The correlation coefficient between PC3 and RMW (Q_{ROE}) is -0.48 (-0.42). The fourth productivity components (PC4) is positively correlated with the investment factors (CMA and Q_{IA}). The magnitude of this correlation with CMA (Q_{IA}) is 0.50 (0.43). Imrohoroglu and Tuzel (2014) also find similar correlations between total firm-level TFP and firm characteristics like size, book-to-market equity ratio, investment, and profitability. The fifth productivity principal component (PC5) and the momentum factor (UMD) are positively correlated, with a correlation coefficient of 0.35. The sixth productivity component has a significant correlation with the mispricing factor (MIS) and the long-horizon behavioral factor (FIN). The correlations are -0.35 and -0.48, respectively. Overall, Panel B shows that PC2-PC4 are highly correlated with the risk-based factors while PC5 and PC6 seem to capture the mispricing and behavioral factors. In other words, these pricing factors provide the economic meanings of the principal components.

¹⁰In 2009, both UMD and PC1 have extreme values, e.g., UMD is -82.91%.

¹¹We also exclude the 2009 observation for the other productivity factors, but their correlations remain stable.

1.2.4 Validating productivity decomposition

Table 1.1 shows that the first six components capture about 53% of TFP across firms. We further validate the productivity decomposition in Table 1.2, i.e., the six principal components reasonably capture the common productivity shocks. We decompose firm-level TFP into the systematic and idiosyncratic parts, using the six principal components. Specifically, for each firm, we run the time-series regression of its TFP growth on six principal components. We then use the predicted TFP growth as the systematic TFP growth and the residuals as the idiosyncratic TFP growth. Imrohoroglu and Tuzel (2014) find that the contemporaneous correlation between stock returns and total firm-level TFP is significantly positive. If TFP and its decomposition are estimated correctly, then both TFP and its systematic part should have positive correlations with contemporaneous stock returns. At the end of each June, we construct the quintile portfolios, sorted on either log TFP growth (ΔTFP) or the systematic TFP growth (ΔTFP_{sys}). The contemporaneous value-weighted portfolio returns are calculated and reported in Panel A of Table 1.2. We see portfolio returns increase with both the total TFP and its systematic part. Also, the long-short portfolios (high minus low, H-L) generate sizable return spreads, 1.47% for log TFP growth and 0.83% for systematic TFP growth, which is consistent with Imrohoroglu and Tuzel (2014).

Next, we examine whether the idiosyncratic productivity shocks are priced to further validate our productivity decomposition. That is, can idiosyncratic productivity shocks predict future stock returns? From the asset pricing perspective, we expect that only systematic productivity shocks are priced because firms cannot hedge against systematic uncertainty. We compute the standard deviation of log TFP growth ($\sigma_{\Delta TFP}$), systematic TFP growth ($\sigma_{\Delta TFP_{sys}}$), and idiosyncratic TFP growth ($\sigma_{\Delta TFP_{idio}}$) over the last 5 years. We exclude stocks with a price lower than \$5 and industry-month observations with fewer than 5 firms. In Panel B of Table 1.2, Models (1) - (3) present the coefficients from Fama-MacBeth regressions of excess stock returns against the total TFP volatilities, systematic TFP volatilities, and idiosyncratic TFP volatilities, together with other control variables. We use the logarithm of the standard deviations. Model (1) shows that the total TFP volatilities are positively

correlated with future stock returns. In model (2), we decompose the total TFP volatilities into systematic and idiosyncratic parts. We see that systematic TFP volatility is positively correlated with future stock returns, while idiosyncratic TFP volatility is only marginally significant. We further control for asset growth (AG) and cash flow (CF/K) in model (3). Asset growth is defined as $\frac{AT_t - AT_{t-1}}{AT_{t-1}}$, where AT is total asset. Cashflow is computed as $\frac{IB_t + DP_t}{PPENT_{t-1}}$, where IB is the income before extraordinary item, DP is the depreciation and amortization, and PPENT is the net property, plant, and equipment. Idiosyncratic TFP volatility becomes insignificant, while systematic TFP volatility remains significantly positive in model (3). Turning to the return volatilities, in model (4) and (5), we run panel regressions of return volatilities against the absolute value of log TFP growth, systematic TFP growth, and idiosyncratic TFP growth, with both firm and month fixed effects. Return volatilities are computed by using daily returns over the last year. Model (4)-(5) show that TFP volatilities are positively related to the stock return volatilities. Bloom et al. (2018) also find that the absolute size of TFP shocks is positively related to stock return volatilities. Overall, the results in Table 1.2 confirm that the six principal components reasonably capture the systematic productivity risks across firms.

1.3 Asset pricing tests

In this section, we first examine the pricing power of productivity factors, using GMM estimation. However, since we only have 44 annual estimates, this might limit the statistical power. To increase the statistical power, we further construct the mimicking portfolios for productivity factors and perform the asset pricing tests at monthly frequency. We verify that the prevailing pricing factors capture the fundamental risks. Then we go further to compare the empirical performances of the productivity-based model with other prevailing models.¹²

¹²Table 1.22, 1.23, and 1.24 in Appendix 1.7.5 report similar results using the expanded sample.

1.3.1 Asset pricing tests: Non-tradable factors

In this section, we directly use six principal components to examine their asset pricing power. First, we construct the pricing kernel with six principal components and testify whether principal components are priced across various test assets. Second, following Lewellen et al. (2010) and Kan et al. (2013), we run GLS cross-sectional regressions and formally compare the explanatory power with other prevailing pricing factor models.

GMM estimation

We directly use the six aggregate TFP factors (PC1 to PC6) to test the pricing power of the productivity-based model via GMM estimation. If the six principal components capture the fundamental shocks in the economy, they must drive the pricing kernel. Therefore, we directly model these non-traded factors via the pricing kernel. Following the tradition of production-based asset pricing models (e.g., Zhang (2005)), we assume that the logarithm of the pricing kernel is a linear function of production shocks, i.e., the six principal components. The innovations of the pricing kernel can be written as

$$m_{t+1} - \mathbb{E}_t[m_{t+1}] = -b'(f_{t+1} - \mu_f). \quad (1.5)$$

where m_{t+1} is the logarithm of the pricing kernel $M_{t,t+1}$, b are the coefficients, and $\mu_f = \mathbb{E}[f_{t+1}]$ are the unconditional means of productivity factors. By log-linearization we have

$$\frac{M_{t,t+1}}{\mathbb{E}[M_{t,t+1}]} \approx 1 + m_{t+1} - \mathbb{E}[m_{t+1}] = 1 - b'(f_{t+1} - \mu_f). \quad (1.6)$$

From the basic asset pricing equation, we have

$$\mathbb{E}[R_{i,t+1}^e M_{t,t+1}] = 0 = \mathbb{E}\left[\frac{M_{t,t+1}}{\mathbb{E}[M_{t,t+1}]} R_{i,t+1}^e\right], \quad (1.7)$$

where $R_{i,t+1}^e$ is the excess return of asset i at time $t + 1$. This implies

$$\mathbb{E}[R_{i,t+1}^e(1 - b'(f_{t+1} - \mu_f))] = 0. \quad (1.8)$$

Therefore, we have the following moment conditions:

$$\mathbb{E} = \begin{bmatrix} R_{i,t+1}^e[1 - b'(f_{t+1} - \mu_f)] \\ f_{t+1} - \mu_f \end{bmatrix}. \quad (1.9)$$

We use a two-step GMM estimation with a Newey-West one-lag adjustment.¹³

We use 155 test assets, including 25 size and book-to-market sorted portfolios, 25 size and operating profitability sorted portfolios, 25 size and investment sorted portfolios, 25 size and momentum sorted portfolios, 25 size and idiosyncratic volatility sorted portfolios, and 30 Fama-French industry portfolios. For comparison, we estimate the Fama and French (1993) three-factor model (FF3), 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. (2018b) q^5 model (HMXZ), and Daniel et al. (2018) behavioral factor model (DHS).¹⁴ The sample period of those pricing factors are from 1972 to 2015. We obtain annual test assets and Fama-French factors from Kenneth French's website.

Table 1.3 presents the GMM estimation results. Panel A of Table 1.3 reports the coefficient estimates for b . Then, in Panel B, we compute the implied price of risk for each factor (λ), i.e., $\lambda = \Sigma_f b$, where Σ_f is the variance-covariance matrix of factors. Panel C shows the goodness of fit. We estimate the adjusted R^2 , root-mean-square errors ($RMSE$), and Hansen's J test of overidentification. The adjusted R^2 is defined as one minus the ratio of the cross-sectional variance of the pricing errors to the cross-sectional variance of realized average test portfolio returns, following Campbell and Vuolteenaho (2004).

First, we see that productivity factors have significant coefficients. That is, the six

¹³We also consider different lags (e.g. using the Newey-West optimal lags) and iterative GMM. We report the most conservative results.

¹⁴We do not estimate Stambaugh and Yuan (2017) because they only provide monthly factors, not annual.

principal components are significantly priced over test portfolios. For example, PC1 has a coefficient of 3.82 with a t -statistic of 16.16. This implies a price of 8.90% per year. The coefficient for PC5 is 4.91 (t -statistics = 21.54) and its price of risk is 11.42% per year. Other principal components have a sizable price of risk as well. For other factor models, the prices of risk vary. For example, five of six factors in FF6 have significant coefficients. For HMXZ, Q_{IA} and EG are the most important factors, which have a sizable price of risk, 3.65% and 6.67%, respectively. But the size factor and the profitability factor are insignificant in HMXZ.

Examining the goodness of fit in Panel C, we see that the productivity-based model (TFP) is comparable to FF5, FF6, HXZ, and HMXZ. TFP model has an R^2 of 0.79. This is comparable to other prevailing factor models like FF5, FF6, HXZ, and HMXZ. Also, TFP has a pricing error, $RMSE=1.61\%$, which is similar to that of HMXZ (1.50%). FF3 has the largest $RMSE$, which is 1.91%. The lowest $RMSE$ is 0.98% from FF6. Last, Hansen's overidentification test cannot reject the TFP model at 1% significance level. Overall, the productivity-based model explains various test portfolios and its performance is comparable to prevailing factor models.

GLS cross sectional regression

Previously, we model the pricing kernel with productivity factors via GMM estimation. The productivity-based model explains various test assets and its asset pricing power is comparable to prevailing factor models. In this subsection, following Kan et al. (2013), we formally evaluate the performance of various asset pricing models based on their R^2 s. That is, we examine whether two pairwise models have equal R^2 s. Kan et al. (2013) suggest that we can testify the equality of R^2 s from competing models by constructing the distribution of R^2 s.

Kan et al. (2013) derive the asymptotic distribution of cross-sectional R^2 estimator. More importantly, they show how to determine the distribution of differences in R^2 s for competing models. Also, while the previous literature assumes that an asset pricing model

is correctly specified by assuming that true R^2 is equal to 1, they relax this assumption and take into account a misspecified factor model in which true R^2 is less than 1. Since an asset pricing model are approximations of reality, a misspecified factor model assumption is more plausible. Following Kan et al. (2013), we testify the null hypothesis of $H_0 : 0 < R_i^2 - R_j^2 < 1$ where i and j are two competing models. That is, we evaluate two competing models under the model misspecification.¹⁵

Empirically, we choose 25 size and book-to-market sorted portfolios as in Kan et al. (2013).¹⁶ Following Lewellen et al. (2010) and Kan et al. (2013), we run the GLS cross-sectional regressions of various models as follows:

- TFP: $\mu_i = \gamma_0 + \gamma_{PC1}\hat{\beta}_{PC1,i} + \gamma_{PC2}\hat{\beta}_{PC2,i} + \gamma_{PC3}\hat{\beta}_{PC3,i} + \gamma_{PC4}\hat{\beta}_{PC4,i} + \gamma_{PC5}\hat{\beta}_{PC5,i} + \gamma_{PC6}\hat{\beta}_{PC6,i} + \epsilon_{it}$
- FF3: $\mu_i = \gamma_0 + \gamma_{MKT}\hat{\beta}_{MKT,i} + \gamma_{SMB}\hat{\beta}_{SMB,i} + \gamma_{HML}\hat{\beta}_{HML,i} + \epsilon_{it}$
- FF5: $\mu_i = \gamma_0 + \gamma_{MKT}\hat{\beta}_{MKT,i} + \gamma_{SMB}\hat{\beta}_{SMB,i} + \gamma_{HML}\hat{\beta}_{HML,i} + \gamma_{CMA}\hat{\beta}_{CMA,i} + \gamma_{RMW}\hat{\beta}_{RMW,i} + \epsilon_{it}$
- FF6: $\mu_i = \gamma_0 + \gamma_{MKT}\hat{\beta}_{MKT,i} + \gamma_{SMB}\hat{\beta}_{SMB,i} + \gamma_{HML}\hat{\beta}_{HML,i} + \gamma_{CMA}\hat{\beta}_{CMA,i} + \gamma_{RMW}\hat{\beta}_{RMW,i} + \gamma_{UMD}\hat{\beta}_{UMD,i} + \epsilon_{it}$
- HXZ: $\mu_i = \gamma_0 + \gamma_{MKT}\hat{\beta}_{MKT,i} + \gamma_{Q_{ME}}\hat{\beta}_{Q_{ME},i} + \gamma_{Q_{IA}}\hat{\beta}_{Q_{IA},i} + \gamma_{Q_{ROE}}\hat{\beta}_{Q_{ROE},i} + \epsilon_{it}$
- HMXZ: $\mu_i = \gamma_0 + \gamma_{MKT}\hat{\beta}_{MKT,i} + \gamma_{Q_{ME}}\hat{\beta}_{Q_{ME},i} + \gamma_{Q_{IA}}\hat{\beta}_{Q_{IA},i} + \gamma_{Q_{ROE}}\hat{\beta}_{Q_{ROE},i} + \gamma_{EG}\hat{\beta}_{EG,i} + \epsilon_{it}$
- DHS: $\mu_i = \gamma_0 + \gamma_{MKT}\hat{\beta}_{MKT,i} + \gamma_{FIN}\hat{\beta}_{FIN,i} + \gamma_{PEAD}\hat{\beta}_{PEAD,i} + \epsilon_{it}$

In the first stage, we run the time-series regressions of each model to estimate the factor loadings for each test asset over the full sample period. Then, we run the cross-sectional regression of the time-series average of test asset returns against the estimated factor loadings in Table 1.4. Table 1.4 reports t -statistics and p -values adjusted for the model misspecification problem as in Kan et al. (2013). The sample period is from 1972 to 2015.

Panel A of Table 1.4 presents the results of GRS cross-sectional regressions in various

¹⁵We thanks Kan et al. (2013) for sharing their codes from <http://www-2.rotman.utoronto.ca/~kan/research.htm>

¹⁶They use 25 size and book-to-market sorted portfolios with 5 Fama-French industry portfolios. We cannot add industry portfolios because of the limited number of observations.

models. First, although the intercept (γ_0) is significant, TFP has 3 of 6 significant price of risks. γ_{PC3} , γ_{PC4} , and γ_{PC5} are 9.65% per year ($t=2.34$), 9.18% per year ($t=2.79$), and -8.85% per year ($t=-2.11$), respectively. These results are similar to FF5, FF6, HXZ, and HMXZ. For example, FF6 has 3 of 6 significant price of risks. γ_{HML} , γ_{CMA} , and γ_{UMD} have 4.32% ($t=2.05$), 4.33% ($t=2.68$), and -10.59% ($t=-3.18$). Also, γ_{QIA} and γ_{QROE} are 3.85% ($t=2.67$) and -6.17% ($t=-2.83$), respectively. This suggests that PC3, PC4, and PC5 share the same information with profitability, investment, and momentum factors. Second, R^2 in TFP is the highest among factor models, followed by HMXZ, HXZ, FF6, and FF5. It seems that productivity factors explain test assets very well.

Panel B of Table 1.4 reports the difference of R^2 s in row i and column j , $R_i^2 - R_j^2$ and their corresponding p -values in parenthesis. Difference in R^2 between FF3 and TFP is about -0.26 with p -value 0.07. Also, the difference between DHS and TFP is about -0.34 with p -value 0.01. These suggest that TFP explains test assets significantly better than FF3 and DHS. We find that there are no significant differences between TFP and the rest of factor models. For example, the difference between FF6 and TFP is about -0.11 but it fails to reject the equality of two R^2 s. For other pairs, FF6 is better than FF3 and FF5 in explaining test assets at 10% significance level. Also, HMXZ has higher R^2 than that of DHS at 10% significance level. Untabulated results show that TFP has comparable R^2 with FF5, FF6, HXZ, and HMXZ in different test assets including 25 size and operating profitability portfolios, 25 size and investment sorted portfolios, 25 size and momentum sorted portfolios, and 25 size and idiosyncratic volatility sorted portfolios, respectively. Overall, the equality tests confirm that the productivity-based model has comparable asset pricing explanatory power.

1.3.2 Asset pricing tests: Mimicking portfolios

One might concern about the statistical power of the above GMM estimation since we only have 44 annual productivity estimates. Next, to increase the statistical power, we adopt the conventional approach to construct the mimicking factors for the six TFP components and perform the asset pricing tests at the monthly frequency. Also, it is easy to interpret

the pricing of productivity factors, which are non-traded, via the mimicking portfolios.

Constructing mimicking productivity factors

Since we only have annual TFP estimates, to construct the monthly mimicking portfolios, we follow Adrian et al. (2014) and Chen and Yang (2019) to use the projection method. First, we project TFP principal component n , PC_n , onto a set of annual base asset returns:

$$PC_n = \kappa_{0,n} + \kappa'_{x,n} X_{t,n}^a + u_t, n = 1, 2, \dots, 6, \quad (1.10)$$

where $X_{t,n}^a$ denotes the annual returns of some base assets in year t , and $\kappa_{0,n}$ and $\kappa_{x,n}$ are the coefficients. The choice of base assets is critical to successfully extract the information of productivity components. Tapping on the empirical success of Hou et al. (2015) and Stambaugh and Yuan (2017), we select the base assets from the portfolios constructed in these papers since they appear to be representative assets and less noisy. We use 9 base assets for each productivity component. First, the excess market return (MKT) and the univariate mispricing factor (MIS) are included in the base assets. Second, we consider 18 portfolios used in Hou et al. (2015), which are from a triple 2-by-3-by-3 independent sort on size, investment, and profitability. However, we can't use all 18 portfolios for two reasons. First, using all 18 portfolios causes the multicollinearity problem. Second, this will limit the degree of freedom in the regressions as we only have 44 annual productivity estimates. Instead, we choose 7 of these 18 portfolios. We start to project each principal component onto all 18 portfolios, the market portfolio, and the mispricing factor. Then, we choose portfolios that have significant coefficients. Ideally, we would use the same base assets across all principal components to avoid arbitrariness, but using the same base assets causes multicollinearity issues. To avoid multicollinearity and to effectively capture productivity-specific information, we change some of the base assets for each principal component. The base assets for each principal component are as follows:

- $X_{t,PC1} = [\text{MKT}, \text{MIS}, \text{SSL}, \text{BLM}, \text{BLH}, \text{BMH}, \text{BSL}, \text{SMH}, \text{BSH}]$

- $X_{t,PC2} = [\text{MKT}, \text{MIS}, \text{SSL}, \text{BLM}, \text{BLH}, \text{BLL}, \text{BMH}, \text{BSL}, \text{SMH}]$
- $X_{t,PC3} = [\text{MKT}, \text{MIS}, \text{SSL}, \text{BLM}, \text{BLL}, \text{BSL}, \text{SMH}, \text{BSH}, \text{SSH}]$
- $X_{t,PC4} = [\text{MKT}, \text{MIS}, \text{SSL}, \text{BLM}, \text{BLH}, \text{BLL}, \text{BMH}, \text{BSL}, \text{SLM}]$
- $X_{t,PC5} = [\text{MKT}, \text{MIS}, \text{SSL}, \text{BLM}, \text{BLH}, \text{BLL}, \text{BSL}, \text{SLM}, \text{SMH}]$
- $X_{t,PC6} = [\text{MKT}, \text{MIS}, \text{SSL}, \text{BLM}, \text{SSM}, \text{BLH}, \text{BLL}, \text{BSL}, \text{SML}]$

For 7 portfolios other than the excess market return (MKT) and the mispricing factor (MIS), the first letter describes the size group, i.e., small (S) or big (B). The second letter describes the investment group, i.e., small (S), medium (M), or large (L). The third letter describes the profitability group, i.e., low (L), medium (M), and high (H). For example, *SSL* denotes the portfolio of stocks with small size, small investment, and low profitability. Overall, 5 base assets are common across all productivity factors, and the rest of them are different. Each annual mimicking productivity portfolio tracks its productivity principal component very well. On average, the annual correlation coefficient between each productivity principal component and its mimicking portfolio is about 0.53.

After we estimate $\kappa'_{x,n}$ at annual frequency, we normalize the coefficients: $\tilde{\kappa}'_{x,n} = \frac{\kappa_{x,n}}{|\Sigma \kappa_{x,n}|}$. The denominator is the sum of the absolute value of 9 coefficients for each principal component. The last step is to compute the mimicking productivity portfolios at a monthly frequency, by multiplying the normalized coefficients and the monthly base asset returns,

$$PC_{n,t} = \tilde{\kappa}'_{x,n} X_t^m \quad (1.11)$$

where X_t^m is the monthly returns of base assets in month t . In this paper, we will use the monthly mimicking portfolios for the time-series and the cross-sectional tests.

When we construct the mimicking productivity portfolios, the full-sample estimation has more statistical power but two look-ahead biases emerge. First, look-ahead bias occurs when we apply the principal component analysis over the TFP matrix using the full sample. Second, it also occurs when we construct the mimicking portfolios since the portfolio weights ($\kappa_{x,n}$) are estimated in the full sample. To avoid the look-ahead biases, we also construct the

mimicking productivity portfolios with an extending window as a robustness check. That is, both principal component analysis and the mimicking portfolio weights are computed with data up to year t . The extending-window starts in 2001 to allow for a sufficient number of observations. In other words, the principal components and their portfolio weights are estimated from 1972 to 2001 first and then extended to 2015. Also, to estimate the weights with a sufficient degree of freedom for the extending-window case, we use only 6 base assets, as follows:

- $X_{t,PC1} = [\text{MKT}, \text{MIS}, \text{BLL}, \text{BMH}, \text{SMH}, \text{BSH}]$
- $X_{t,PC2} = [\text{MKT}, \text{MIS}, \text{BLL}, \text{BSL}, \text{SMH}, \text{BLM}]$
- $X_{t,PC3} = [\text{MKT}, \text{MIS}, \text{SSL}, \text{BSL}, \text{SMH}, \text{BLM}]$
- $X_{t,PC4} = [\text{MKT}, \text{MIS}, \text{SSL}, \text{BLH}, \text{SLM}, \text{BLM}]$
- $X_{t,PC5} = [\text{MKT}, \text{MIS}, \text{BLL}, \text{BSL}, \text{SLM}, \text{SMH}]$
- $X_{t,PC6} = [\text{MKT}, \text{MIS}, \text{SSL}, \text{BLM}, \text{BLL}, \text{BSL}]$

One caveat for the extending window approach is that the principal components vary with the estimation windows, which makes the estimation results not comparable with those from the full-sample estimation and hard to interpret. Also, the testing window is short for the extending window approach. Therefore, we mainly report results from the full-sample estimation while using the extending-window estimation as robustness checks.

Panel C of Table 1.1 reports the mean, standard deviation (S.D.), Sharpe ratio (SR), and pairwise correlations among mimicking portfolios. The first mimicking productivity portfolio (PC1) has an average return of 1.31% per month and a standard deviation of 7.38% per month. Its monthly Sharpe ratio is 0.18. Other mimicking portfolios also have sizable mean returns and Sharpe ratios. Since the pairwise correlation coefficients across the mimicking factors are not very sizable, this alleviates the multicollinearity concern.

Using productivity factors to explain other pricing factors: Time-series regressions

Panel B of Table 1.1 shows that PC2-PC6 are highly correlated with the prevailing pricing factors. In this subsection, we formally test whether productivity factors can capture these pricing factors. We use the six mimicking productivity factors, and the empirical asset pricing model is as follows:

$$R_{it} = \alpha_i + \beta_{PC1,i}PC1_t + \beta_{PC2,i}PC2_t + \beta_{PC3,i}PC3_t + \beta_{PC4,i}PC4_t + \beta_{PC5,i}PC5_t + \beta_{PC6,i}PC6_t + \epsilon_{i,t}, \quad (1.12)$$

where R_{it} is the excess return of asset i in month t , and $PC1$ to $PC6$ are the returns of the mimicking productivity factors in month t . We call this the productivity-based model. This can be viewed as an equivalent way to study asset returns as the standard factor models. If the mimicking productivity factors correctly capture the common risk sources, this model should explain those pricing factors. We run the time-series regressions of each pricing factor on our mimicking productivity portfolios. Table 1.5 presents the intercept, factor loadings, R^2 , and Newey-West adjusted t -statistics with 6-month lags.

Panel A reports the results using full-sample estimation. First, 13 of 15 pricing factors have insignificant pricing errors after we control for six mimicking productivity portfolios. This suggests that these 13 pricing factors share common fundamental risk sources. Only 2 pricing factors have significant alphas. The expected investment growth factor (EG) in Hou et al. (2018b) has an alpha of 0.32% per month. The alpha is significantly positive ($t=2.79$), but its magnitude is about 43% of the factor return after we control for the six productivity factors. The post-earnings-announcement drift (PEAD) also has a significantly positive alpha of 0.46% per month, and our productivity-based model captures about 30% of its factor return.¹⁷

Turning to the factor-loadings, we see that our mimicking portfolios track their princi-

¹⁷Hou et al. (2018c) also find that the q -factor and q^5 models fail to capture the PEAD factor in Daniel et al. (2018).

pal components very well. Specifically, two size factors (SMB and Q_{ME}) have significant factor-loadings on the second mimicking productivity factor (PC2). β_{PC2} of SMB is -0.52 ($t=-11.84$), and that of Q_{ME} is -0.62 ($t=-14.64$). The third mimicking productivity factor loadings (β_{PC3}) are negatively significant for the profitability factors, -0.11 ($t=-4.72$) for RMW, and -0.21 ($t=-9.21$) for Q_{ROE} . Investment factors (CMA and Q_{IA}) and the value factor (HML) are significantly correlated with the fourth mimicking productivity factor. β_{PC4} of CMA, Q_{IA} , and HML are 0.14 ($t=5.55$), 0.16 ($t=25.03$), and 0.14 ($t=20.50$), respectively. Therefore, Fama-French factors and q -factors are quite similar.¹⁸ They represent the same set of productivity shocks, i.e., the second, third, and fourth principal components of productivity shocks.

The fifth mimicking productivity factor is significantly priced for the momentum factor (UMD), with a factor loading of 1.07 ($t=7.75$). As we observe in Panel B of Table 1.1, the sixth productivity component has a significant correlation with the univariate mispricing factor (MIS), with a factor loading of -0.30 ($t=-9.44$). The two components, MGMT and PERF, have significantly negative coefficients on the sixth mimicking productivity factor, -0.13 ($t=-3.67$) and -0.42 ($t=-5.55$), respectively. We also can see that MGMT and MIS are highly correlated with the fourth productivity factor (PC4), which suggests that they capture a lot of the investment factor as well. This is consistent with the findings of Hou et al. (2018a). The long-horizon behavioral factor (FIN) is fully captured by our productivity-based model. In short, these mispricing and behavioral factors appear to capture the systematic productivity shocks.

To avoid the look-ahead bias, we use the extending-window estimation as a robustness check and report results in Panel B of Table 1.5. Because the principal components vary with the estimation windows during the extending-window estimation, this makes the estimation results not comparable with those from the full-sample estimation. Still, we see qualitatively similar results from the extending-window estimation. That is, our model fully explains 14 of 15 pricing factors, and only PEAD remains marginally significant.

¹⁸Hou et al. (2018c) show that the q -factor model subsumes the Fama-French five-factor premiums.

Overall, Table 1.5 shows that although various pricing factors are motivated and constructed in different ways, they capture the same set of fundamental risks.

Using productivity factors to explain test portfolios: Time-series regression

Next, we apply our productivity-based model to many tests portfolios. Since the productivity factors can explain many pricing factors, we expect them to explain broad test portfolios as well. We report the alphas from time-series regressions of each test asset in Table 1.6, using the full sample.¹⁹ Our playing fields include 155 portfolios used in Table 1.3.

Generally, the productivity-based model explains the test portfolios very well. In panel A, all 25 size and book-to-market sorted portfolios have insignificant alphas. In panel B, all 25 size and operating profitability sorted portfolios have insignificant abnormal returns. The highest alpha is 0.28% per month, which is fairly low. We see similar results in Panel C for 25 size and investment sorted portfolios. In Panel D and E, the abnormal returns are generally small, and only 2 of 50 portfolios are marginally significant. In Panel F, we see that 27 of 30 Fama-French industry portfolios have insignificant abnormal returns. Only industries like smoke (0.72%), drugs (0.55%), and gold (1.07%) have significant alphas. These results suggest that even though TFP and its principal components are estimated mainly from the manufacturing industry, the productivity factors reflect the aggregate risks across different industries.²⁰

Using productivity factors to explain test portfolios: Fama-MacBeth regressions

We further examine the ability of productivity factors to explain the cross-sectional return variations by using Fama-MacBeth two-pass regressions. The test assets are the 155 portfolios used in Table 1.3. Following Lewellen et al. (2010), we also add the pricing factors of the tested factor model to the test assets in order to restrict the price of risk to be equal to the average factor return.

¹⁹We tabulate the complete results in Appendix 1.7.3.

²⁰Table 1.23 shows similar results from the expanded sample.

We compare the productivity-based model (TFP) with other factor models, including the 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. (2018b) q^5 model (HMXZ), Stambaugh and Yuan (2017) mispricing factor model (SY), and Daniel et al. (2018) behavioral factor model (DHS), as follows:

- TFP: $R_{it} = \gamma_0 + \gamma_{PC1}\hat{\beta}_{PC1,i} + \gamma_{PC2}\hat{\beta}_{PC2,i} + \gamma_{PC3}\hat{\beta}_{PC3,i} + \gamma_{PC4}\hat{\beta}_{PC4,i} + \gamma_{PC5}\hat{\beta}_{PC5,i} + \gamma_{PC6}\hat{\beta}_{PC6,i} + \epsilon_{it}$
- FF3: $R_{it} = \gamma_0 + \gamma_{MKT}\hat{\beta}_{MKT,i} + \gamma_{SMB}\hat{\beta}_{SMB,i} + \gamma_{HML}\hat{\beta}_{HML,i} + \epsilon_{it}$
- FF4: $R_{it} = \gamma_0 + \gamma_{MKT}\hat{\beta}_{MKT,i} + \gamma_{SMB}\hat{\beta}_{SMB,i} + \gamma_{HML}\hat{\beta}_{HML,i} + \gamma_{UMD}\hat{\beta}_{UMD,i} + \epsilon_{it}$
- FF5: $R_{it} = \gamma_0 + \gamma_{MKT}\hat{\beta}_{MKT,i} + \gamma_{SMB}\hat{\beta}_{SMB,i} + \gamma_{HML}\hat{\beta}_{HML,i} + \gamma_{CMA}\hat{\beta}_{CMA,i} + \gamma_{RMW}\hat{\beta}_{RMW,i} + \epsilon_{it}$
- FF6: $R_{it} = \gamma_0 + \gamma_{MKT}\hat{\beta}_{MKT,i} + \gamma_{SMB}\hat{\beta}_{SMB,i} + \gamma_{HML}\hat{\beta}_{HML,i} + \gamma_{CMA}\hat{\beta}_{CMA,i} + \gamma_{RMW}\hat{\beta}_{RMW,i} + \gamma_{UMD}\hat{\beta}_{UMD,i} + \epsilon_{it}$
- HXZ: $R_{it} = \gamma_0 + \gamma_{MKT}\hat{\beta}_{MKT,i} + \gamma_{Q_{ME}}\hat{\beta}_{Q_{ME},i} + \gamma_{Q_{IA}}\hat{\beta}_{Q_{IA},i} + \gamma_{Q_{ROE}}\hat{\beta}_{Q_{ROE},i} + \epsilon_{it}$
- HMXZ: $R_{it} = \gamma_0 + \gamma_{MKT}\hat{\beta}_{MKT,i} + \gamma_{Q_{ME}}\hat{\beta}_{Q_{ME},i} + \gamma_{Q_{IA}}\hat{\beta}_{Q_{IA},i} + \gamma_{Q_{ROE}}\hat{\beta}_{Q_{ROE},i} + \gamma_{EG}\hat{\beta}_{EG,i} + \epsilon_{it}$
- SY: $R_{it} = \gamma_0 + \gamma_{MKT}\hat{\beta}_{MKT,i} + \gamma_{MIS_{ME}}\hat{\beta}_{MIS_{ME},i} + \gamma_{MGMT}\hat{\beta}_{MGMT,i} + \gamma_{PERF}\hat{\beta}_{PERF,i} + \epsilon_{it}$
- DHS: $R_{it} = \gamma_0 + \gamma_{MKT}\hat{\beta}_{MKT,i} + \gamma_{FIN}\hat{\beta}_{FIN,i} + \gamma_{PEAD}\hat{\beta}_{PEAD,i} + \epsilon_{it}$

In the first stage, we run the time-series regressions of each model to estimate the factor loadings for each test asset, using the full sample. Second, we run the cross-sectional regression of all test assets against the estimated factor loadings in each month and report the time-series average of the price of risk in Table 1.7. Table 1.7 also reports t -statistics adjusted for the errors-in-variables problem (Shanken (1992)). We also compute the adjusted R^2 as in Jagannathan and Wang (1996). Following Lewellen et al. (2010), we construct a sampling distribution of the adjusted R^2 . Specifically, we bootstrap the time-series data of returns and factors by sampling with replacement to estimate the adjusted R^2 . We repeat these procedures 10,000 times and report the 5th and 95th percentiles of the sampling distribution. The sample period is from January 1972 to December 2015, except for the

DHS model sample period, which is from July 1972 to December 2014 due to limited data availability.

Table 1.7 presents the price of risk of each factor across the tested factor models. First, we see that FF3, FF6, and DHS have significant intercepts, γ_0 , which are 0.51%, -0.07%, and 0.30%, respectively. Other models, i.e., FF5, HXZ, HMXZ, SY, and TFP, have insignificant intercepts. That is, these models explain almost all return variations among test portfolios.

Next, we check the price of risk for each pricing factor. The price of risk should be equal to the mean excess return of the corresponding factor. Mimicking productivity factors have significant prices of risk and their magnitudes are close to the average of mimicking productivity factors. The results are qualitatively consistent with those from GMM estimation in Table 1.3.²¹ For FF5, even though the intercept is insignificant, the price of risk for HML, γ_{HML} , is insignificant, and its magnitude (0.07%) is quite different from the average return of HML (0.36%). Also, the price of risk for SMB, $\gamma_{SMB}=0.22$, is only marginally significant ($t=1.65$). Factors from the HXZ, HMXZ, and SY models have prices of risk close to the average factor returns.

Finally, we compare the explanatory power (adjusted R^2) across different models. Although the FF5, HXZ, HMXZ, SY, and TFP models have insignificant intercepts, the TFP model has the highest adjusted R^2 , 0.78. Even the 5th percentile of its adjusted R^2 , 0.59, is comparable to the R^2 of the FF5, HMXZ, and SY models. This suggests the strong explanatory power of productivity factors.

Comparing different models

Previously, we used the left-hand-side (LHS) approach to examine the pricing power of the productivity-based model and compare it with other factor models. That is, we use a set of test assets as the LHS variables to test whether unexplained average returns from competing models are significant (see, e.g., Fama and French (1996, 2015, 2016, 2017); Hou et al. (2015, 2018c)). However, this approach is often sensitive to the choice of LHS portfolios.

²¹Note that the price of the sixth component appears to have different signs in Table 1.3 and 1.7. The reason is that the signs of coefficient used in Eq. (1.11) change after we normalize the coefficients.

Alternatively, following Barillas and Shanken (2018) and Fama and French (2018), in this subsection, we use the right-hand-side approach to compare different factor models. If the goal is to minimize the maximum squared Sharpe ratio of the intercepts for all LHS portfolios, Barillas and Shanken (2018) suggest that we rank competing models on the maximum squared Sharpe ratio for model factors.

To test a factor model i with factors f_i , let's consider the time-series regressions of test assets (Π_i) , which include nonfactor test assets and factors from other competing models, on model i 's factors f_i . The maximum squared Sharpe ratio of the intercepts is

$$SH^2(a_i) = a_i' \Sigma_i^{-1} a_i, \quad (1.13)$$

where $Sh^2(\cdot)$ denotes the maximum squared Sharpe ratio, a_i is the vector of intercepts from the time-series regressions of Π_i on model i 's factors (f_i) , and Σ_i is the residual covariance matrix. Gibbons et al. (1989) further show 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:

$$SH^2(a_i) = SH^2(\Pi_i, f_i) - SH^2(f_i). \quad (1.14)$$

Since Π_i and f_i together include all competing factors, $Sh^2(\Pi_i, f_i)$ does not depend on i . Therefore, to minimize the maximum squared Sharpe ratio of the intercepts, it is sufficient 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.

Panel A of Table 1.8 presents the maximum squared Sharpe ratios for various factor models. Limited by data availability, we compare the FF3, FF4, FF5, FF6, HXZ, HMXZ, DHS, and TFP models.²² Of all competing models, the productivity-based model delivers the highest maximum squared Sharpe ratio of 0.32. The HMXZ and DHS models have a similar

²²We can't compute $Sh^2(f)$ for the SY model as we have only the data for spread factors, not the corresponding portfolios.

maximum squared Sharpe ratio of 0.26 and 0.27, respectively. In contrast, other models have much lower maximum squared Sharpe ratios of below 0.15. One concern about this right-hand-side approach is that there are sampling errors when we estimate tangent portfolios, which are larger for models with more factors. This becomes an issue when we compare non-nested models. Following Fama and French (2018), we use bootstrap simulations to provide the distribution of the maximum squared Sharpe ratios. Specifically, we bootstrap the time-series data of factors by sampling with replacement. Then we estimate the maximum squared Sharpe ratio. We repeat these procedures 10,000 times and report the 5th and 95th percentiles of the maximum squared Sharpe ratios from the competing models in Panel A of Table 1.8. We see that even the 5th percentile of the maximum squared Sharpe ratio from the productivity-based model (which is 0.26) is higher than or close to that of other models.

Next, we run spanning regressions to examine the marginal contribution of each productivity factor. We regress each productivity factor against the rest of the productivity factors. Panel B reports the intercept (α), its t -statistics, loadings, R^2 , residual standard error ($s(e)$), and each productivity factor's marginal contribution to the model, i.e., $\frac{\alpha^2}{s(e)^2}$. The t -statistic for the intercept indicates whether a factor statistically contributes to the model $Sh^2(f)$. We see that except for PC2, all productivity factors have a significant intercept, with a t -statistics above 3. Examining the marginal contribution to the model $Sh^2(f)$, we see that PC5, PC3, and PC4 contribute most, followed by PC6 and PC1, but the contribution from PC2 is negligible.

Overall, this right-hand-side approach further confirms that the productivity factors span the largest space of asset returns. We close this section by concluding that the productivity-based model explains most of the pricing factors and test assets in both time-series and cross-section tests. These findings support that the idea that fundamental risks are embodied in most pricing factors.

1.4 Explaining Mispricing portfolios

It is surprising to see that in Table 1.5, the productivity-based model explains the Stambaugh and Yuan (2017) mispricing factors (MGMT, PERF, and MIS). Stambaugh and Yuan (2017) construct the mispricing factors by using 11 mispricing anomalies, which they attribute to behavioral bias and market frictions. But Table 1.5 seems to suggest that fundamental risks explain most of the mispricing. In this section, we dig deeply by investigating the 11 mispricing portfolios, the building blocks for the mispricing factors, to see if the productivity-based model is able to explain these 11 anomalies. The 11 mispricing anomalies are the net equity issuance (ISS, Ritter (1991)), the composite equity issuance (CI, Daniel and Titman (2006)), the accrual (ACC, Sloan (1996)), the net operating assets (NOA, Hirshleifer et al. (2004)), the asset growth (AG, Cooper et al. (2008)), the investment-to-asset (InvA, Titman et al. (2004)), the financial distress (DIST, Campbell et al. (2008)), O-score (OSCO, Ohlson (1980)), the momentum (Mom, Jegadeesh and Titman (1993)), the gross profitability (GP, Novy-Marx (2013)), and the return on asset (ROA, Fama and French (2006)). Stambaugh and Yuan (2017) cluster the first six anomalies (which are more related to managerial decisions) as MGMT and the next five anomalies (which are more related to firm performance) as PERF. We obtain portfolio return data for 11 anomalies from Robert Stambaugh's website and use the long-short portfolio returns of 11 anomalies. Due to the data limitation, the sample period is from January 1972 to December 2015, except for the distress risk sample period, which is from October 1973 to December 2015.

We present the time-series regression coefficients of these 11 anomaly portfolios on mimicking productivity factors in Panel A of Table 1.9. First, Panel A shows that 9 of 11 anomaly portfolios do not have significant abnormal returns after we control for the productivity factors. The accrual portfolio (ACC), and the O-score portfolio (OSCO) have only marginally significant abnormal returns. The accrual portfolio has an intercept of 0.23% per month ($t=1.78$), and the O-score portfolio has 0.31% per month ($t=1.67$). It seems that the mimicking productivity factors capture most information from the 11 mispricing portfolios. Second, these anomaly portfolios show significant exposure to the fourth productivity fac-

tor, which captures firm investment. All 6 anomalies clustered in MGMT have significant coefficients on PC4. For example, the accrual portfolio has a loading of 0.14 ($t=7.07$) on PC4. The asset growth portfolio has a very significant loading on PC4, 0.23 ($t=15.58$). Also, 3 of 5 anomalies clustered in PERF have significant loadings on PC4. Only the distress and momentum anomalies have insignificant exposures to PC4. Third, 7 of 11 anomalies have significant loadings on PC3, which captures profitability. Fourth, momentum is strongly related with PC5, as PC5 captures the momentum effect.

As we use the mispricing factor as part of the base assets in constructing mimicking productivity factors in our benchmark case, this might mechanically relate mispricing portfolios with the productivity factors. To alleviate this concern, we reconstruct the mimicking productivity factors without using the mispricing factor and present the results in Panel B. Again, we see that the productivity-based model explains 9 of 11 anomalies. The accrual (ACC) and the gross profitability (GP) anomalies have significant abnormal returns. Except for the momentum anomaly, all anomalies have significant exposure to the investment factor (PC4). 9 of 11 anomalies are highly correlated with PC3, the profitability factor.

Overall, Table 1.9 demonstrates that most anomalies used in Stambaugh and Yuan (2017) can be traced back to the fundamental risks. This echoes Hou et al. (2018c), who show that MGMT (PERF) has a strong correlation with the investment (profitability) factor.

1.5 Identifying a missing factor

So far, we have shown that productivity factors explain most pricing factors and test portfolios. In this chapter, we explore whether the mimicking productivity portfolios can be explained by other pricing factors. If the mimicking productivity portfolios have the same risk sources as other pricing factors, the mimicking productivity portfolios should also be explained by other pricing factors. We show that the first productivity factor is not captured by other prevailing factors.²³ Next, we explore the risk behind the first productivity factor.

²³Table 1.25 in Appendix 1.7.5 reports similar results using the expanded sample.

We suggest that this missing risk factor is related to the labor risk.

Identifying a missing factor

If productivity factors and other pricing factors share common fundamental risks, they should represent similar risks. We test whether productivity factors can be explained by prevailing pricing factors. The benchmark 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), Stambaugh and Yuan (2017) mispricing factor model (SY), Daniel et al. (2018) behavioral model (DHS), Hou et al. (2015) q -factor model (HXZ), and Hou et al. (2018b) q^5 model (HMXZ). We run time-series regressions for each productivity factor. Table 1.10 reports the intercept (α^{model}) and R^2 from each model. Panel A uses the full sample while Panel B uses the extending window.

Examining Panel A, we see that all six mimicking productivity portfolios have sizable and significant raw excess returns, similar to those shown in Table 1.1. Except for PC1, all productivity factors (PC2-PC6) can be explained by some benchmark models. That is, PC2-PC6 share common fundamental risks with other pricing factors. For example, the abnormal return of the second mimicking productivity factor (PC2) loses its significance when we apply the SY mispricing factor model or the DHS behavioral model, i.e., $\alpha^{SY}=0.15\%$ ($t=1.28$) and $\alpha^{DHS}=-0.08\%$ ($t=-0.48$), respectively. PC2 has a high correlation with the size factor. The unreported results show that the size factor of SY explains most of the PC2 return variations. The third mimicking productivity factor (PC3), which captures profitability, has insignificant abnormal returns for the HXZ model. α^{HXZ} is -0.11% per month ($t=-0.37$). The coefficient on the profitability factor (Q_{ROE}) is -0.69 ($t=-6.19$). FF5 can partially explain PC3, which brings the excess returns from -0.95% to -0.59% per month. But the Q_{ROE} from the q -factor model seems to have stronger explanatory power than RMW from the Fama-French five-factor model. The abnormal returns of the fourth mimicking productivity factor (PC4) disappear when we control for the mispricing factor. Coefficients on both the size factor and

MGMT are very significant, 2.28 ($t=7.54$) and 1.33 ($t=5.93$), respectively. This suggests that MGMT contains information about the investment factor (Hou et al. (2018b)). The fifth mimicking productivity factor (PC5) is fully captured by the SY or DHS model. Also, the HMXZ model generates a marginally significant alpha for PC5. These insignificant alphas are mainly driven by PERF, PEAD, and EG, which are highly correlated with the momentum factor (UMD). FF4 and FF6 explain more than half of the abnormal returns, but the alphas remain significant. Lastly, the sixth mimicking productivity factor (PC6) is explained by the FF6, DHS, HXZ, and HMXZ models.

Importantly, Panel A shows that the first mimicking productivity factor (PC1) is missed by prevailing factors. PC1 has significant alphas after we control for these prevailing pricing factors.²⁴ Its raw return is 1.30% per month ($t=4.71$). Across 9 factor models, the magnitudes of their alphas are similar. The lowest alpha of 0.91% per month ($t=3.04$) is from the Stambaugh and Yuan (2017) model. This can be inferred from Panel B of Table 1.1, where PC1 has a moderate correlation with the momentum factor but very low correlations with all other pricing factors. Overall, the explanatory power (R^2) is fairly low, ranging from 0 to 0.12. The low R^2 further suggests that the first mimicking productivity factor is a missing factor from the prevailing factor models.

Turning to the extending-window results in Panel B, we see similar results. That is, PC1 has significant alphas from various benchmark models. The sign of the abnormal returns is different from that in Panel A because the first principal component in the extending window is negatively correlated with the first principal component from the full-sample estimation. The raw excess return of PC1 is -1.71% per month. The abnormal returns vary from -0.92% to -1.85% per month. PC2 and PC4 have significant raw returns, but their intercepts become insignificant once we control for other pricing factors.

²⁴Appendix 1.7.4 shows more details regarding the regression of PC1 on various factor models. We see that PC1 has significant exposures to the size factor (SMB, Q_{ME} , MIS_{ME}), RMW, and momentum (UMD).

Interpreting the missing factor

We interpret the missing factor, PC1, as a labor factor, for two theoretical reasons. First, total factor productivity in Eq. (1.2) contains the labor factor. For example, total factor productivity can be decomposed into labor productivity and capital productivity:

$$\begin{aligned}
 \text{LogTFP}_{it} &= \text{Log}Y_{it} - \beta_L \text{Log}L_{it} - \beta_K \text{Log}K_{it} \\
 &= \beta_L (\text{Log}Y_{it} - \text{Log}L_{it}) + \beta_K (\text{Log}Y_{it} - \text{Log}K_{it}) + (1 - \beta_L - \beta_K) \text{Log}Y_{it} \quad (1.15) \\
 &= \beta_L \underbrace{\text{Log} \frac{Y}{L}_{it}}_{\text{Labor productivity}} + \beta_K \underbrace{\text{Log} \frac{Y}{K}_{it}}_{\text{Capital productivity}} + (1 - \beta_L - \beta_K) \text{Log}Y_{it}
 \end{aligned}$$

Therefore, by construction, TFP measures labor productivity as well as capital productivity when we estimate TFP following Olley and Pakes (1996). Indeed, Imrohoroglu and Tuzel (2014) show that firm-level TFP is correlated with labor hiring. However, prevailing pricing factors, like the investment or profitability factors in Fama and French (2018), Hou et al. (2015), and Hou et al. (2018b), capture mainly capital productivity and are not specifically designed to capture labor productivity. This suggests that the missing factor (PC1) likely captures the labor risk.

Second, recent literature suggests that labor risks are important sources of the equity premium. Installed labor affects firm value when labor market frictions exist. The current literature considers several sources of labor frictions: costs of hiring or firing employees (Merz and Yashiv (2007); Belo et al. (2014)), wage rigidity (Favilukis and Lin (2016b,a)), and search frictions (search and matching) in labor markets (Petrosky-Nadeau et al. (2018)). Installed labor can increase equity risks because labor leverage plays a role similar to that of operating leverage (Danthine and Donaldson (2002); Donangelo (2014); Donangelo et al. (Forthcoming)), or because shareholders provide insurance to workers (Marfè (2016, 2017); Hartman-Glaser et al. (2019); Lettau et al. (2019)).

Moreover, we empirically establish the connection between PC1 and labor risk in four steps. First, we explore how labor productivity and capital productivity contribute to total

productivity at the firm level. In the first column of Panel A of Table 1.11, we report the Fama-MacBeth regression of log TFP growth on labor productivity growth, capital productivity growth, and output growth. Labor productivity growth is the log growth of labor productivity, $\text{Log} \frac{Y_{it}}{L_{it}}$; capital productivity is the log growth of capital productivity, $\text{Log} \frac{Y_{it}}{K_{it}}$; and output growth is the log growth of output. The coefficient on labor productivity growth is 0.39 ($t=44.50$), which is larger than that on capital productivity growth, 0.22 ($t=23.19$). Hence, labor productivity is an important part of total factor productivity.

Second, we link the first productivity principal component (PC1) with aggregate labor productivity, by running time-series regressions of either PC1 or its mimicking productivity portfolio, labeled as R^{PC1} , on aggregate labor growth and capital growth. The aggregate labor growth and capital growth data are from the Federal Reserve Bank of San Francisco.²⁵ The second and third columns of Panel A of Table 1.11 show that both PC1 and R^{PC1} have significant coefficients on aggregate labor growth, but not on aggregate capital growth. Therefore, PC1 captures mainly labor productivity.

Third, we investigate the asset pricing implications of labor risk. Following Donangelo et al. (Forthcoming), we construct the labor share portfolios. Labor share is defined as the ratio of the labor expense over the value-added.²⁶ We exclude financial and utility firms. We also exclude firms with a stock price below \$5, total assets below \$12.5 million, the number of employees below 100, or sales growth or asset growth above 100%. Finally, we trim the labor share at the 0.5th and 99.5th percentiles. We sort all stocks at the end of June at year t based on the labor share into 5 portfolios and compute equally weighted portfolio returns in the next 12 months.

We report returns of 5 labor sorted portfolios and the long-short portfolio in Panel B of Table 1.11. Consistent with Donangelo et al. (Forthcoming), the portfolio returns monotonically increase with labor share. As the labor share increases, the labor risk increases because

²⁵<http://www.frbsf.org/economic-research/indicators-data/total-factor-productivity-tfp/>

²⁶Labor share computed using the staff expense (XLR) in Compustat covers about 15.7% of imputed labor share. On average, labor share computed using the staff expense is 0.65 as the imputed labor share is 0.66. Donangelo et al. (Forthcoming) present the average of labor share, imputed labor share, and US Census labor share in Table 1 (p.502). The estimates are 0.61, 0.67, and 0.49, respectively. That is, our labor share estimation is very close to their estimations.

the wage is sticky (Belo et al. (2014); Donangelo et al. (Forthcoming)). The long-short portfolio has an average of 0.47% per month ($t=2.98$) and significant alphas across all models except for the productivity-based model. This suggests that the prevailing factors cannot explain the labor risk. However, the six productivity factors track the labor risk well.

Fourth, we check whether the first productivity component is related to the labor risk. In Panel C of Table 1.11, we present the annual correlation coefficients between the annual long-short labor share portfolio return (LS factor) and the six productivity components (PC1 to PC6). LS factor is highly correlated with the first productivity principal component (PC1), with a correlation coefficient of 0.43, while its correlations with other productivity components are very minor. This further confirms that PC1 captures the labor risk.

If the labor share factor and the first productivity factor capture similar labor risks, we expect the productivity-based model to explain other pricing factors when we replace the first productivity factor with the labor share factor. We run the time-series regressions of each pricing factor on the labor share factor and the second to sixth mimicking productivity factors. The intercepts and the coefficients of each factor appear in Panel A of Table 1.12. The labor factor, LS , is significantly priced among most pricing factors, except for HML and $PEAD$. Similar to the productivity-based model, this labor-share-augmented productivity model explains most of the pricing factors. However, it cannot fully explain the profitability factors (RMW and Q_{ROE}), the investment factors (CMA and Q_{IA}), the expected investment growth factor (EG), or PEAD. Overall, it performs worse than the productivity-based model. This is not surprising as the labor-augmented productivity model can't fully explain PC1 as well, which suggests that PC1 may better capture labor risk than the LS measure.

Lastly, we run a Fama-MacBeth regression using the prevailing factor models augmented with the first mimicking productivity portfolio (PC1) or the labor share factor (LS). If the prevailing factor models miss the labor risk, adding the missing factor should improve their empirical performances. In Panel B of Table 1.12, we report the Fama-MacBeth regression results, using the 155 portfolios from Table 1.7 as test assets. First, we see that PC1 is significantly priced in all models while LS is priced in the FF6, HMXZ, and DHS models.

Adding the labor factor (PC1 or LS) improves the model performances, especially for the FF6 and DHS models. For example, after we add PC1, the FF6 model has an insignificant intercept ($t=-1.41$). Also, the adjusted R^2 increases by 0.04. When the DHS model includes the LS factor, the intercept becomes insignificant ($t=-0.03$) and the adjusted R^2 increases from 0.18 to 0.51. Overall, the missing factor (PC1 or LS) helps to reduce the intercepts of various models. Also, even though some factor models, such as FF5 or HXZ, already have insignificant intercepts, the missing factor increases their explanatory power. Therefore, the labor risk helps other factor models to explain the stock returns.

Interpreting principal components at firm-level

Productivity factors capture prevailing pricing factors over time-series in Panel B of Table 1.1. Also, previous asset pricing tests using either non-traded factors or mimicking portfolios show that the productivity-based model explains various test assets and its performance is comparable to prevailing pricing factor models. In this subsection, we interpret productivity factors directly, using firm-level analysis.

Following Kelly et al. (2018), we can infer each of the productivity factors from their factor loadings. Firm-level TFP is decomposed into systematic TFP, which is predicted by principal components, and residual TFP. Further, systematic TFP consists of principal components and firms' exposures with respect to corresponding principal components. If principal components track prevailing pricing factors, factor loadings should contain firm characteristics, used to construct pricing factors. That is, we interpret principal components via their factor loadings at a firm-level.

Empirically, we estimate factor loadings by regressing TFP against six principal components for each firm. We compute time-varying factor loadings in 20-year rolling-window where we ask at least 13 observations in each window. That is, the first factor loadings for each principal component are estimated from 1972 to 1991. Although we estimate principal components from manufacturing industries, we estimate factor loadings of firms in all industries except for financial and utility industries. Also, we exclude firms with a stock price of

less than \$5 at the end of the year t .

We include firm characteristics that represent prevailing factors and help us to understand the connection between principal components and pricing factors. Those variables are as follows: labor share (LS), market capitalization (Size), cash flow (CF), book-to-market ratio (BM), asset growth (AG^r), cumulative stock return ($R_{2,12}^r$), and mispricing score (MIS). Labor share (LS) is the ratio of labor expense over value-added. Size is a logarithmic price (PRC) times shares outstanding (SHROUT). Cash flow (CF) is income before extraordinary items (IB) plus depreciation and amortization (DP) divided by lagged net property, plant, and equipment (PPENT). Book-to-market (BM) is the ratio of book value of equity to market value of equity. Asset growth (AG) is the ratio of the first difference of total asset (AT) over an average of current and lagged total assets. Cumulative return ($R_{2,12}$) is the cumulative stock return from twelve months to two months. Mispricing score (MIS) is the average rank score estimated from 11 mispricing portfolios in Stambaugh and Yuan (2017). Because mispricing score includes asset growth and cumulative return in Stambaugh and Yuan (2017), we regress both asset growth and cumulative return on mispricing score and use their residuals, AG^r and $R_{2,12}^r$ respectively, to see link mispricing score and 6th principal components. We also add three more variables to control omitted variables. Leverage (LEV) is the ratio of long-term debt (DLCC) plus debt in current liabilities (DLC) over long-term debt, debt in liabilities, and shareholder's equity (SEQ). Cash-flow volatility (σ_{CF}) is the standard deviation of cash flow over the last 10 years. R&D intensity is the ratio of R&D expense (XRD) over sales (SALE), where R&D expense is equal to 0 if missing. To compare the firm characteristics, we standardize firm characteristics. We run panel regressions of firms' factor loadings against firm characteristics with firm and year fixed effects. The sample period is from 1991 to 2015.

Table 1.13 presents the regression results. In column (1), we regress the factor loadings of PC1 on firm characteristics. b_{PC1} is significantly positive on labor share (LS) with a coefficient of 0.057 ($t=3.247$). That is, if a firm has high exposure to PC1, its labor share increases. Since PC1 is positively correlated with the labor share factor in Table 1.11, the

positive coefficient of LS suggests that PC1 is interpretable as the labor share risk factor. Also, the magnitude of LS is sizable. Only BM has a higher coefficient (-0.063) than LS. Turning to column (2) to (6), all of the factor loadings support the consistent findings of Panel B of Table 1.1. b_{PC2} increases in firm size. The coefficient is 0.081 with t -statistics of 2.647. PC2 is negatively related to size factor (SMB and Q_{ME}) so a firm with higher exposure to PC2 should be a larger firm. Also, size has the largest magnitude of coefficient. PC3 is negatively related to profitability factors (RMW and Q_{ROE}). We see that b_{PC3} is negatively related to cash flow (CF) with a coefficient of -0.018 ($t=-1.973$). PC4 is positively related to investment factors (CMA and Q_{IA}) and value factor (HML). Consistent with the correlations, b_{PC4} has the negative coefficient on asset growth with -0.015 ($t=-2.075$) and the positive coefficient on book-to-market ratio (BM) with 0.045 ($t=2.149$). b_{PC5} is significantly positive on $R_{2,12}^r$. The coefficient is 0.017 ($t=2.187$), reflecting the positive correlation between PC5 and UMD. b_{PC6} is positively related to MIS with a coefficient of 0.018 ($t=1.947$). Overall, we interpret principal components via factor loadings and their cross-sectional variations with firm characteristics, which represent the prevailing pricing factors.

1.6 Conclusion

Inspired by production-based asset pricing models, we start with productivity shocks in firms' production to identify multiple systematic productivity risks and explore their asset pricing implications. Fundamental shocks drive firms' optimal investment decisions and the pricing kernel, suggesting a productivity-based model. We find that the first six productivity factors well explain many test assets and 13 of 15 prevailing pricing factors, including the Fama and French (2018) six factors, the Hou et al. (2015) q factors, the mispricing factors in Stambaugh and Yuan (2017), and the long-horizon behavioral factor in Daniel et al. (2018). This indicates productivity shocks are priced and these prevailing factors indeed represent the fundamental risks in the economy. In fact, these factors share common risk sources even

though they are motivated and constructed differently. In particular, we find that these empirical asset pricing models miss an important productivity factor, which we interpret as the labor risk. This suggests the importance of recognizing labor risk in asset pricing models.

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Table 1.1. **TFP growth factors: Descriptive statistics and relations with other factors**

Panel A summarizes the annual log TFP growth and six principal components (PC1 to PC6), including the mean, standard deviation, and percentiles. Full-sample data are used in estimating principal components. AR(1) denotes the first-order autocorrelation. R^2 denotes the average explanatory power of principal components at firm-level. Panel B reports the annual time-series correlation coefficients between principal components and other pricing factors. The pricing factors include Fama and French (2015) market factor (MKT), size factor (SMB), value factor (HML), investment factor (CMA), and profitability factor (RMW); Carhart (1997) momentum factor (UMD); Hou et al. (2015) size factors (Q_{ME}), investment factor (Q_{IA}), and profitability factor (Q_{ROE}); Hou et al. (2018b) expected investment growth factor (EG); Stambaugh and Yuan (2017) mispricing factor (MIS); and Daniel et al. (2018) long-horizon behavioral factor (FIN) and short-horizon behavioral factor (PEAD). Panel C presents the monthly mean (% per month), standard deviation (% per month, S.D.), Sharpe ratio (SR), and correlations for the mimicking portfolios of six principal components. The sample period is from January 1972 to December 2015, except for Daniel et al. (2018) factors, which have a sample period of July 1972 to December 2014.

Panel A: TFP and its 6 principal components													
	Mean	S.D.	Min	Max	10%	25%	50%	75%	90%	AR(1)	R^2		
ΔTFP	0.01	0.19	-1.35	1.26	-0.20	-0.08	0.01	0.10	0.22	0.07			
PC1	-0.08	1.01	-3.54	3.38	-0.76	-0.46	-0.15	0.25	0.74	-0.03	0.15		
PC2	-0.06	1.01	-3.51	2.55	-1.15	-0.57	0.01	0.38	1.18	0.20	0.24		
PC3	0.05	1.01	-2.77	3.32	-0.88	-0.46	-0.03	0.63	1.07	0.24	0.32		
PC4	0.17	1.00	-1.54	3.86	-1.08	-0.41	0.24	0.55	0.87	0.45	0.39		
PC5	0.03	1.01	-3.57	2.87	-0.82	-0.35	0.12	0.51	0.82	0.45	0.46		
PC6	0.12	1.00	-2.15	3.11	-1.02	-0.40	0.11	0.62	1.30	0.25	0.52		
Panel B: Correlations between 6 TFP components and pricing factors													
	MKT	SMB	HML	CMA	RMW	UMD	Q_{ME}	Q_{IA}	Q_{ROE}	EG	MIS	FIN	PEAD
MKT	1.00												
SMB	0.15	1.00											
HML	-0.27	0.17	1.00										
CMA	-0.36	0.17	0.71	1.00									
RMW	-0.30	-0.13	0.21	0.04	1.00								
UMD	-0.21	-0.26	-0.16	-0.11	0.02	1.00							
Q_{ME}	0.10	0.99	0.20	0.17	-0.08	-0.20	1.00						
Q_{IA}	-0.38	0.05	0.68	0.93	0.09	-0.05	0.07	1.00					
Q_{ROE}	-0.27	-0.38	-0.08	-0.13	0.72	0.52	-0.30	0.00	1.00				
EG	-0.26	-0.10	0.10	0.23	0.29	0.36	-0.06	0.21	0.37	1.00			
MIS	-0.52	-0.39	0.11	0.31	0.31	0.61	-0.33	0.33	0.52	0.66	1.00		
FIN	-0.56	-0.22	0.67	0.57	0.55	0.16	-0.19	0.59	0.35	0.36	0.57	1.00	
PEAD	0.00	-0.07	-0.06	-0.02	-0.27	0.55	-0.03	0.01	0.18	0.29	0.43	-0.04	1.00
PC1	-0.01	0.01	-0.07	-0.14	0.11	-0.28	0.01	-0.14	-0.08	0.14	-0.01	-0.05	-0.22
PC2	0.12	-0.24	-0.14	-0.12	-0.16	0.17	-0.25	0.00	0.05	-0.24	0.09	0.05	0.20
PC3	0.19	0.06	-0.15	-0.07	-0.48	-0.06	0.01	-0.23	-0.42	-0.02	-0.18	-0.27	0.11
PC4	-0.14	0.28	0.21	0.50	0.00	-0.13	0.26	0.43	-0.22	0.12	0.03	0.17	-0.12
PC5	0.09	-0.10	0.01	-0.04	-0.09	0.35	-0.09	-0.07	0.13	0.09	0.17	-0.04	0.19
PC6	0.34	-0.14	-0.23	-0.29	-0.44	-0.17	-0.18	-0.26	-0.29	-0.27	-0.35	-0.48	-0.07
Panel C: Statistics of monthly mimicking productivity portfolios													
	Mean	SD	SR	PC2	PC3	PC4	PC5	PC6					
PC1	1.31	7.38	0.18	0.36	0.05	0.22	-0.03	-0.27					
PC2	0.39	3.55	0.11		-0.21	-0.38	0.26	-0.07					
PC3	-0.95	5.67	-0.17			0.15	0.21	0.20					
PC4	1.59	10.25	0.16				-0.30	-0.24					
PC5	0.70	2.12	0.33					-0.39					
PC6	-0.99	4.85	-0.20										

Table 1.2. **Validating TFP decompositions**

Panel A tabulates the contemporaneous excess value-weighted returns (% per month) and t -statistics (in parentheses) of portfolios sorted by total TFP growth (ΔTFP) and systematic TFP growth (ΔTFP_{sys}). Systematic TFP growth is the predicted TFP growth from the regression of total TFP growth on 6 principal components for each firm. Panel B regresses the monthly excess returns or annual return volatility on TFP and its components. Annual return volatility is the standard deviation of daily excess return over the last year. Models (1)-(3) use logarithmic total TFP volatility ($\sigma_{\Delta TFP}$), logarithmic systematic TFP volatility ($\sigma_{\Delta TFP,sys}$), logarithmic idiosyncratic TFP volatility ($\sigma_{\Delta TFP,idio}$), asset growth (AG), and logarithmic cash flow (CF/K) as regressors. Total TFP volatility is the standard deviation of the last 5 year TFP growth. Systematic TFP volatility is the standard deviation of the last 5 year systematic TFP growth. Idiosyncratic TFP volatility is the standard deviation of the last 5 year idiosyncratic TFP growth. Idiosyncratic TFP growth is total TFP growth - systematic TFP growth. Asset growth is $\frac{AT_t - AT_{t-1}}{AT_{t-1}}$ where AT is total asset. Cash flow is $\frac{IB_t + DP_t}{PPENT_{t-1}}$. IB is the income before extraordinary item. DP is the depreciation and amortization. PPENT is the net property, plant, and equipment. Models (1)-(3) are Fama-MacBeth regressions with industry fixed effects (4-digit SIC). Newey-West adjusted t -statistics with 6-month lags are reported in parentheses. Models (4)-(5) are panel regressions of logarithmic return volatility on absolute value of TFP growth ($|\Delta TFP|$), systematic TFP growth ($|\Delta TFP_{sys}|$), and idiosyncratic TFP growth ($|\Delta TFP_{idio}|$) with firm and month fixed effects. The standard errors are clustered by both firm and month. All coefficients are multiplied by 100. The sample period is from January 1972 to December 2015.

Panel A: Contemporaneous returns of TFP sorted portfolios						
	Low	2	3	4	High	H-L
ΔTFP	0.16 (0.66)	0.74 (3.27)	0.95 (4.95)	1.20 (6.23)	1.63 (7.36)	1.47 (9.49)
ΔTFP_{sys}	0.65 (2.58)	0.79 (3.86)	0.84 (4.35)	1.14 (5.78)	1.48 (6.27)	0.83 (4.88)
Panel B: Predicting return and volatility with TFP and its components						
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	
	Excess returns			Return volatilities		
$\sigma_{\Delta TFP}$	0.22 (3.61)					
$\sigma_{\Delta TFP,sys}$		0.15 (2.44)	0.14 (2.35)			
$\sigma_{\Delta TFP,idio}$		0.09 (1.78)	0.08 (1.63)			
AG			-0.84 (-4.46)			
CF/K			-0.11 (-1.51)			
$ \Delta TFP $				0.20 (7.49)		
$ \Delta TFP_{sys} $					0.11 (2.76)	
$ \Delta TFP_{idio} $					0.22 (7.37)	
Firm FE	No	No	No	Yes	Yes	
Ind. FE	Yes	Yes	Yes	No	No	
Time FE	No	No	No	Yes	Yes	
R^2	0.36	0.37	0.37	0.67	0.67	
N	177416	177416	177416	28138	28138	

Table 1.3. Estimating prevailing factor models and productivity-based model: Two-step GMM with Newey-West one-lag adjustment

This table presents the two-step GMM estimation with one-lag Newey-West adjustment of various factor models. Factor models include the Fama and French (1993) three-factor model (FF3), Fama and French (2015) five-factor model (FF5), Fama and French (2015) six-factor model (FF6), Hou et al. (2015) q -factor model (HMZ), Hou et al. (2018b) q^5 model (HMXZ), Daniel et al. (2018) (DHS), and the productivity-based model (TFP). The productivity-based model use six principal components estimated from firm-level TFP. Test assets are 155 portfolios: 25 size and book-to-market sorted portfolios, 25 size and operating profitability sorted portfolios, 25 size and investment sorted portfolios, 25 size and momentum sorted portfolios, 25 size and idiosyncratic volatility portfolios, and 30 Fama-French industry portfolios. Panel A shows the coefficients (coeff, b) from the GMM estimation and their t -statistics (t -stat). Panel B reports the implied price of risk (λ) for each factor, based on the coefficients in Panel A. Panel C presents the statistics of goodness of fit, including R^2 , root-mean-square errors ($RMSSE$), and p -value of Hansen's J test of overidentification. R^2 is defined as one minus the ratio of the cross-sectional variance to the cross-sectional variance of realized average portfolio returns, following Campbell and Vuolteenaho (2004). The sample period is from 1973 to 2014 for DHS and from 1972 to 2015 for other models.

	FF3		FF5		FF6		HXZ		HMXZ		DHS		TFP	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Panel A: Coefficients														
b_{MKT}	1.82	24.27	1.16	10.33	1.80	14.55	1.84	13.08	1.88	19.06	1.77	15.12		
b_{SMB}	-1.15	-12.01	0.01	0.07	0.19	1.00								
b_{HML}	3.32	58.04	-4.36	-25.18	-3.67	-11.61								
b_{CMA}			8.31	38.65	8.51	16.78								
b_{RMW}			2.23	9.39	2.23	10.64								
b_{UMD}					0.87	5.30								
b_{QME}							0.53	1.67	-0.05	-0.19				
b_{QIA}							5.10	19.03	3.65	10.93				
b_{QROE}							2.39	10.39	0.21	1.23				
b_{EG}									6.67	25.14				
b_{FIN}											2.09	19.09		
b_{PEAD}											5.32	24.81		
b_{PC1}													3.82	16.16
b_{PC2}													-1.35	-3.64
b_{PC3}													-0.83	-3.40
b_{PC4}													0.70	4.07
b_{PC5}													4.91	21.54
b_{PC6}													1.02	4.19

	FF3	FF5	FF6	HXZ	HMXZ	DHS	TFP
Panel B: Implied Price of risk (%)							
λ_{MKT}	3.45	0.65	1.59	2.68	2.04	3.02	
λ_{SMB}	-0.13	0.33	0.53				
λ_{HML}	4.87	-0.91	-0.13				
λ_{CMA}		2.60	2.90				
λ_{RMW}		0.59	0.46				
λ_{UMD}			1.88				
$\lambda_{Q_{ME}}$				0.95	0.47		
$\lambda_{Q_{IA}}$				2.48	2.37		
$\lambda_{Q_{ROE}}$				1.93	1.55		
λ_{EG}					3.98		
λ_{FIN}						1.39	
λ_{PEAD}						2.79	
λ_{PC1}							8.90
λ_{PC2}							-3.13
λ_{PC3}							-1.95
λ_{PC4}							1.60
λ_{PC5}							11.42
λ_{PC6}							2.35
Panel C: Goodness of Fit							
R^2	0.63	0.89	0.90	0.82	0.87	0.78	0.79
RMSE (%)	1.91	1.08	0.98	1.34	1.14	1.50	1.61
P-value(J)	0.98	0.94	0.91	0.97	0.94	0.98	0.91

Table 1.4. Asset pricing tests: GLS Cross-sectional regressions and Tests of R^2 s

Panel A presents the coefficients (Coeff) and t -statistics (t -stat) from the GLS cross-sectional regressions of various factor models. Factor models include the Fama and French (1993) three-factor model (FF3), Fama and French (2015) five-factor model (FF5), Fama and French (2018) six-factor model (FF6), Hou et al. (2015) q -factor model (HMZ), Hou et al. (2018b) q^5 model (HMXZ), Daniel et al. (2018) (DHS), and productivity-based model (TFP). The productivity-based model use six principal components estimated from firm-level TFP. Test assets are 25 size and book-to-market sorted portfolios. All coefficients are multiplied by 100. Panel B reports the pairwise tests of the GLS cross-sectional R^2 s of factor models. We report the difference between the cross-sectional R^2 s of the models in row i and column j , $R_i^2 - R_j^2$, and the corresponding p -value in parentheses for the test of null hypothesis, $H_0 : R_i^2 = R_j^2$. The t -statistics and p -values are adjusted under the assumption that the models are potentially misspecified, following Kan et al. (2013). The sample period is from 1972 to 2015 but DHS model is from 1973 to 2014.

Panel A: GLS regression														
	FF3		FF5		FF6		HXZ		HMXZ		DHS		TFP	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	5.64	1.14	6.19	1.02	7.51	1.21	6.93	1.30	7.61	1.44	5.82	1.10	9.03	2.82
γ_{MKT}	2.74	0.50	2.33	0.36	1.01	0.15	1.60	0.27	0.92	0.16	2.71	0.45		
γ_{SMB}	1.34	0.75	1.21	0.67	1.19	0.66								
γ_{HML}	4.33	2.06	4.31	2.06	4.32	2.05								
γ_{CMA}			4.26	2.64	4.33	2.68								
γ_{RMW}			-3.37	-1.54	-3.58	-1.59								
γ_{UMD}					-10.59	-3.18								
γ_{QME}							0.67	0.41	0.74	0.45				
γ_{QIA}							3.85	2.67	4.07	2.56				
γ_{QROE}							-6.17	-2.83	-6.34	-2.72				
γ_{EBG}									-4.55	-1.73				
γ_{FIN}											2.51	0.95	-4.13	-0.84
γ_{PEAD}											-2.29	-0.88	2.19	0.65
γ_{PC1}													9.65	2.34
γ_{PC2}													9.18	2.79
γ_{PC3}													-8.85	-2.11
γ_{PC4}													1.97	0.57
γ_{PC5}													0.31	
γ_{PC6}														
R^2	0.05		0.12		0.20		0.20		0.26		0.04			
Panel B: Tests of Equality of cross-sectional R^2 s														
	FF5		FF6		HXZ		HMXZ		DHS		TFP			
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
FF3	-0.07	-0.17	-0.17	-0.21	0.01	-0.26								
p-value	(0.11)	(0.09)	(0.13)	(0.11)	(0.90)	(0.07)								
FF5			-0.08	-0.14	0.14	-0.19								
p-value		(0.08)	(0.25)	(0.25)	(0.22)	(0.20)								
FF6			-0.00	-0.06	0.23	-0.11								
p-value			(0.95)	(0.52)	(0.12)	(0.47)								
HXZ				-0.06	0.24	-0.11								
p-value				(0.25)	(0.10)	(0.46)								
HMXZ					0.27	-0.05								
p-value					(0.09)	(0.78)								
DHS						-0.34								
p-value						(0.01)								

Table 1.5. Using productivity factors to explain other pricing factors

This table reports the intercepts (α , % per month) and factor loadings from time-series regressions of various pricing factors on productivity factors. The pricing factors include Fama and French (2015) market factor (MKT), size factor (SMB), value factor (HML), investment factor (CMA), and profitability factor (RMW); Carhart (1997) momentum factor (UMD); Hou et al. (2015) size factors (Q_{ME}), investment factor (Q_{IA}), and profitability factor (Q_{ROE}); Stambaugh and Yuan (2017) univariate mispricing factor (MIS) and two separate mispricing factors related to the management (MGMT) and to the firm performance (PERF); Hou et al. (2018b) expected investment growth factor (EG); and Daniel et al. (2018) short horizon earning surprise factor (PEAD) and long horizon financing factor (FIN). The intercepts and factor loadings are estimated either over the full sample (Panel A) or in extending windows (Panel B). The Newey-West adjusted t -statistics (t -stat) with 6-month (4-month) lags are provided. The sample period is from January 1972 to December 2015 but the Daniel et al. (2018) factors are from July 1972 to December 2014. The testing period for Panel B is from January 2001 to December 2015, but it is from January 2001 to December 2014 for Daniel et al. (2018) factors.

Panel A: Full-sample estimation

	MKT	SMB	HML	CMA	RMW	UMD	Q_{ME}	Q_{IA}	Q_{ROE}	EG	MGMT	PERF	MIS	FIN	PEAD
α	0.10	0.05	0.02	-0.06	0.10	-0.35	0.02	-0.03	0.08	0.32	0.08	-0.02	-0.11	0.15	0.46
t-stat.	0.49	0.44	0.11	-0.97	1.48	-1.60	0.17	-0.64	1.17	2.79	0.84	-0.11	-1.27	1.14	5.47
β_{PC1}	0.13	0.16	-0.14	-0.13	0.00	0.10	0.16	-0.10	0.07	-0.02	-0.17	0.08	-0.04	-0.20	0.04
t-stat.	4.62	9.15	-6.21	-11.75	-0.32	2.28	8.97	-12.44	5.91	-0.98	-8.51	2.85	-2.55	-8.19	1.72
β_{PC2}	0.00	-0.52	0.25	0.19	0.02	-0.26	-0.62	0.15	-0.28	0.00	0.33	-0.12	0.15	0.37	-0.08
t-stat.	0.03	-11.84	3.79	10.18	0.59	-2.14	-14.64	10.49	-9.54	-0.12	7.25	-1.64	3.70	4.89	-1.96
β_{PC3}	0.05	0.12	-0.18	-0.12	-0.11	-0.07	0.07	-0.20	-0.21	-0.11	-0.19	0.03	-0.08	-0.26	0.00
t-stat.	1.32	3.60	-4.42	-9.43	-4.72	-0.98	2.48	-24.33	-9.21	-3.78	-6.25	0.51	-3.00	-7.31	0.03
β_{PC4}	0.00	0.06	0.14	0.16	-0.11	0.04	0.06	0.14	-0.15	0.02	0.17	-0.06	0.09	0.10	0.01
t-stat.	-0.06	4.35	5.55	25.03	-8.14	0.96	4.61	20.50	-13.93	1.59	14.40	-2.07	6.84	3.53	0.50
β_{PC5}	1.29	0.23	-0.06	0.06	-0.07	1.07	0.38	0.08	0.37	0.22	0.11	0.51	0.51	0.02	0.22
t-stat.	8.87	3.08	-0.45	1.24	-1.58	7.75	5.37	2.03	8.54	3.42	1.39	3.55	7.42	0.22	3.80
β_{PC6}	0.60	0.01	-0.09	-0.08	-0.28	-0.16	0.03	-0.07	-0.21	-0.14	-0.13	-0.42	-0.30	-0.34	0.00
t-stat.	10.30	0.32	-1.25	-3.87	-9.52	-1.54	1.18	-4.08	-11.93	-4.84	-3.67	-5.55	-9.44	-6.84	-0.16
R^2	0.47	0.61	0.37	0.70	0.58	0.35	0.64	0.80	0.75	0.32	0.57	0.50	0.70	0.54	0.08

Panel B: Extending-window estimation

	MKT	SMB	HML	CMA	RMW	UMD	Q_{ME}	Q_{IA}	Q_{ROE}	EG	MGMT	PERF	MIS	FIN	PEAD
α	0.40	0.12	-0.09	0.10	0.21	-0.19	0.05	0.10	0.04	0.19	0.17	0.49	0.16	0.27	0.24
t-stat.	1.33	0.73	-0.44	0.70	1.25	-0.56	0.31	0.76	0.19	1.26	0.93	1.43	0.64	1.23	1.98
β_{PC1}	0.05	-0.07	-0.08	-0.06	-0.02	-0.09	-0.09	-0.07	-0.03	-0.05	-0.09	-0.09	-0.10	-0.06	-0.03
t-stat.	1.00	-2.50	-1.78	-1.68	-0.66	-1.74	-3.30	-1.90	-1.15	-1.40	-1.72	-1.19	-1.71	-1.00	-1.74
β_{PC2}	-0.05	0.02	0.02	0.01	0.05	0.08	0.03	0.02	0.05	0.03	0.02	0.05	0.04	0.07	0.01
t-stat.	-2.91	2.61	2.38	0.74	4.07	4.76	3.14	1.22	4.33	3.26	1.40	3.59	3.38	5.75	2.38
β_{PC3}	0.28	0.23	-0.17	-0.11	-0.14	0.09	0.23	-0.11	-0.09	-0.15	-0.23	0.04	-0.04	-0.35	-0.02
t-stat.	2.65	3.67	-2.30	-1.84	-2.68	0.57	3.61	-1.84	-1.51	-2.36	-2.65	0.25	-0.36	-3.61	-0.51
β_{PC4}	0.09	-0.01	0.00	-0.01	-0.01	0.02	0.00	-0.01	0.02	0.01	0.00	0.01	0.01	-0.04	-0.04
t-stat.	3.79	-0.46	0.16	-0.57	-0.65	0.71	0.04	-0.89	1.58	0.37	0.07	0.25	0.28	-1.46	-1.70
β_{PC5}	-0.14	-0.04	-0.06	-0.01	0.02	0.25	-0.04	-0.01	0.12	0.03	0.04	0.19	0.11	0.02	0.05
t-stat.	-5.95	-1.92	-2.38	-0.41	1.39	2.00	-2.10	-0.81	3.54	1.53	2.11	2.38	1.99	0.64	1.53
β_{PC6}	0.02	0.00	0.01	0.01	-0.01	0.00	0.00	0.01	-0.01	-0.01	0.00	-0.02	-0.01	-0.01	-0.01
t-stat.	2.49	-0.08	1.39	1.21	-0.75	0.10	-0.79	1.02	-2.27	-1.79	-0.22	-1.85	-1.39	-0.54	-2.58
R^2	0.36	0.19	0.20	0.13	0.32	0.32	0.23	0.19	0.42	0.27	0.22	0.22	0.27	0.40	0.18

Table 1.6. **Explaining various test portfolios with productivity factors**

This table presents the intercepts (α , % per month) and their t -statistics from time-series regressions of various portfolios on productivity factors. Test portfolios include 25 size and book-to-market sorted portfolios (panel A), 25 size and operating profitability sorted portfolios (panel B), 25 size and investment sorted portfolios (panel C), 25 size and momentum sorted portfolios (panel D), 25 size and idiosyncratic volatility sorted portfolios (panel E), and 30 Fama-French industry portfolios (panel F). Factors include the 6 mimicking productivity portfolios constructed from the full sample. Newey-West t -statistics with 6-month lags are provided. The sample period is from January 1972 to December 2015.

α (% per month)						t-statistics				
Panel A: 25 size and book-to-market sorted portfolios										
	Low BM	2	3	4	High BM	Low BM	2	3	4	High BM
Small	-0.19	0.30	0.14	0.33	0.43	-0.55	1.03	0.48	1.21	1.31
2	0.03	0.12	0.19	0.18	0.11	0.09	0.46	0.70	0.73	0.35
3	0.20	0.18	0.17	0.22	0.26	0.69	0.69	0.70	0.85	0.82
4	0.33	0.08	0.10	0.23	0.07	1.27	0.30	0.40	0.91	0.23
Big	0.22	0.08	-0.01	-0.19	0.07	1.10	0.40	-0.05	-0.73	0.29
Panel B: 25 size and operating profitability sorted portfolios										
	Low Op	2.00	3.00	4.00	High Op	Low Op	2	3	4	High Op
Small	0.06	0.24	0.13	0.17	0.03	0.19	0.86	0.45	0.54	0.08
2	0.06	0.00	0.12	0.25	0.19	0.21	0.02	0.46	0.89	0.62
3	0.19	0.15	0.15	0.11	0.28	0.66	0.62	0.62	0.44	0.99
4	0.24	0.17	0.12	0.23	0.15	0.89	0.72	0.51	0.92	0.56
Big	0.07	0.00	0.05	0.20	0.17	0.27	0.01	0.23	0.97	0.90
Panel C: 25 size and investment sorted portfolios										
	Low Inv	2	3	4	High Inv	Low Inv	2	3	4	High Inv
Small	0.38	0.37	0.29	0.13	-0.19	1.15	1.26	1.02	0.47	-0.58
2	0.12	0.13	0.21	0.21	0.02	0.39	0.50	0.89	0.79	0.05
3	0.24	0.20	0.18	0.23	0.22	0.87	0.82	0.74	0.94	0.79
4	0.09	0.10	0.14	0.26	0.35	0.32	0.40	0.62	1.11	1.32
Big	0.08	-0.04	0.02	0.13	0.37	0.34	-0.21	0.13	0.70	1.69
Panel D: 25 size and momentum sorted portfolios										
	Loser	2	3	4	Winner	Loser	2	3	4	Winner
Small	0.24	0.19	0.32	0.40	0.49	0.54	0.60	1.10	1.42	1.58
2	0.38	0.31	0.25	0.23	0.26	0.93	1.00	0.94	0.87	0.97
3	0.63	0.33	0.21	0.03	0.14	1.59	1.12	0.77	0.12	0.54
4	0.66	0.37	0.24	0.15	0.04	1.70	1.29	0.93	0.63	0.14
Big	0.49	0.40	0.04	-0.04	-0.13	1.38	1.70	0.18	-0.23	-0.57
Panel E: 25 size and idiosyncratic volatility sorted portfolios										
	Low Ivoll	2	3	4	High Ivoll	Low Ivoll	2	3	4	High Ivoll
Small	0.48	0.48	0.46	0.46	-0.29	1.93	1.56	1.26	1.12	-0.64
2	0.29	0.26	0.30	0.29	-0.05	1.36	0.94	1.02	0.83	-0.12
3	0.17	0.21	0.21	0.23	0.08	0.83	0.85	0.73	0.75	0.24
4	0.18	0.16	0.17	0.18	0.29	0.91	0.74	0.67	0.63	0.89
Big	-0.02	-0.02	-0.04	0.10	0.42	-0.11	-0.12	-0.18	0.43	1.56

α (% per month)					t-statistics				
Panel F: 30 Fama-French industry portfolios									
Agric	Food	Soda	Beer	Smoke	Agric	Food	Soda	Beer	Smoke
0.08	0.13	0.19	0.10	0.72	0.24	0.51	0.52	0.38	2.05
Toys	Fun	Books	Hshld	Clths	Toys	Fun	Books	Hshld	Clths
-0.19	0.59	-0.08	0.02	0.06	-0.49	1.30	-0.24	0.11	0.16
Hlth	MedEq	Drugs	Chems	Rubbr	Hlth	MedEq	Drugs	Chems	Rubbr
-0.16	0.33	0.55	0.08	-0.02	-0.37	1.41	2.57	0.25	-0.04
Txtls	BldMt	Cnstr	Steel	FabPr	Txtls	BldMt	Cnstr	Steel	FabPr
0.07	-0.07	-0.16	0.13	0.00	0.15	-0.19	-0.42	0.36	0.00
Mach	ElcEq	Autos	Aero	Ships	Mach	ElcEq	Autos	Aero	Ships
0.35	0.18	0.09	0.23	-0.10	1.09	0.65	0.21	0.63	-0.24
Guns	Gold	Mines	Coal	Oil	Guns	Gold	Mines	Coal	Oil
0.20	1.07	0.50	0.32	0.11	0.57	2.29	1.26	0.51	0.41

Table 1.7. Cross-sectional regressions of various factor models

This table reports the coefficients (Coeff) and t -statistics (t -stat) from Fama-MacBeth regressions of various factor models. Test assets are 155 portfolios and the tested pricing factors: 25 size and book-to-market sorted portfolios, 25 size and operating profitability sorted portfolios, 25 size and investment sorted portfolios, 25 size and momentum sorted portfolios, 25 size and idiosyncratic volatility sorted portfolios, 30 Fama-French industry portfolios, and the tested pricing factors. Tested factor models are Fama and French (1993) three-factor model (FF3), Fama and French (2015) five-factor model (FF5), Fama and French (2015) six-factor model (FF6), Hou et al. (2015) q -factor model (HXZ), Hou et al. (2018) q^5 model (HMXZ), Stambaugh and Yuan (2017) mispricing factor model (SY), Daniel et al. (2018) behavioral factor model (DHS), and productivity-based model (TFP). The factor betas are computed over the full sample period. 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 sample period is from January 1972 to December 2015.

	FF3		FF5		FF6		HXZ		HMXZ		SY		DHS		TFP	
	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	0.51	5.35	0.01	0.29	-0.07	-2.24	0.00	-0.03	-0.06	-1.10	-0.03	-0.44	0.30	2.43	0.12	0.98
γ_{MKT}	0.06	0.29	0.47	2.30	0.59	2.91	0.49	2.32	0.57	2.73	0.57	2.70	0.42	1.81		
γ_{SMB}	0.09	0.70	0.22	1.65	0.21	1.55										
γ_{HML}	0.24	1.65	0.07	0.53	0.28	2.10										
γ_{CMA}			0.29	2.52	0.26	2.29										
γ_{RMW}			0.43	4.01	0.27	2.75										
γ_{UMD}					0.73	3.72										
γ_{QME}							0.33	2.31	0.31	2.22						
γ_{QIA}							0.35	2.91	0.38	3.24						
γ_{QROE}							0.56	3.98	0.52	3.63						
γ_{EG}									0.64	4.29						
γ_{MISME}											0.32	2.39				
γ_{MGMT}											0.52	3.31				
γ_{PERF}											0.61	3.21				
γ_{FIN}													0.35	1.56		
γ_{PEAD}													0.38	2.25		
γ_{PC1}															1.13	3.31
γ_{PC2}															0.16	0.76
γ_{PC3}															-1.02	-3.61
γ_{PC4}															1.28	2.79
γ_{PC5}															0.67	5.09
γ_{PC6}															-0.84	-3.24
R^2	0.06		0.44		0.60		0.52		0.58		0.61		0.18		0.78	
(5 th , 95 th)	(0.03, 0.49)		(0.27, 0.59)		(0.44, 0.70)		(0.32, 0.63)		(0.40, 0.66)		(0.40, 0.68)		(0.03, 0.49)		(0.59, 0.81)	

Table 1.8. **Explaining Pricing Factors from Competing Models: Maximum squared Sharpe ratio**

Panel A presents the maximum squared Sharpe ratio ($Sh^2(f)$) of the tangency portfolios constructed with pricing factors from different factor models. Factor models include the 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. (2018b) q^5 model (HMXZ), Daniel et al. (2018) behavioral factor model (DHS), and the productivity-based model (TFP). The 5th and 95th percentiles of the $Sh^2(f)$ distribution from a bootstrap simulation of 10,000 times are reported in brackets. Panel B reports the intercepts (α , %), its t -statistics (t -stat), loadings, R^2 , residual standard error ($s(e)$, % per month), and each productivity portfolio's marginal contribution to $Sh^2(f)$, i.e., $\frac{\alpha^2}{s(e)^2}$ by regressing each productivity factor on the rest of productivity factors. The sample period is from January 1972 to December 2015 but the sample period for Daniel et al. (2018) factors is from July 1972 to December 2014.

Panel A: Maximum squared Sharpe ratio												
	FF3	FF4	FF5	FF6	HXZ	HMXZ	DHS	TFP				
$Sh^2(f)$	0.04	0.09	0.10	0.14	0.15	0.26	0.27	0.32				
$(5^{th}, 95^{th})$	(0.02, 0.08)	(0.06, 0.16)	(0.07, 0.17)	(0.10, 0.22)	(0.10, 0.22)	(0.19, 0.36)	(0.20, 0.37)	(0.26, 0.44)				
Panel B: Spanning regressions and marginal contributions to $Sh^2(f)$ for the TFP model												
	α	PC1	PC2	PC3	PC4	PC5	PC6	t-stat	R^2	$s(e)$	$\frac{\alpha^2}{s(e)^2}$	
PC1	1.13		1.15	0.35	0.16	-1.03	-0.53	3.59	0.36	5.89	0.037	
PC2	-0.15	0.24		-0.18	-0.11	0.50	0.12	-1.22	0.43	2.68	0.003	
PC3	-1.76	0.20	-0.51		0.16	1.62	0.65	-7.22	0.36	4.52	0.152	
PC4	2.63	0.27	-0.90	0.46		-2.14	-0.92	5.05	0.44	7.69	0.117	
PC5	0.75	-0.06	0.15	0.17	-0.08		-0.27	8.48	0.52	1.46	0.261	
PC6	0.85	-0.18	0.20	0.38	-0.18	-1.48		3.86	0.50	3.44	0.062	

Table 1.9. **Explaining mispricing portfolios with productivity factors**

Panel A reports the intercepts (in % per month) and factor loadings from full-sample time-series regressions of 11 mispricing portfolios from Stambaugh and Yuan (2017) against productivity factors. Mispricing portfolios cluster in either mispricing related to the management (MGMT) or mispricing related to the performance (PERF). Panel B tabulates the similar results but the mimicking portfolios of productivity factors are constructed with base assets excluding mispricing factor. Acc denotes the accruals, following Sloan (1996). AG denotes the asset growth, following Cooper et al. (2008). CI denotes the composite equity issuance, following Daniel and Titman (2006). InvA denotes the investment-to-asset, following Titman et al. (2004). NOA denotes the net operating assets, following Hirshleifer et al. (2004). ISS denotes the net equity issuance, following Ritter (1991). DIST denotes the financial distress, following Campbell et al. (2008). GP denotes the gross profitability, following Novy-Marx (2013). Mom denotes the momentum following Jegadeesh and Titman (1993). OSCO denotes O-score, following Ohlson (1980). ROA denotes the return on asset, following F.Fama and R.French (2006). Factors include 6 mimicking productivity portfolios constructed from the full-sample estimation. Newey-West t -statistics (t-stat) with 6-month lags are provided. R^2 and standard errors of residuals (s(e), %) are reported. The sample period is from January 1972 to December 2015, except for DIST (October 1973 to December 2015).

Panel A: Including mispricing factor as base assets											
	MGMT						PERF				
	Acc	AG	CI	InvA	NOA	ISS	DIST	GP	Mom	OSCO	ROA
α	0.23	-0.14	0.08	0.04	0.18	0.05	-0.26	0.22	-0.27	0.31	0.18
t-stat	1.78	-1.06	0.55	0.29	1.34	0.45	-0.77	1.25	-0.76	1.67	1.04
β_{PC1}	-0.13	-0.18	-0.21	-0.08	0.02	-0.13	-0.04	0.01	0.19	-0.05	0.07
t-stat	-4.64	-8.03	-7.45	-2.54	0.63	-6.90	-0.67	0.38	3.07	-1.26	2.70
β_{PC2}	0.50	0.25	0.42	0.14	-0.02	0.25	-0.10	0.02	-0.38	0.30	-0.21
t-stat	8.06	4.93	7.44	2.21	-0.31	5.56	-0.68	0.19	-2.18	4.13	-3.71
β_{PC3}	0.02	-0.14	-0.10	-0.12	-0.12	-0.12	-0.12	0.19	-0.07	0.03	-0.19
t-stat	0.76	-3.77	-2.47	-2.88	-2.68	-4.35	-1.03	4.44	-0.73	0.75	-4.66
β_{PC4}	0.14	0.23	0.14	0.18	0.08	0.08	-0.06	-0.09	0.08	-0.12	-0.19
t-stat	7.07	15.58	6.60	9.13	3.39	5.93	-0.99	-3.74	1.29	-5.63	-10.11
β_{PC5}	-0.09	0.22	0.00	0.24	0.35	0.18	0.33	-0.15	1.48	-0.41	0.16
t-stat	-0.93	2.36	0.02	2.57	2.58	2.68	1.13	-1.03	7.14	-2.74	1.61
β_{PC6}	0.04	-0.10	-0.22	0.05	0.15	-0.18	-0.63	-0.42	-0.19	-0.20	-0.38
t-stat	0.88	-2.39	-5.10	1.25	3.45	-4.82	-4.74	-6.05	-1.37	-4.51	-8.51
R^2	0.22	0.50	0.38	0.27	0.07	0.37	0.31	0.25	0.31	0.20	0.46
s(e)	2.89	2.33	2.67	2.49	2.79	2.14	5.19	3.19	5.48	3.27	2.99
Panel B: Excluding mispricing factor as base assets											
	MGMT						PERF				
	Acc	AG	CI	InvA	NOA	ISS	DIST	GP	Mom	OSCO	ROA
α	0.44	-0.01	0.12	0.14	0.21	0.11	-0.20	0.45	0.50	0.05	-0.03
t-stat	2.97	-0.08	0.94	1.18	1.41	0.92	-0.48	2.20	1.17	0.28	-0.22
β_{PC1}	-0.01	-0.02	-0.03	-0.01	0.00	-0.01	0.00	0.03	0.03	0.00	0.01
t-stat	-2.95	-4.35	-4.67	-2.40	0.42	-2.57	-0.15	4.97	1.84	-0.30	1.75
β_{PC2}	0.08	0.04	0.07	0.03	-0.01	0.02	-0.10	-0.05	-0.16	0.03	-0.08
t-stat	6.06	2.94	6.18	2.22	-0.85	2.16	-2.58	-3.08	-3.94	2.13	-6.67
β_{PC3}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
t-stat	-0.22	-2.57	-2.00	-2.26	-3.57	-5.20	-2.90	0.89	-2.22	-1.96	-9.39
β_{PC4}	0.11	0.23	0.16	0.18	0.05	0.06	-0.15	-0.14	-0.11	-0.10	-0.22
t-stat	4.73	14.32	6.63	7.88	2.09	2.97	-2.79	-5.13	-1.57	-3.35	-10.27
β_{PC5}	-0.02	0.09	0.06	0.08	0.07	0.04	0.01	-0.08	0.13	-0.03	0.01
t-stat	-0.68	4.45	2.78	4.71	3.36	2.20	0.20	-2.59	2.17	-0.92	0.39
β_{PC6}	0.01	-0.06	-0.10	-0.01	0.06	-0.04	-0.12	-0.06	-0.01	-0.01	-0.05
t-stat	0.68	-3.33	-5.52	-0.66	2.96	-2.87	-2.05	-2.44	-0.22	-0.70	-2.89
R^2	0.18	0.46	0.37	0.29	0.08	0.27	0.24	0.20	0.18	0.16	0.49
s(e)	2.97	2.42	2.70	2.46	2.76	2.32	5.44	3.29	5.98	3.36	2.90

Table 1.10. **Explaining productivity factors with other pricing factors**

This table presents the excess returns (R^{EX}) and alphas of productivity factors, using full-sample estimation in Panel A and extending-window estimation in Panel B. Alphas are computed from various factor models, including CAPM (α^{CAPM}), the Fama and French (1993) three-factor model (α^{FF3}), Carhart (1997) four-factor model (α^{FF4}), Fama and French (2015) five-factor model (α^{FF5}), Fama and French (2015) six-factor model (α^{FF6}), Stambaugh and Yuan (2017) mispricing factor model (α^{SY}), Daniel et al. (2018) behavioral model (α^{DHS}), Hou et al. (2015) q -factor model (α^{HXZ}), and Hou et al. (2018b) q^5 model (α^{HMXZ}). Panel B presents similar results from the extending-window estimation. R^2 is reported. All returns are multiplied with 100. Newey-West adjusted t -statistics with 6-month (4-month for panel B) lags are provided in parentheses. The sample period is from January 1972 to December 2015 but the Daniel et al. (2018) factors are from July 1972 to December 2014. The testing period for panel B is from January 2001 to December 2015, but it is from January 2001 to December 2014 for the Daniel et al. (2018) factors.

Panel A: Full-sample estimation						
	PC1	PC2	PC3	PC4	PC5	PC6
R^{EX}	1.31 (4.71)	0.39 (2.78)	-0.95 (-3.13)	1.59 (3.29)	0.70 (7.40)	-0.99 (-4.30)
α^{CAPM}	1.29 (4.41)	0.32 (2.26)	-1.17 (-3.94)	1.93 (4.18)	0.62 (6.87)	-1.20 (-5.53)
R^2	0.00	0.03	0.11	0.08	0.13	0.13
α^{FF3}	1.37 (4.82)	0.34 (2.89)	-0.96 (-3.28)	1.32 (3.28)	0.63 (7.15)	-1.05 (-5.52)
R^2	0.06	0.41	0.34	0.47	0.14	0.20
α^{FF4}	1.17 (3.79)	0.32 (2.82)	-1.00 (-4.08)	1.10 (2.60)	0.38 (4.53)	-0.57 (-3.11)
R^2	0.08	0.42	0.34	0.48	0.43	0.39
α^{FF5}	1.31 (4.27)	0.27 (2.08)	-0.59 (-2.03)	1.08 (3.67)	0.46 (4.15)	-0.40 (-2.49)
R^2	0.09	0.43	0.43	0.71	0.28	0.53
α^{FF6}	1.15 (3.53)	0.25 (2.09)	-0.67 (-2.56)	0.96 (3.26)	0.27 (3.26)	-0.09 (-0.65)
R^2	0.10	0.43	0.43	0.71	0.52	0.65
α^{SY}	0.91 (3.04)	0.15 (1.28)	-0.95 (-3.79)	0.28 (0.72)	0.06 (0.81)	0.26 (1.82)
R^2	0.12	0.39	0.27	0.50	0.63	0.66
α^{DHS}	1.27 (3.60)	-0.08 (-0.48)	-0.73 (-2.42)	2.09 (3.64)	0.15 (1.28)	-0.34 (-1.56)
R^2	0.02	0.16	0.28	0.09	0.33	0.28
α^{HXZ}	1.35 (4.20)	0.45 (3.59)	-0.11 (-0.37)	1.22 (3.41)	0.38 (3.29)	-0.15 (-0.94)
R^2	0.04	0.50	0.53	0.75	0.38	0.54
α^{HMXZ}	1.16 (3.90)	0.41 (3.34)	-0.42 (-2.01)	0.74 (2.68)	0.21 (1.95)	0.06 (0.34)
R^2	0.05	0.50	0.56	0.77	0.44	0.56

Panel B: Extending-window estimation						
	PC1	PC2	PC3	PC4	PC5	PC6
R^{EX}	-1.71 (-3.53)	3.36 (1.89)	0.18 (0.74)	1.98 (2.29)	-0.63 (0.92)	0.19 (0.14)
α^{CAPM}	-1.85 (-3.84)	4.42 (2.28)	0.08 (0.29)	1.65 (1.80)	-0.37 (-0.68)	-0.36 (-0.24)
R^2	0.04	0.13	0.10	0.07	0.11	0.06
α^{FF3}	-1.51 (-3.50)	3.32 (2.25)	0.03 (0.13)	1.79 (1.74)	-0.31 (-0.56)	-0.18 (-0.12)
R^2	0.23	0.32	0.20	0.08	0.13	0.06
α^{FF4}	-1.39 (-3.24)	2.76 (1.94)	0.00 (0.00)	1.53 (1.49)	-0.49 (-0.79)	-0.27 (-0.19)
R^2	0.27	0.40	0.22	0.13	0.20	0.07
α^{FF5}	-1.08 (-2.41)	0.81 (0.73)	0.08 (0.33)	1.16 (1.04)	-0.17 (-0.31)	-0.09 (-0.05)
R^2	0.27	0.46	0.21	0.10	0.14	0.07
α^{FF6}	-1.11 (-2.63)	0.97 (0.93)	0.10 (0.41)	1.26 (1.17)	-0.07 (-0.15)	-0.05 (-0.03)
R^2	0.29	0.49	0.23	0.14	0.23	0.07
α^{SY}	-0.92 (-2.19)	1.43 (1.09)	-0.01 (-0.03)	0.70 (0.68)	-0.73 (-0.83)	0.36 (0.20)
R^2	0.30	0.38	0.20	0.13	0.14	0.07
α^{DHS}	-1.19 (-2.68)	1.93 (1.49)	0.25 (0.91)	0.70 (1.03)	-0.53 (-0.78)	0.28 (0.15)
R^2	0.13	0.32	0.18	0.11	0.14	0.07
α^{HXX}	-1.04 (-2.86)	1.11 (0.99)	0.12 (0.48)	0.86 (0.78)	-0.60 (-0.87)	0.17 (0.10)
R^2	0.33	0.52	0.16	0.18	0.17	0.09
α^{HMXZ}	-0.96 (-2.64)	0.93 (0.82)	0.15 (0.56)	0.61 (0.55)	-0.47 (-0.74)	0.58 (0.34)
R^2	0.33	0.52	0.16	0.20	0.18	0.10

Table 1.11. **Interpreting the missing factor as labor risk factor**

In panel A, the first column presents the Fama-MacBeth regressions of total TFP growth (ΔTFP) on labor productivity growth (Δ Labor productivity), capital productivity growth (Δ Capital productivity), and output growth (Δ Output). The second and third columns report the time-series regressions of first principal components (PC1) and its mimicking portfolio (R^{PC1}) against aggregate labor growth ($\Delta Labor^{Agg}$) and capital growth ($\Delta Capital^{Agg}$). Panel A reports the coefficients, t -statistics, and R^2 . Panel B reports the monthly quintile portfolios and long-short portfolio returns sorted on the labor share, in percentage. Newey-West adjusted t -statistics (t-stat) with 6-month lags are provided. Panel C tabulates the annual time-series correlation coefficients between the labor share factor and productivity principal components. The sample period is from January 1972 to December 2015.

Panel A: Productivity and labor risk							
	ΔTFP	PC1	R^{PC1}				
Δ Labor productivity	0.39 (44.50)						
Δ Capital productivity	0.22 (23.19)						
Δ Output	0.04 (4.50)						
$\Delta Labor^{Agg}$		-0.20 (-2.67)	-3.70 (-3.39)				
$\Delta Capital^{Agg}$		0.18 (1.04)	2.34 (0.92)				
R^2	0.70	0.24	0.14				
Panel B: Portfolios sorted by labor share							
	Low	2	3	4	High	H-L	t-stat
R^{EX}	0.55	0.52	0.64	0.71	1.02	0.47	(2.98)
α^{CAPM}	0.08	-0.05	0.06	0.10	0.41	0.33	(2.18)
α^{FF3}	0.14	-0.02	0.01	0.04	0.38	0.24	(1.88)
α^{FF4}	0.19	0.14	0.17	0.18	0.51	0.32	(2.46)
α^{FF5}	0.09	-0.05	-0.02	0.03	0.38	0.29	(2.09)
α^{FF6}	0.14	0.09	0.11	0.15	0.49	0.35	(2.59)
α^{SY}	0.14	0.08	0.09	0.11	0.42	0.28	(2.09)
α^{DHS}	0.10	0.11	0.16	0.27	0.61	0.51	(2.82)
α^{HXZ}	0.15	0.04	0.04	0.08	0.47	0.31	(2.07)
α^{HMXZ}	0.08	0.09	0.14	0.19	0.55	0.47	(3.11)
α^{TFP}	0.28	0.28	0.33	0.25	0.58	0.30	(1.58)
Panel C: Correlation between the labor share factor and productivity factors							
	PC1	PC2	PC3	PC4	PC5	PC6	
LS factor	0.43	-0.11	0.14	0.15	-0.11	0.09	

Table 1.12. Testing factor models augmented with the labor factor

Panel A presents the time-series regression of various pricing factors on productivity factors, replacing the first mimicking productivity factor (PC1) with the labor share factor (LS). Intercepts are in percentage. Newey-West adjusted t -statistics (t-stat) with 6-month lags are provided. Panel B reports Fama-MacBeth regressions of various factor models augmented with either the first mimicking productivity factor (PC1) or the labor share factor (LS). Test portfolios include 25 size and book-to-market sorted portfolios, 25 size and operating profitability sorted portfolios, 25 size and investment sorted portfolios, 25 size and momentum sorted portfolios, 25 size and idiosyncratic volatility sorted portfolios, 30 Fama-French industry portfolios, and the tested pricing factors. Factor models include the Fama and French (1993) three-factor model (FF3), 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. (2018b) q^5 model (HMXZ), Stambaugh and Yuan (2017) mispricing factor model (SY), Daniel et al. (2018) behavioral factor model (DHS). All coefficients are multiplied by 100. The t -statistics (t-stat) 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 sample period is from January 1972 to December 2015 but the sample period for the Daniel et al. (2018) factors is from July 1972 to December 2014.

Panel A: Regression of risk factors on TFP factor-mimicking portfolio augmented with labor share factor															
	MKT	SMB	HML	CMA	RMW	UMD	Q_{ME}	Q_{IA}	Q_{ROE}	EG	MGMT	PERF	MIS	FIN	PC1
α	0.01	0.04	-0.13	-0.17	0.16	-0.10	0.00	-0.11	0.22	0.41	0.01	0.18	-0.02	0.07	0.88
t-stat.	0.05	0.37	-0.81	-2.41	2.27	-0.54	-0.05	-2.16	2.94	4.05	0.14	1.14	-0.34	0.48	3.39
β_{LS}	0.50	0.42	-0.04	-0.08	-0.13	-0.29	0.44	-0.07	-0.12	-0.23	-0.27	-0.23	-0.28	-0.33	0.53
t-stat.	9.15	17.24	-0.80	-3.71	-5.39	-3.80	19.60	-4.09	-5.09	-9.43	-8.12	-4.94	-12.38	-5.33	6.15
β_{PC2}	0.17	-0.32	0.08	0.04	0.01	-0.16	-0.42	0.03	-0.21	-0.03	0.12	-0.04	0.09	0.13	1.17
t-stat.	3.37	-13.73	1.61	1.63	0.35	-1.89	-19.64	1.62	-9.28	-1.22	3.60	-0.71	3.98	2.22	12.02
β_{PC3}	0.02	0.11	-0.22	-0.15	-0.10	0.01	0.07	-0.23	-0.17	-0.08	-0.21	0.09	-0.05	-0.29	0.27
t-stat.	0.74	5.43	-5.28	-9.45	-3.74	0.11	3.82	-17.55	-8.29	-3.52	-7.06	1.72	-2.71	-6.47	3.40
β_{PC4}	-0.02	0.06	0.12	0.14	-0.10	0.08	0.06	0.13	-0.13	0.03	0.16	-0.03	0.11	0.09	0.12
t-stat.	-0.55	5.33	4.46	14.77	-7.54	1.82	5.47	13.92	-13.56	3.26	12.41	-1.21	10.76	3.17	2.71
β_{PC5}	1.13	0.04	0.09	0.19	-0.06	0.98	0.19	0.19	0.31	0.26	0.30	0.44	0.57	0.24	1.06
t-stat.	9.37	0.61	0.65	3.51	-1.32	8.38	2.89	4.10	6.30	4.04	4.21	3.25	9.50	2.76	-4.95
β_{PC6}	0.53	-0.08	-0.01	-0.01	-0.27	-0.21	-0.05	-0.02	-0.25	-0.13	-0.04	-0.46	-0.27	-0.23	-0.53
t-stat.	10.21	-2.86	-0.15	-0.47	-9.91	-2.25	-1.92	-0.86	-12.21	-5.02	-1.09	-6.93	-10.40	-4.84	-6.15
R^2	0.57	0.70	0.30	0.57	0.61	0.38	0.75	0.72	0.74	0.45	0.53	0.52	0.80	0.52	0.41

Panel B: Fama-MacBeth regressions of factor models augmented the first productivity factor or labor factor

	FF3+PC1		FF3+LS		FF5+PC1		FF5+LS		FF6+PC1		FF6+LS		HXZ+PC1		HXZ+LS	
	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	0.48	5.29	0.45	5.58	0.00	0.03	0.03	0.80	-0.05	-1.41	-0.06	-1.99	0.03	0.47	0.02	0.42
γ_{MKT}	0.09	0.40	0.14	0.63	0.49	2.35	0.46	2.26	0.57	2.79	0.57	2.80	0.46	2.20	0.47	2.28
γ_{SMB}	0.09	0.65	0.10	0.70	0.21	1.58	0.22	1.66	0.20	1.52	0.21	1.55				
γ_{HML}	0.25	1.79	0.26	1.85	0.10	0.68	0.07	0.53	0.27	2.00	0.27	2.05				
γ_{CMA}					0.32	2.74	0.29	2.58	0.29	2.56	0.24	2.12				
γ_{RMW}					0.45	4.06	0.42	4.11	0.28	2.9	0.28	2.91				
γ_{UMD}									0.73	3.72	0.73	3.74				
γ_{QME}													0.28	2.01	0.33	2.30
γ_{QIA}													0.37	3.08	0.34	2.93
γ_{QROE}													0.55	3.90	0.56	3.96
γ_{PC1}	0.72	2.14			1.15	3.47			1.10	3.36			1.08	3.27		
γ_{LS}			-0.14	-0.74			0.15	0.87			0.31	1.86			0.15	0.80
R^2	0.12		0.08		0.48		0.44		0.60		0.61		0.55		0.53	
$(5^{th}, 95^{th})$	(0.05, 0.37)		(0.03, 0.34)		(0.32, 0.62)		(0.28, 0.60)		(0.45, 0.71)		(0.50, 0.71)		(0.36, 0.65)		(0.35, 0.64)	
	HMXZ+PC1		HMXZ+LS		SY+PC1		SY+LS		DHS+PC1		DHS+LS					
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat				
γ_0	-0.02	-0.44	-0.05	-1.01	-0.01	-0.15	-0.01	-0.11	0.19	1.78	0.00	-0.03				
γ_{MKT}	0.53	2.57	0.54	2.62	0.55	2.63	0.54	2.62	0.50	2.14	0.56	2.51				
γ_{QME}	0.28	1.96	0.30	2.15												
γ_{QIA}	0.40	3.35	0.37	3.15												
γ_{QROE}	0.51	3.59	0.49	3.46												
γ_{EG}	0.62	4.16	0.71	5.19												
γ_{MISME}					0.31	2.37	0.31	2.38								
γ_{MGMT}					0.53	3.41	0.51	3.30								
γ_{PERF}					0.64	3.33	0.62	3.24								
γ_{FIN}									0.48	2.17	0.65	3.10				
γ_{PEAD}									0.39	2.32	0.66	3.87				
γ_{PC1}	1.11	3.36			1.08	3.28			1.12	3.28						
γ_{LS}			0.33	1.83			0.23	1.27			0.60	2.67				
R^2	0.60		0.60		0.62		0.62		0.33		0.51					
$(5^{th}, 95^{th})$	(0.43, 0.68)		(0.43, 0.68)		(0.42, 0.69)		(0.43, 0.68)		(0.13, 0.58)		(0.27, 0.61)					

Table 1.13. **Interpreting Productivity factors**

This table presents the coefficients and t -statistics from panel regressions of factor loadings of each productivity factor on firm characteristics with firm and year fixed effects (Year FE). We estimate factor loadings for each firm by regressing firm level TFP against productivity factors (PC1 to PC6) in 20 year rolling-window, starting from 1991. Labor share (LS) is the ratio of labor expense over value added. Size is logarithmic price (PRC) times shares outstanding (SHROUT). Cash-flow (CF) is income before extraordinary items (IB) plus depreciation and amortization (DP) divided by lagged net property, plant, and equipment (PPENT). Book-to-market (BM) is the ratio of book value of equity to market value of equity. Asset growth (AG) is the ratio of first difference of total asset (AT) over average of current and lagged total asset. Cumulative return ($R_{2,12}$) is the cumulative stock return from twelve months to two months. Mispricing score (MIS) is the average rank score estimated from 11 mispricing portfolios in Stambaugh and Yuan (2017). Since mispricing score include both asset growth and cumulative return, we regress asset growth and cumulative return on mispricing score and use their residuals, AG^r and $R_{2,12}^r$, respectively. Leverage (LEV) is the ratio of long-term debt (DLCC) plus debt in current liabilities (DLC) over long-term debt, debt in liabilities, and shareholder's equity (SEQ). Cash-flow volatility (σ_{CF}) is the standard deviation of cash flow over last 10 years. R&D intensity is the ratio of R&D expense (XRD) over sales (SALE), where R&D expense is equal to 0 if missing. t -statistics are in the parentheses. All variables are standardized. The sample period is from 1991 to 2015.

	(1)	(2)	(3)	(4)	(5)	(6)
	b1	b2	b3	b4	b5	b6
LS	0.057 (3.247)	-0.011 (-0.597)	0.004 (0.250)	-0.003 (-0.136)	0.031 (1.599)	0.052 (2.495)
Size	0.011 (0.376)	0.081 (2.647)	-0.128 (-4.455)	0.204 (6.780)	-0.005 (-0.156)	-0.135 (-3.997)
CF	0.001 (0.058)	-0.012 (-1.232)	-0.018 (-1.973)	0.003 (0.354)	-0.039 (-3.837)	0.004 (0.400)
BM	-0.063 (-3.234)	0.066 (3.108)	-0.030 (-1.485)	0.045 (2.149)	-0.018 (-0.834)	-0.105 (-4.487)
AG^r	0.016 (2.444)	-0.010 (-1.446)	0.025 (3.677)	-0.015 (-2.075)	-0.005 (-0.620)	0.027 (3.437)
$R_{2,12}^r$	0.003 (0.489)	0.018 (2.370)	0.016 (2.232)	-0.013 (-1.701)	0.017 (2.187)	-0.004 (-0.448)
MIS	0.015 (1.874)	-0.005 (-0.644)	0.012 (1.495)	-0.012 (-1.504)	0.010 (1.176)	0.018 (1.947)
LEV	-0.047 (-3.988)	0.017 (1.298)	-0.082 (-6.878)	0.016 (1.264)	0.006 (0.454)	-0.059 (-4.184)
σ_{CF}	-0.004 (-0.342)	-0.025 (-2.220)	-0.001 (-0.093)	-0.006 (-0.563)	-0.014 (-1.189)	-0.023 (-1.868)
R&D	-0.005 (-0.232)	-0.073 (-3.036)	-0.046 (-2.074)	0.015 (0.646)	-0.072 (-2.928)	-0.026 (-0.989)
Cons	-0.000 (-0.087)	0.000 (0.077)	0.000 (0.051)	-0.001 (-0.143)	0.001 (0.155)	0.001 (0.130)
Obs	10717	10717	10717	10717	10717	10717
R^2	0.698	0.641	0.689	0.657	0.621	0.572
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

1.7 Appendices

1.7.1 Productivity shocks and stock returns: A motivating model

Consider a one-period setting where an all-equity firm uses physical capital and labor to generate outputs. Assume the simple Cobb-Douglas production function:

$$Y_{it} = Z_{it} L_{it}^{\beta_L} K_{it}^{\beta_K} \quad (1.16)$$

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 , respectively. Suppose the capital depreciation rate is δ and the labor separation rate is ψ . The capital installation equation is

$$K_{it+1} = I_{it} + (1 - \delta)K_{it} \quad (1.17)$$

where I_{it} is capital investment at time t . Capital adjustment is subject to a cost of $G(I_{it}, K_{it})$. Similarly, the labor evolves as

$$L_{it+1} = H_{it} + (1 - \psi)L_{it} \quad (1.18)$$

where H_{it} is labor hiring at time t . The labor hiring costs are $\phi(H_{it}, L_{it})$. Given a one-period pricing kernel of $M_{t,t+1}$, this firm optimally chooses capital investment and labor hiring to maximize the firm value, as follows:

$$\max_{I_{it}, H_{it}} Y_{it} - I_{it} - G(I_{it}, K_{it}) - W_t L_{it} - \phi(H_{it}, L_{it}) \quad (1.19)$$

$$+ \mathbb{E}_t \{ M_{t,t+1} [Y_{it+1} + (1 - \delta)K_{it+1} - W_{t+1}L_{it+1}] \}$$

$$s.t. \quad K_{it+1} = I_{it} + (1 - \delta)K_{it} \quad (1.20)$$

$$L_{it+1} = H_{it} + (1 - \psi)L_{it} \quad (1.21)$$

where W_t is exogenously given wage.²⁷

The Lagrangian function is

$$\begin{aligned}
\mathcal{L} = & Y_{it} - I_{it} - G(I_{it}, K_{it}) - W_t L_{it} - \phi(H_{it}, L_{it}) \\
& + \mathbb{E}_t\{M_{t,t+1}[Y_{it+1} + (1 - \delta)K_{it+1} - W_{t+1}L_{it+1}]\} \\
& - q_{it}^K[K_{it+1} - I_{it} - (1 - \delta)K_{it}] \\
& - q_{it}^L[L_{it+1} - H_{it} - (1 - \psi)L_{it}].
\end{aligned} \tag{1.22}$$

where q_{it}^K and q_{it}^L are the Lagrangian multipliers associated with capital installation and labor hiring constraints in Eq. (1.20) and (1.21), respectively. G_{it} , $Y_{K_{it+1}}$, $\phi_{H_{it}}$, and $Y_{L_{it+1}}$ indicate the partial derivatives of the corresponding functions.

The first order conditions give the optimal investment and hiring decisions, as follows:

$$q_{it}^K - 1 - G_{I_{it}} = 0 \tag{1.23}$$

$$\mathbb{E}_t\{M_{t,t+1}[Y_{K_{it+1}} + (1 - \delta)]\} - q_{it}^K = 0 \tag{1.24}$$

$$q_{it}^L - \phi_{H_{it}} = 0 \tag{1.25}$$

$$\mathbb{E}_t\{M_{t,t+1}[Y_{L_{it+1}} - W_{t+1}]\} - q_{it}^L = 0. \tag{1.26}$$

Therefore, the marginal costs and benefits of adding one additional unit of physical capital is given by

$$q_{it}^K = 1 + G_{I_{it}} = \mathbb{E}_t\{M_{t,t+1}[Y_{K_{it+1}} + (1 - \delta)]\}. \tag{1.27}$$

The marginal costs and benefits of labor hiring is given by

$$q_{it}^L = \phi_{H_{it}} = \mathbb{E}_t\{M_{t,t+1}[Y_{L_{it+1}} + W_{t+1}]\}. \tag{1.28}$$

²⁷For simplicity, we don't consider wage bargaining process here.

The ex-dividend stock price is

$$P_{it} = \mathbb{E}_t\{M_{t,t+1}[Y_{it+1} + (1 - \delta)K_{it+1} - W_{t+1}L_{it+1}]\}. \quad (1.29)$$

If the production function is homogenous of degree one with respect to capital and labor, then the stock price can be simplified as

$$P_{it} = q_{it}^K K_{it+1} + q_{it}^L L_{it+1}. \quad (1.30)$$

That is, firm value equals the summation of current values of physical capital and labor, which can be computed from their marginal q directly. The cash flows at time $t + 1$ is $Y_{it+1} + (1 - \delta)K_{it+1} - W_{t+1}L_{it+1}$. Therefore, the stock return is

$$R_{it} = \frac{Y(Z_{it+1}, K_{it+1}, L_{it+1}) + (1 - \delta)K_{it+1} - W_{t+1}L_{it+1}}{\mathbb{E}_t\{M_{t,t+1}[Y(Z_{it+1}, K_{it+1}, L_{it+1}) + (1 - \delta)K_{it+1} - W_{t+1}L_{it+1}]\}}. \quad (1.31)$$

Suppose the productivity is governed by some systematic components, as follows

$$\log Z_{it} = b_i X_t + \varepsilon_{it} \quad (1.32)$$

where X_t is a vector consisting of the systematic productivity components, b_i is firm i 's exposure to the systematic productivity shocks, ε_{it} is the idiosyncratic productivity shocks. Then Eq. (1.31) says that the expected stock returns are affected by these systematic risks. In other words, if the expected returns are governed by multiple pricing factors, these factors should correspond to the common productivity components in firms' production. Moreover, if we attribute the total factor productivity to capital productivity and labor productivity, then we see common shocks to both capital productivity and labor productivity affect stock returns.

1.7.2 TFP estimation

(1) Data

In order to estimate the total factor productivity (TFP), we use two main datasets: annual Compustat and CRSP files. By matching Compustat and CRSP, we estimate TFP for public firms in the United States. The sample period starts from 1965 to 2015. 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), depreciation, depletion and amortization (DPACT), employees (EMP), and staff expense (XLR).

We apply several filters to estimate coefficients of labor and capital. Our main results use common stocks listed at NYSE/AMEX/Nasdaq with 4-digit SIC codes less than 4900. This corresponds to the agriculture, mining, construction, manufacturing, and transportation industries. We also consider an expanded sample, by further including firms in wholesale trade and retail trade (SIC codes between 5000 and 5999), and services (SIC codes between 7000 and 8999), as a robustness check. Also, firms with sales or total assets less than \$1 million, or with negative employees, capital expenditure, and depreciation are excluded. Firms with value-added and material costs less than 0.1 are excluded as well. The stock price of each firm must be greater than \$1 at the end of a year. The labor expense ratio, which we will describe below, should be between 0 and 1. Finally, the sample firms should report their accounting information for 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 the price index for nonresidential private fixed investment (NIPA table 5.3.4 qtr line2). We obtain employees' earnings data from the Bureau of Labor Statistics (CES0500000030). Because this table reports weekly earnings which are annualized to be used in calculations.

(2) Input variables

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

Value-added (Y_{it}) is $\frac{SALE_{it} - Materials_{it}}{GDP_deflator}$. 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 staff expense (XLR). However, only a small number of firms report their staff expense. We replace the missing observations with the interaction of the industry average labor expense ratio and total expense. To be specific, we calculate the labor expense ratio, $\frac{XLR_{it}}{SALE_{it}-OIBDP_{it}}$, for each firm. Next, 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 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 wages 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 by following Imrohoroglu and Tuzel (2014). First, we compute the age of capital each year. Age of capital stock is $\frac{DPACT_{it}}{DP_{it}}$. We take a 3-year moving average to smooth the capital age. Then, we match capital stock with the price index for private fixed investment at the current year minus capital age. Finally, we take a 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 deflated by the current fixed investment price index.

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

(3) TFP estimation

We follow Olley and Pakes (1996) to estimate the total factor productivity (TFP) because this is one of the robust ways of measuring production function parameters by 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 to avoid the selection bias. Imrohoroglu and Tuzel (2014) show how to estimate Olley and Pakes (1996) TFP using annual Compustat and

share their codes.²⁸ Our TFP estimation process is based on Imrohoroglu and Tuzel (2014) with some modifications.

We start from the simple Cobb-Douglas production technology.

$$Y_{it} = L_{it}^{\beta_L} K_{it}^{\beta_K} Z_{it} \quad (1.33)$$

where Y_{it} , L_{it} , K_{it} , and Z_{it} are value-added, labor, capital stock, and productivity 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 the labor coefficient without scaling. After being scaled by the capital stock and transformed into logarithmic values, Eq. (1.33) can be rewritten as

$$\text{Log} \frac{Y_{it}}{K_{it}} = \beta_L \text{Log} \frac{L_{it}}{K_{it}} + (\beta_K + \beta_L - 1) \text{Log} K_{it} + \text{Log} Z_{it} \quad (1.34)$$

We define $\text{Log} \frac{Y_{it}}{K_{it}}$, $\text{Log} \frac{L_{it}}{K_{it}}$, $\text{Log} K_{it}$, and $\text{Log} Z_{it}$ 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. (1.34) as

$$yk_{it} = \beta_l lk_{it} + \beta_k k_{it} + z_{it} \quad (1.35)$$

When facing the productivity shock (z_{it}) at t , a firm decides the optimal labor and the capital investment. Because the productivity (z_{it}) is a state variable, the optimal capital investment (ik_{it}^*) is a function of the productivity (z_{it}). Olley and Pakes (1996) assume a monotonic relationship between the investment and productivity, so the productivity is a function of investment, i.e., $z_{it} = h(ik_{it})$. We assume that the function $h(ik_{it})$ is 3^{rd} -order polynomials of ik_{it} .

²⁸<http://www-bcf.usc.edu/~tuzel/TFPUUpload/Programs/>

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

$$y_{it} = \beta_l l k_{it} + \beta_k k_{it} + \beta_0 + \beta_{ik} i k_{it} + \beta_{ik^2} i k_{it}^2 + \beta_{ik^3} i k_{it}^3 + \eta_j + \epsilon_{it} \quad (1.36)$$

where $h(ik_{it}) = \beta_0 + \beta_{ik} i k_{it} + \beta_{ik^2} i k_{it}^2 + \beta_{ik^3} i k_{it}^3$ and η_j is 4-digit SIC code to capture the differences of industrial technologies. From this stage, we estimate the labor coefficients, $\hat{\beta}_l$.

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

$$\begin{aligned} E_t(y k_{i,t+1} - \hat{\beta}_l l k_{i,t+1} - \eta_j) &= \beta_k k_{i,t+1} + E_t(z_{i,t+1} | z_{i,t}, survival) \\ &= \beta_k k_{i,t+1} + g(z_{it}, \hat{P}_{survival,t}) \end{aligned} \quad (1.37)$$

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 3rd-order polynomials of investment rate. When we run the Probit regression, we include all firms without financial industry and regulated industry to have enough number of observations and use this exit probability to estimate TFP for manufacturing industry. z_{it} is computed as $\beta_0 + \beta_{ik} i k_{it} + \beta_{ik^2} i k_{it}^2 + \beta_{ik^3} i k_{it}^3$. 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:

$$TFP_{it} = \exp(y k_{it} - \hat{\beta}_l l k_{i,t} - (\hat{\beta}_K + \hat{\beta}_l - 1) k_{it} - \eta_j) \quad (1.38)$$

. We estimate TFP growth as the innovations of logarithmic TFP from the first-order autoregressions using a 5-year rolling window. TFP estimates are available from 1972 to 2015.

1.7.3 Alternative test assets

Tables 1.14 - 1.19 show the complete time-series regression results of various test portfolios on the productivity factors.

1.7.4 Explaining the first mimicking productivity factor

Table 1.20 reports the time-series regression results of PC1 on various factor models.

1.7.5 Robustness checks: Using an expanded sample

In this section, we replicate all main results, using an expanded sample. That is, we estimate TFP for firms with a four-digit SIC code lower than 4900 (agriculture, mining, manufacturing, construction, and transportation industry), or between 5000 and 5999 (wholesale trade and retail trade), or between 7000 and 8999 (services industry). We present the descriptive statistics in Table 1.21. Table 1.22 presents the time-series regression results, using productivity factors to explain other pricing factors. Table 1.23 reports the time-series regression results, using productivity factors to explain various test portfolios. Table 1.24 reports the cross-sectional regression results, using various factor models, including the productivity-based model. Table 1.25 reports the time-series regression results, using other pricing factors to explain productivity factors. Overall, the results are qualitatively similar to those reported in Table 1.1, 1.5, 1.6, 1.7 and 1.10.

Table 1.14. **Alternative test assets: 25 Size and Book-to-market sorted portfolios**

This table reports the intercepts (α , in % per month) and factor loadings from the full-sample time-series regressions of 25 size and book-to-market sorted portfolios. Factors include six productivity factors. The Newey-West t -statistics with six months lags are provided. The sample period is from January 1972 to December 2015. R^2 and standard errors of residuals (s(e), %) are reported.

	Low BM	2	3	4	High BM	Low BM	2	3	4	High BM
	α (% per month)					t-statistics				
Small	-0.19	0.30	0.14	0.33	0.43	-0.55	1.03	0.48	1.21	1.31
2	0.03	0.12	0.19	0.18	0.11	0.09	0.46	0.70	0.73	0.35
3	0.20	0.18	0.17	0.22	0.26	0.69	0.69	0.70	0.85	0.82
4	0.33	0.08	0.10	0.23	0.07	1.27	0.30	0.40	0.91	0.23
Big	0.22	0.08	-0.01	-0.19	0.07	1.10	0.40	-0.05	-0.73	0.29
	PC1 loading					t-statistics				
Small	0.40	0.32	0.26	0.22	0.20	7.00	6.92	6.28	5.86	4.67
2	0.39	0.26	0.20	0.17	0.19	7.52	6.28	4.71	4.46	4.23
3	0.36	0.20	0.14	0.09	0.11	7.69	4.82	3.34	2.26	2.41
4	0.28	0.15	0.09	0.05	0.07	6.32	3.43	2.13	1.31	1.47
Big	0.12	0.08	0.03	-0.01	0.04	4.57	2.34	0.81	-0.29	0.93
	PC2 loading					t-statistics				
Small	-0.77	-0.68	-0.50	-0.48	-0.36	-5.34	-5.84	-4.42	-4.61	-2.68
2	-0.67	-0.44	-0.32	-0.27	-0.34	-4.83	-3.54	-2.66	-2.49	-2.87
3	-0.57	-0.26	-0.12	-0.05	-0.04	-4.83	-2.26	-1.07	-0.45	-0.26
4	-0.34	-0.08	0.06	0.08	0.11	-3.24	-0.69	0.48	0.81	0.88
Big	0.06	0.09	0.17	0.28	0.29	0.77	1.01	2.05	2.91	2.43
	PC3 loading					t-statistics				
Small	0.31	0.28	0.14	0.12	0.12	4.98	4.87	2.06	1.93	1.41
2	0.23	0.14	0.06	0.03	0.04	3.66	2.08	0.85	0.48	0.53
3	0.23	0.09	0.02	0.00	0.00	4.01	1.56	0.33	-0.03	-0.05
4	0.23	0.02	0.00	-0.02	-0.06	4.88	0.32	-0.06	-0.32	-0.68
Big	0.11	-0.03	-0.11	-0.14	-0.10	3.05	-0.77	-2.43	-2.29	-1.65
	PC4 loading					t-statistics				
Small	0.08	0.12	0.11	0.13	0.15	1.67	3.00	2.60	3.20	3.19
2	-0.02	0.04	0.05	0.08	0.13	-0.31	0.93	1.19	1.98	2.68
3	-0.05	0.01	0.03	0.06	0.11	-1.23	0.26	0.71	1.45	2.14
4	-0.06	-0.01	0.04	0.08	0.10	-1.35	-0.14	0.76	2.01	1.97
Big	-0.08	-0.01	0.02	0.08	0.11	-2.20	-0.26	0.72	1.99	2.48

PC5 loading						t-statistics				
Small	1.64	1.55	1.42	1.37	1.28	6.66	7.74	6.29	6.12	4.72
2	1.67	1.52	1.34	1.38	1.56	7.61	7.58	6.22	6.33	5.88
3	1.55	1.46	1.23	1.20	1.33	8.04	7.60	5.77	6.11	5.40
4	1.44	1.34	1.24	1.22	1.40	9.17	6.79	5.91	6.90	6.24
Big	1.16	1.28	1.26	1.28	1.23	8.05	7.78	7.59	5.78	5.71
PC6 loading						t-statistics				
Small	0.90	0.70	0.58	0.51	0.52	11.40	9.42	6.43	5.75	4.76
2	0.79	0.57	0.46	0.48	0.57	9.71	6.61	5.13	5.08	4.58
3	0.74	0.52	0.45	0.43	0.47	10.57	5.79	5.15	4.55	4.51
4	0.68	0.51	0.48	0.51	0.60	10.92	6.14	4.69	5.56	5.20
Big	0.52	0.53	0.52	0.58	0.67	9.68	8.16	7.09	4.79	5.99
R^2						s(e)				
Small	0.48	0.49	0.37	0.36	0.29	5.71	4.95	4.67	4.49	5.06
2	0.45	0.36	0.27	0.27	0.27	5.38	4.82	4.62	4.44	5.21
3	0.48	0.33	0.24	0.21	0.19	4.84	4.51	4.35	4.38	5.10
4	0.48	0.30	0.25	0.26	0.24	4.40	4.38	4.41	4.15	4.96
Big	0.50	0.41	0.39	0.35	0.29	3.35	3.53	3.46	3.87	4.63

Table 1.15. **Alternative test assets: 25 Size and Profitability sorted portfolios**

This table reports the intercepts (α , in % per month) and factor loadings from the full-sample time-series regressions of 25 size and operating profitability sorted portfolios. Factors include six productivity factors. The Newey-West t -statistics with six months lags are provided. The sample period is from January 1972 to December 2015. R^2 and standard errors of residuals (s(e), %) are reported.

	Low Op	2	3	4	High Op	Low Op	2	3	4	High Op
	α (% per month)					t-statistics				
Small	0.06	0.24	0.13	0.17	0.03	0.19	0.86	0.45	0.54	0.08
2	0.06	0.00	0.12	0.25	0.19	0.21	0.02	0.46	0.89	0.62
3	0.19	0.15	0.15	0.11	0.28	0.66	0.62	0.62	0.44	0.99
4	0.24	0.17	0.12	0.23	0.15	0.89	0.72	0.51	0.92	0.56
Big	0.07	0.00	0.05	0.20	0.17	0.27	0.01	0.23	0.97	0.90
	PC1 loading					t-statistics				
Small	0.31	0.24	0.24	0.26	0.32	6.77	5.85	5.66	5.67	6.26
2	0.30	0.24	0.22	0.25	0.29	6.25	6.01	5.49	6.00	6.19
3	0.24	0.15	0.18	0.20	0.25	5.43	4.09	4.79	4.93	5.57
4	0.15	0.13	0.12	0.15	0.20	3.79	3.36	3.07	3.59	4.51
Big	0.11	0.04	0.09	0.09	0.09	3.20	1.27	3.04	3.14	3.73
	PC2 loading					t-statistics				
Small	-0.61	-0.49	-0.44	-0.48	-0.52	-5.03	-4.12	-3.50	-3.52	-3.38
2	-0.51	-0.36	-0.37	-0.41	-0.45	-4.03	-3.10	-3.46	-3.46	-3.10
3	-0.28	-0.24	-0.21	-0.25	-0.32	-2.49	-2.50	-2.22	-2.25	-2.37
4	-0.04	-0.05	-0.04	-0.09	-0.20	-0.40	-0.44	-0.38	-0.84	-1.78
Big	0.14	0.19	0.15	0.12	0.06	1.61	2.25	1.79	1.64	0.82
	PC3 loading					t-statistics				
Small	0.32	0.08	0.04	0.02	0.09	5.10	1.08	0.48	0.28	1.11
2	0.25	0.08	0.04	0.07	0.06	3.54	1.18	0.54	1.00	0.75
3	0.25	0.07	0.05	0.03	0.07	3.82	1.36	0.97	0.48	0.98
4	0.19	0.08	0.03	0.03	0.06	3.62	1.71	0.56	0.54	1.02
Big	0.04	0.00	0.00	0.03	0.04	0.92	0.05	-0.07	0.82	1.04
	PC4 loading					t-statistics				
Small	0.17	0.09	0.06	0.04	0.05	3.96	1.93	1.34	0.88	1.03
2	0.10	0.06	0.04	0.01	-0.01	2.10	1.38	0.98	0.12	-0.17
3	0.09	0.04	0.03	0.00	-0.04	2.16	1.05	0.76	-0.02	-0.92
4	0.10	0.06	0.01	-0.01	-0.03	2.40	1.49	0.21	-0.36	-0.76
Big	0.04	0.05	0.02	-0.04	-0.05	1.05	1.45	0.58	-1.30	-1.51

PC5 loading						t-statistics				
Small	1.47	1.38	1.37	1.41	1.61	6.23	5.60	5.49	5.83	6.70
2	1.64	1.51	1.42	1.35	1.53	7.15	7.01	7.02	5.90	6.60
3	1.45	1.36	1.33	1.38	1.44	7.32	7.49	7.73	6.68	7.16
4	1.34	1.33	1.25	1.32	1.45	8.07	8.39	6.62	7.26	8.40
Big	1.33	1.23	1.26	1.14	1.22	7.88	8.19	7.89	7.96	8.69
PC6 loading						t-statistics				
Small	0.78	0.50	0.46	0.48	0.58	9.77	4.98	4.33	4.55	5.89
2	0.82	0.54	0.48	0.45	0.51	9.43	5.63	5.09	4.23	5.20
3	0.85	0.49	0.49	0.47	0.47	12.02	5.79	6.55	4.95	5.20
4	0.83	0.60	0.49	0.49	0.52	12.11	7.58	5.34	5.83	6.90
Big	0.87	0.64	0.63	0.55	0.47	11.33	10.33	8.96	9.75	8.43
R^2						s(e)				
Small	0.49	0.31	0.28	0.26	0.31	5.22	4.71	4.64	4.97	5.43
2	0.44	0.32	0.29	0.28	0.29	5.35	4.66	4.45	4.74	5.14
3	0.45	0.31	0.31	0.29	0.31	5.00	4.24	4.13	4.43	4.81
4	0.43	0.35	0.30	0.32	0.34	4.61	4.13	4.14	4.18	4.41
Big	0.48	0.44	0.47	0.48	0.47	4.09	3.46	3.30	3.25	3.24

Table 1.16. **Alternative test assets: 25 Size and Investment sorted portfolios**

This table reports the intercepts (α , in % per month) and factor loadings from the full-sample time-series regressions of 25 size and investment sorted portfolios. Factors include six productivity factors. The Newey-West t -statistics with six months lags are provided. The sample period is from January 1972 to December 2015. R^2 and standard errors of residuals (s(e), %) are reported.

	Low Inv	2	3	4	High Inv	Low Inv	2	3	4	High Inv
	α (% per month)					t-statistics				
Small	0.38	0.37	0.29	0.13	-0.19	1.15	1.26	1.02	0.47	-0.58
2	0.12	0.13	0.21	0.21	0.02	0.39	0.50	0.89	0.79	0.05
3	0.24	0.20	0.18	0.23	0.22	0.87	0.82	0.74	0.94	0.79
4	0.09	0.10	0.14	0.26	0.35	0.32	0.40	0.62	1.11	1.32
Big	0.08	-0.04	0.02	0.13	0.37	0.34	-0.21	0.13	0.70	1.69
	PC1 loading					t-statistics				
Small	0.29	0.22	0.26	0.27	0.34	6.58	5.59	6.14	6.27	7.03
2	0.24	0.19	0.21	0.23	0.36	5.16	4.79	5.53	5.79	7.67
3	0.19	0.12	0.15	0.20	0.31	4.17	3.16	4.10	5.38	6.80
4	0.12	0.10	0.12	0.15	0.27	2.84	2.60	3.08	4.20	5.75
Big	0.05	0.03	0.01	0.09	0.25	1.44	1.15	0.43	3.54	8.56
	PC2 loading					t-statistics				
Small	-0.60	-0.47	-0.51	-0.52	-0.62	-4.99	-4.56	-4.91	-4.55	-4.38
2	-0.40	-0.28	-0.38	-0.37	-0.60	-3.29	-2.35	-3.95	-3.22	-4.65
3	-0.16	-0.16	-0.18	-0.30	-0.45	-1.25	-1.70	-1.68	-3.00	-3.91
4	0.11	0.08	-0.08	-0.19	-0.31	0.99	0.70	-0.82	-2.12	-2.87
Big	0.25	0.17	0.14	0.07	-0.01	2.56	2.57	1.97	0.92	-0.10
	PC3 loading					t-statistics				
Small	0.30	0.12	0.09	0.11	0.24	4.93	1.99	1.33	1.66	3.02
2	0.14	0.04	0.07	0.09	0.22	2.03	0.62	1.23	1.36	2.92
3	0.10	0.04	0.03	0.11	0.20	1.46	0.71	0.45	2.00	3.02
4	0.03	-0.03	0.01	0.07	0.26	0.41	-0.58	0.28	1.43	4.96
Big	-0.07	-0.08	-0.03	0.03	0.18	-1.87	-2.39	-0.92	0.78	3.96
	PC4 loading					t-statistics				
Small	0.22	0.12	0.10	0.10	0.07	4.91	2.96	2.38	2.37	1.50
2	0.15	0.06	0.09	0.04	-0.01	3.17	1.40	2.31	0.77	-0.22
3	0.10	0.09	0.04	0.01	-0.05	2.08	2.67	0.88	0.28	-1.26
4	0.09	0.06	0.04	-0.01	-0.05	2.07	1.38	1.19	-0.23	-1.22
Big	0.09	0.05	0.01	-0.04	-0.14	2.20	1.82	0.47	-1.10	-3.88

PC5 loading						t-statistics				
Small	1.53	1.32	1.42	1.46	1.54	6.43	5.97	5.96	6.14	6.67
2	1.60	1.35	1.45	1.47	1.64	6.73	6.35	8.07	6.64	7.33
3	1.34	1.36	1.32	1.41	1.48	6.22	7.52	7.30	7.53	7.28
4	1.36	1.27	1.33	1.35	1.43	6.53	7.62	8.31	8.36	8.43
Big	1.29	1.28	1.29	1.24	1.08	7.79	8.87	9.12	8.88	7.13
PC6 loading						t-statistics				
Small	0.78	0.51	0.52	0.56	0.73	9.14	5.67	5.53	6.13	9.01
2	0.70	0.45	0.51	0.52	0.76	7.06	4.78	6.01	5.01	9.84
3	0.58	0.47	0.47	0.52	0.71	6.54	6.16	5.50	5.98	9.84
4	0.61	0.52	0.53	0.52	0.74	7.26	6.17	7.31	6.75	11.18
Big	0.59	0.54	0.51	0.55	0.66	7.84	9.70	8.15	8.44	11.92
R^2						s(e)				
Small	0.49	0.35	0.35	0.36	0.42	5.23	4.49	4.53	4.64	5.39
2	0.37	0.26	0.34	0.32	0.43	5.15	4.48	4.28	4.65	5.26
3	0.28	0.29	0.29	0.35	0.43	4.92	4.11	4.08	4.32	4.91
4	0.28	0.28	0.32	0.35	0.48	4.69	4.14	3.92	4.05	4.63
Big	0.34	0.43	0.46	0.48	0.56	3.87	3.10	3.10	3.29	3.73

Table 1.17. **Alternative test assets: 25 Size and Momentum sorted portfolios**

This table reports the intercepts (α , in % per month) and factor loadings from the full-sample time-series regressions of 25 size and momentum sorted portfolios. Factors include six productivity factors. The Newey-West t -statistics with six months lags are provided. The sample period is from January 1972 to December 2015. R^2 and standard errors of residuals (s(e), %) are reported.

	Loser	2	3	4	Winner	Loser	2	3	4	Winner
	α (% per month)					t-statistics				
Small	0.24	0.19	0.32	0.40	0.49	0.54	0.60	1.10	1.42	1.58
2	0.38	0.31	0.25	0.23	0.26	0.93	1.00	0.94	0.87	0.97
3	0.63	0.33	0.21	0.03	0.14	1.59	1.12	0.77	0.12	0.54
4	0.66	0.37	0.24	0.15	0.04	1.70	1.29	0.93	0.63	0.14
Big	0.49	0.40	0.04	-0.04	-0.13	1.38	1.70	0.18	-0.23	-0.57
	PC1 loading					t-statistics				
Small	0.25	0.20	0.18	0.21	0.32	3.9466	4.26	4.097	5.0426	7.2253
2	0.24	0.20	0.19	0.22	0.37	3.7063	4.3079	4.5071	5.5312	8.3135
3	0.16	0.15	0.16	0.17	0.32	2.665	3.3855	3.8717	4.5031	8.1938
4	0.11	0.11	0.11	0.11	0.29	1.7179	2.0177	2.4484	3.02	7.5045
Big	0.08	0.05	0.06	0.07	0.21	1.4937	1.1795	1.8459	2.2366	6.4268
	PC2 loading					t-statistics				
Small	-0.35	-0.32	-0.33	-0.38	-0.59	-1.54	-2.12	-2.49	-3.29	-5.08
2	-0.28	-0.27	-0.30	-0.34	-0.65	-1.39	-1.90	-2.73	-3.27	-6.75
3	-0.10	-0.14	-0.20	-0.17	-0.46	-0.48	-1.00	-1.74	-1.59	-5.25
4	0.09	0.03	-0.01	-0.02	-0.35	0.49	0.19	-0.06	-0.22	-4.22
Big	0.22	0.13	0.08	0.06	-0.12	1.36	1.09	0.93	0.88	-1.81
	PC3 loading					t-statistics				
Small	0.29	0.10	0.08	0.11	0.17	2.50	1.10	1.00	1.79	3.22
2	0.25	0.10	0.06	0.08	0.13	2.37	1.13	0.89	1.19	2.52
3	0.20	0.08	0.02	0.01	0.13	2.06	1.00	0.26	0.21	2.74
4	0.18	0.00	-0.01	0.01	0.11	1.92	-0.03	-0.16	0.20	2.25
Big	0.09	-0.03	-0.04	-0.07	0.03	1.14	-0.57	-0.83	-1.76	0.58
	PC4 loading					t-statistics				
Small	0.10	0.10	0.09	0.09	0.12	1.33	1.84	1.88	2.28	3.34
2	0.03	0.04	0.03	0.06	0.06	0.41	0.61	0.71	1.50	1.56
3	-0.01	-0.01	0.01	0.03	0.04	-0.19	-0.14	0.29	0.67	1.24
4	-0.04	-0.01	-0.01	0.00	0.03	-0.54	-0.21	-0.20	0.05	0.85
Big	-0.07	-0.03	-0.02	0.00	0.00	-1.19	-0.71	-0.56	-0.13	0.00

PC5 loading						t-statistics				
Small	0.69	1.09	1.19	1.30	1.81	2.08	4.24	4.94	5.30	7.59
2	0.82	1.08	1.29	1.50	2.04	2.78	4.53	6.04	7.00	9.99
3	0.62	1.01	1.22	1.42	2.05	2.50	4.74	5.72	6.73	10.79
4	0.60	0.98	1.12	1.37	1.92	2.33	4.55	5.72	8.16	11.16
Big	0.65	0.81	1.12	1.34	1.84	2.55	4.46	6.45	8.17	11.64
PC6 loading						t-statistics				
Small	0.86	0.54	0.45	0.45	0.66	5.51	4.31	4.27	4.99	9.07
2	0.87	0.53	0.46	0.48	0.71	5.18	4.18	4.61	5.41	10.38
3	0.83	0.54	0.49	0.44	0.64	6.16	4.85	4.62	4.85	9.85
4	0.87	0.60	0.49	0.44	0.59	5.72	5.29	5.11	5.98	9.99
Big	0.84	0.59	0.54	0.49	0.58	5.68	5.65	7.18	8.66	11.26
R^2						s(e)				
Small	0.32	0.25	0.26	0.31	0.44	6.69	5.04	4.56	4.45	4.97
2	0.30	0.22	0.27	0.33	0.46	6.69	5.24	4.53	4.39	4.95
3	0.29	0.24	0.25	0.29	0.47	6.33	4.89	4.43	4.20	4.60
4	0.32	0.24	0.26	0.33	0.46	6.23	4.91	4.24	3.94	4.35
Big	0.36	0.32	0.39	0.41	0.49	5.66	4.15	3.49	3.38	3.81

Table 1.18. **Alternative test assets: 25 Size and Idiosyncratic volatility sorted portfolios**

This table reports the intercepts (α , in % per month) and factor loadings from the full-sample time-series regressions of 25 size and idiosyncratic sorted portfolios. Factors include six productivity factors. The Newey-West t -statistics with six months lags are provided. The sample period is from January 1972 to December 2015. R^2 and standard errors of residuals (s(e), %) are reported.

	Low Ivoll	2	3	4	High Ivoll	Low Ivoll	2	3	4	High Ivoll
	α (% per month)					t-statistics				
Small	0.48	0.48	0.46	0.46	-0.29	1.93	1.56	1.26	1.12	-0.64
2	0.29	0.26	0.30	0.29	-0.05	1.36	0.94	1.02	0.83	-0.12
3	0.17	0.21	0.21	0.23	0.08	0.83	0.85	0.73	0.75	0.24
4	0.18	0.16	0.17	0.18	0.29	0.91	0.74	0.67	0.63	0.89
Big	-0.02	-0.02	-0.04	0.10	0.42	-0.11	-0.12	-0.18	0.43	1.56
	PC1 loading					t-statistics				
Small	0.12	0.20	0.24	0.29	0.32	3.57	4.16	4.32	4.72	4.67
2	0.11	0.19	0.24	0.28	0.39	3.42	4.30	4.80	4.93	6.38
3	0.06	0.14	0.17	0.24	0.36	2.06	3.62	3.86	4.58	6.46
4	0.01	0.08	0.12	0.18	0.30	0.33	2.16	2.62	3.66	5.51
Big	-0.01	0.05	0.10	0.14	0.24	-0.37	1.82	3.10	4.26	5.58
	PC2 loading					t-statistics				
Small	-0.23	-0.36	-0.41	-0.47	-0.49	-2.37	-2.58	-2.43	-2.36	-2.25
2	-0.19	-0.28	-0.37	-0.44	-0.58	-2.22	-2.22	-2.81	-2.71	-3.56
3	-0.06	-0.15	-0.18	-0.28	-0.47	-0.77	-1.24	-1.39	-1.91	-3.02
4	0.09	0.03	0.00	-0.07	-0.29	1.05	0.30	-0.02	-0.57	-2.04
Big	0.19	0.14	0.13	0.03	-0.04	2.90	2.04	1.71	0.31	-0.33
	PC3 loading					t-statistics				
Small	-0.01	0.02	0.09	0.21	0.42	-0.13	0.21	0.92	2.03	4.31
2	-0.02	0.00	-0.01	0.07	0.31	-0.37	0.00	-0.09	0.85	3.65
3	-0.06	-0.04	0.00	0.07	0.27	-1.17	-0.52	0.02	0.97	3.72
4	-0.09	-0.06	-0.02	0.04	0.31	-1.87	-0.96	-0.27	0.58	4.48
Big	-0.06	-0.06	-0.05	0.04	0.27	-1.85	-1.82	-1.06	1.02	5.32
	PC4 loading					t-statistics				
Small	0.06	0.06	0.07	0.10	0.17	1.51	1.16	1.22	1.51	2.53
2	0.04	0.04	0.02	0.01	0.07	1.13	0.79	0.37	0.16	1.17
3	0.03	0.01	0.00	-0.01	0.02	0.92	0.24	0.08	-0.19	0.32
4	0.03	-0.01	-0.02	-0.02	0.00	0.92	-0.19	-0.40	-0.32	0.07
Big	0.00	-0.02	-0.01	-0.02	-0.03	0.15	-0.53	-0.18	-0.53	-0.75

PC5 loading						t-statistics				
Small	0.95	1.27	1.31	1.28	1.10	4.67	5.10	4.59	3.95	2.97
2	1.11	1.36	1.48	1.60	1.61	6.04	6.02	5.96	6.07	6.04
3	1.07	1.30	1.37	1.53	1.55	6.43	6.37	6.06	6.52	6.80
4	1.03	1.18	1.31	1.40	1.48	6.66	6.89	6.75	6.76	6.81
Big	1.13	1.29	1.34	1.35	1.30	10.61	9.21	9.24	7.76	6.60
PC6 loading						t-statistics				
Small	0.31	0.46	0.59	0.77	0.98	3.23	4.04	4.57	5.44	7.13
2	0.32	0.41	0.50	0.63	1.03	3.64	3.79	4.47	4.78	8.91
3	0.32	0.42	0.45	0.54	0.94	4.16	4.40	4.18	4.96	10.19
4	0.34	0.40	0.48	0.57	0.93	4.77	5.11	5.21	5.70	10.22
Big	0.42	0.49	0.56	0.65	0.86	8.55	9.45	8.36	7.91	10.75
R^2						se				
Small	0.18	0.21	0.24	0.32	0.42	3.79	4.98	5.63	6.24	6.86
2	0.22	0.22	0.23	0.27	0.44	3.64	4.70	5.22	5.81	6.37
3	0.23	0.24	0.24	0.29	0.43	3.39	4.26	4.79	5.24	5.85
4	0.26	0.27	0.28	0.30	0.46	3.34	3.92	4.46	4.86	5.53
Big	0.48	0.47	0.43	0.43	0.52	2.70	3.10	3.52	3.90	4.53

Table 1.19. **Alternative test assets: Fama-French 30 industry portfolios**

This table reports the intercepts (α , in % per month) and factor loadings from the full-sample time-series regressions of 25 size and Fama-French 30 industry portfolios. Factors include six productivity factors. The Newey-West t -statistics with six months lags are provided. The sample period is from January 1972 to December 2015. R^2 and standard errors of residuals (s(e), %) are reported.

	Agric	Food	Soda	Beer	Smoke	Toys	Fun	Books	Hshld	Clths
α	0.08	0.13	0.19	0.10	0.72	-0.19	0.59	-0.08	0.02	0.06
t-stat	0.24	0.51	0.52	0.38	2.05	-0.49	1.30	-0.24	0.11	0.16
β_{PC1}	0.13	-0.02	-0.01	-0.02	-0.07	0.13	0.17	0.11	-0.01	0.16
t-stat	3.72	-0.68	-0.17	-0.77	-1.98	2.42	4.06	3.22	-0.34	3.73
β_{PC2}	0.42	0.19	0.23	0.21	-0.01	0.28	0.27	0.17	0.12	0.20
t-stat	3.91	2.03	1.76	2.12	-0.10	1.71	1.82	1.65	1.42	1.31
β_{PC3}	0.03	-0.04	-0.03	-0.05	-0.04	0.05	0.07	0.03	-0.03	0.04
t-stat	1.74	-2.70	-1.49	-2.01	-2.57	1.55	2.31	1.59	-2.49	1.25
β_{PC4}	-0.14	-0.05	-0.12	-0.10	-0.16	-0.18	-0.26	-0.12	-0.18	-0.18
t-stat	-2.15	-1.22	-1.64	-1.91	-2.61	-2.07	-3.66	-2.11	-3.80	-2.47
β_{PC5}	0.64	0.64	0.56	0.64	0.35	0.58	0.44	0.65	0.42	0.69
t-stat	3.04	4.50	2.35	4.16	1.78	2.43	1.84	3.55	3.05	3.29
β_{PC6}	-0.53	-0.57	-0.65	-0.66	-0.48	-0.66	-0.82	-0.68	-0.65	-0.52
t-stat	-5.12	-7.42	-5.33	-7.60	-3.54	-4.80	-5.89	-7.14	-8.48	-3.93
R^2	0.06	0.00	-0.08	-0.16	-0.41	-0.09	-0.01	0.04	-0.31	0.03
s(e)	0.33	-0.02	-0.39	-1.19	-2.36	-0.37	-0.03	0.26	-2.38	0.18
	Hlth	MedEq	Drugs	Chems	Rubbr	Txtls	BldMt	Cnstr	Steel	FabPr
α	-0.16	0.33	0.55	0.08	-0.02	0.07	-0.07	-0.16	0.13	0.00
t-stat	-0.37	1.41	2.57	0.25	-0.04	0.15	-0.19	-0.42	0.36	0.00
β_{PC1}	0.13	0.08	0.00	0.10	0.12	0.11	0.10	0.19	0.19	0.20
t-stat	2.23	2.38	-0.05	2.53	3.27	2.38	2.86	4.15	4.53	5.24
β_{PC2}	0.42	0.24	0.18	0.03	0.35	0.15	0.14	0.25	-0.02	0.26
t-stat	2.47	3.42	2.51	0.31	3.07	1.02	1.11	2.00	-0.11	1.94
β_{PC3}	0.04	0.01	-0.05	0.00	0.06	0.06	0.02	0.04	0.10	0.08
t-stat	1.03	0.50	-3.33	0.08	3.11	1.75	0.82	1.75	4.63	3.07
β_{PC4}	-0.15	-0.29	-0.30	-0.16	-0.09	-0.03	-0.13	-0.22	-0.19	-0.24
t-stat	-1.68	-5.31	-5.40	-2.39	-1.44	-0.36	-1.94	-3.05	-2.57	-3.07
β_{PC5}	0.91	0.27	0.18	0.54	0.74	0.63	0.65	0.66	0.29	0.26
t-stat	3.70	1.98	1.45	3.00	3.78	2.18	3.19	2.98	1.34	1.12
β_{PC6}	-0.54	-0.70	-0.79	-0.67	-0.64	-0.52	-0.69	-0.71	-0.78	-0.48
t-stat	-4.69	-7.89	-10.77	-6.97	-5.11	-3.00	-5.82	-5.74	-7.11	-3.62
R^2	0.03	-0.35	-0.42	-0.04	0.06	0.11	-0.08	-0.04	-0.02	-0.05
s(e)	0.14	-3.10	-3.68	-0.20	0.40	0.44	-0.45	-0.23	-0.10	-0.27

	Mach	ElcEq	Autos	Aero	Ships	Guns	Gold	Mines	Coal	Oil
α	0.35	0.18	0.09	0.23	-0.10	0.20	1.07	0.50	0.32	0.11
t-stat	1.09	0.65	0.21	0.63	-0.24	0.57	2.29	1.26	0.51	0.41
β_{PC1}	0.17	0.16	0.09	0.08	0.15	0.08	0.08	0.12	0.14	0.05
t-stat	4.90	4.82	2.38	1.69	2.80	1.52	1.04	2.28	1.76	1.28
β_{PC2}	0.13	0.17	-0.02	0.18	0.22	0.12	-0.41	-0.08	0.12	0.08
t-stat	1.09	1.65	-0.13	1.31	1.72	0.95	-2.22	-0.57	0.55	0.69
β_{PC3}	0.06	0.03	0.03	0.01	0.01	0.01	0.06	0.04	0.06	-0.03
t-stat	2.68	1.41	1.15	0.25	0.33	0.58	1.90	1.46	1.43	-1.78
β_{PC4}	-0.30	-0.26	-0.11	-0.15	-0.18	-0.09	-0.37	-0.24	-0.25	-0.08
t-stat	-4.41	-4.64	-1.56	-2.54	-2.36	-1.20	-2.89	-2.89	-1.73	-1.19
β_{PC5}	0.26	0.55	0.37	0.64	0.65	0.70	-0.76	0.08	0.18	0.51
t-stat	1.39	3.31	1.51	3.23	2.68	3.36	-2.40	0.32	0.51	2.71
β_{PC6}	-0.70	-0.90	-0.62	-0.69	-0.64	-0.35	-0.03	-0.51	-0.71	-0.66
t-stat	-5.82	-10.92	-4.08	-6.00	-4.73	-2.76	-0.20	-4.25	-4.05	-6.60
R^2	-0.17	-0.11	0.01	-0.05	-0.07	-0.05	-0.93	-0.31	-0.21	0.08
s(e)	-1.03	-0.75	0.07	-0.30	-0.36	-0.26	-3.21	-1.42	-0.59	0.50

Table 1.20. **Explaining the first principal component of productivity with other pricing factors: identifying a missing factor**

Panel A presents the abnormal returns and the factor loadings of the first productivity factor from various factor models, using the full sample. Panel B shows similar results from the extending-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 (2015) six-factor model (FF6), Stambaugh and Yuan (2017) model (SY), Daniel et al. (2018) model (DHS), Hou et al. (2015) q -factor model (HXZ), and Hou et al. (2018b) q^5 model (HMXZ). All returns are multiplied with 100. Newey-West adjusted t -statistics with 6-month (4-month) lags are provided in Panel A (Panel B). R^2 denotes the explanatory power of the corresponding factor model. The sample period is from January 1972 to December 2015, except for the Daniel et al. (2018) factors, which have a sample peiord of July 1972 to December 2014. The testing period for panel B starts from January 2001.

Panel A. Full-sample estimation									
	α	MKT							R^2
CAPM	1.29	0.04							0.00
t-stat	4.41	0.45							
	α	MKT	SMB	HML					R^2
3FF	1.37	-0.10	0.54	-0.30					0.06
t-stat	4.82	-1.05	3.38	-1.98					
	α	MKT	SMB	HML	UMD				R^2
4FF	1.17	-0.06	0.54	-0.23	0.21				0.08
t-stat	3.79	-0.59	3.14	-1.39	2.14				
	α	MKT	SMB	HML	CMA	RMW			R^2
5FF	1.31	-0.11	0.67	-0.14	-0.45	0.44			0.09
t-stat	4.27	-1.17	5.25	-0.78	-1.42	2.36			
	α	MKT	SMB	HML	CMA	RMW	UMD		R^2
6FF	1.15	-0.08	0.66	-0.01	-0.56	0.39	0.22		0.10
t-stat	3.53	-0.81	5.24	-0.04	-1.59	2.00	2.18		
	α	MKT	MIS_ME	MGMT	PERF				R^2
SY	0.91	-0.02	0.64	-0.20	0.43				0.12
t-stat	3.04	-0.18	4.54	-1.17	3.77				
	α	MKT	FIN	PEAD					R^2
DHS	1.27	-0.03	-0.19	0.34					0.02
t-stat	3.60	-0.30	-1.57	1.25					
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}				R^2
HXZ	1.35	-0.09	0.42	-0.45	0.19				0.04
t-stat	4.20	-0.93	3.15	-1.80	1.34				
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}	EG			R^2
HXMZ	1.16	-0.05	0.43	-0.55	0.06	0.38			0.05
t-stat	3.90	-0.58	3.04	-1.92	0.29	1.22			

Panel B. Extending-window estimation									
	α	MKT							R^2
CAPM	-1.85	0.32							0.04
t-stat	-3.84	2.10							
	α	MKT	SMB	HML					R^2
FF3	-1.51	0.49	-0.86	-0.60					0.23
t-stat	-3.50	4.82	-4.64	-3.29					
	α	MKT	SMB	HML	UMD				R^2
FF4	-1.39	0.33	-0.86	-0.59	-0.28				0.27
t-stat	-3.24	2.92	-4.98	-4.18	-2.36				
	α	MKT	SMB	HML	CMA	RMW			R^2
FF5	-1.08	0.25	-0.98	-0.32	-0.31	-0.71			0.27
t-stat	-2.41	1.90	-5.63	-1.75	-1.24	-2.72			
	α	MKT	SMB	HML	CMA	RMW	UMD		R^2
FF6	-1.11	0.20	-0.95	-0.41	-0.19	-0.52	-0.20		0.29
t-stat	-2.63	1.52	-5.76	-2.27	-0.81	-1.84	-1.88		
	α	MKT	MIS_{ME}	MGMT	PERF				R^2
SY	-0.92	0.26	-1.25	-0.51	-0.21				0.30
t-stat.	-2.19	1.82	-6.60	-3.54	-1.85				
	α	MKT	FIN	PEAD					R^2
DHS	-1.19	-0.05	-0.56	-0.57					0.13
t-stat	-2.68	-0.42	-3.03	-1.81					
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}				R^2
HXZ	-1.04	0.21	-1.13	-0.72	-0.65				0.33
t-stat	-2.86	1.60	-6.31	-3.95	-3.10				
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}	EG			R^2
HXMZ	-0.96	0.18	-1.16	-0.55	-0.54	-0.36			0.33
t-stat	-2.64	1.34	-6.46	-2.52	-2.27	-1.72			

Table 1.21. **TFP growth factors: Descriptive statistics and relations with other factors, using an extended sample**

This table presents descriptive statistics of TFP, estimated from firms with a four-digit SIC code lower than 4900 (agriculture, mining, construction, and transportation), or between 5000 and 5999 (wholesale trade and retail trade), or between 7000 and 8999 (services). Panel A summarizes the annual log TFP growth and six principal components (PC1 to PC6), including the mean, standard deviation, and percentiles. All firms except for financial and utility firms are included to estimate TFP. Full-sample data are used in estimating principal components. $AR(1)$ denotes the first-order autocorrelation. R^2 denotes the average explanatory power of principal components at firm-level. Panel B reports the annual time-series correlation coefficients between principal components and other pricing factors. The pricing factors include Fama and French (2015) market factor (MKT), size factor (SMB), value factor (HML), investment factor (CMA), and profitability factor (RMW); Carhart (1997) momentum factor (UMD); Hou et al. (2015) size factors (Q_{ME}), investment factor (Q_{IA}), and profitability factor (Q_{ROE}); Hou et al. (2018b) expected investment growth factor (EG); Stambaugh and Yuan (2017) mispricing factor (MIS); and Daniel et al. (2018) long-horizon behavioral factor (FIN) and short-horizon behavioral factor (PEAD). Panel C presents the monthly mean (% per month), standard deviation (% per month, S.D.), Sharpe ratio (SR), and correlations for the mimicking portfolios of six principal components. The sample period is from January 1972 to December 2015. The sample period for Daniel et al. (2018) factors is from July 1972 to December 2014 because of the data availability.

Panel A: TFP and its 6 principal components													
	Mean	S.D.	Min	Max	10%	25%	50%	75%	90%	AR(1)	R^2		
ΔTFP	0.01	0.20	-1.15	1.13	-0.20	-0.08	0.01	0.10	0.23	0.07			
PC1	-0.11	1.01	-3.18	3.34	-1.06	-0.53	-0.16	0.24	0.90	0.03	0.14		
PC2	-0.12	1.00	-4.19	3.13	-0.83	-0.38	-0.13	0.21	0.59	-0.11	0.22		
PC3	-0.24	0.98	-4.13	1.53	-1.11	-0.47	-0.10	0.25	0.62	0.20	0.29		
PC4	-0.14	1.00	-3.51	1.73	-0.93	-0.55	-0.10	0.35	1.30	0.32	0.37		
PC5	0.01	1.01	-3.21	2.63	-0.91	-0.42	0.01	0.46	1.10	0.27	0.43		
PC6	0.01	1.01	-2.28	3.71	-0.94	-0.54	-0.09	0.55	1.19	0.35	0.50		
Panel B: Correlations between 6 TFP components and pricing factors													
	MKT	SMB	HML	CMA	RMW	UMD	Q_{ME}	Q_{IA}	Q_{ROE}	EG	MIS	FIN	PEAD
MKT	1.00												
SMB	0.15	1.00											
HML	-0.27	0.17	1.00										
CMA	-0.36	0.17	0.71	1.00									
RMW	-0.30	-0.13	0.21	0.04	1.00								
UMD	-0.21	-0.26	-0.16	-0.11	0.02	1.00							
Q_{ME}	0.10	0.99	0.20	0.17	-0.08	-0.20	1.00						
Q_{IA}	-0.38	0.05	0.68	0.93	0.09	-0.05	0.07	1.00					
Q_{ROE}	-0.27	-0.38	-0.08	-0.13	0.72	0.52	-0.30	0.00	1.00				
EG	-0.26	-0.10	0.10	0.23	0.29	0.36	-0.06	0.21	0.37	1.00			
MIS	-0.52	-0.39	0.11	0.31	0.31	0.61	-0.33	0.33	0.52	0.66	1.00		
FIN	-0.56	-0.22	0.67	0.57	0.55	0.16	-0.19	0.59	0.35	0.36	0.57	1.00	
PEAD	0.00	-0.07	-0.06	-0.02	-0.27	0.55	-0.03	0.01	0.18	0.29	0.43	-0.04	1.00
PC1	-0.03	0.00	-0.09	-0.13	0.15	-0.27	0.01	-0.08	-0.09	0.16	0.02	-0.01	-0.22
PC2	-0.07	0.02	0.32	0.12	0.30	-0.19	0.04	0.08	0.12	0.16	0.03	0.10	-0.08
PC3	0.00	-0.29	0.02	-0.21	0.30	-0.02	-0.31	-0.08	0.30	-0.29	-0.01	0.20	-0.11
PC4	0.21	-0.06	-0.20	-0.31	-0.33	-0.11	-0.05	-0.35	-0.27	-0.13	-0.28	-0.28	-0.11
PC5	-0.24	0.19	0.20	0.42	0.25	-0.21	0.18	0.39	-0.06	0.13	0.07	0.32	-0.14
PC6	0.22	-0.07	-0.13	-0.07	-0.31	0.06	-0.11	-0.15	-0.12	-0.07	0.07	-0.16	0.40
Panel C: Statistics of monthly mimicking productivity portfolios													
	Mean	S.D.	SR	PC2	PC3	PC4	PC5	PC6					
PC1	0.69	4.12	0.17	0.11	-0.13	-0.18	0.25	0.33					
PC2	1.49	15.78	0.09		-0.03	-0.46	0.38	-0.03					
PC3	-0.44	4.40	-0.10			-0.14	-0.50	-0.23					
PC4	-1.78	6.81	-0.26			115	-0.64	-0.15					
PC5	0.76	13.19	0.06					0.04					
PC6	0.10	2.37	0.04										

Table 1.22. Using productivity factors to explain other pricing factors: An expanded sample

This table reports the intercepts (α , % per month) and factor loadings from time-series regressions of various pricing factors on productivity factors, which are estimated from firms with a four-digit SIC code lower than 4900 (agriculture, mining, construction, and transportation), or between 5000 and 5999 (wholesale trade and retail trade), or between 7000 and 8999 (services). The pricing factors include Fama and French (2015) market factor (MKT), size factor (SMB), value factor (HML), investment factor (CMA), and profitability factor (RMW); Carhart (1997) momentum factor (UMD); Hou et al. (2015) size factors (Q_{ME}), investment factor (Q_{IA}), and profitability factor (Q_{ROE}); Stambaugh and Yuan (2017) univariate mispricing factor (MIS) and two separate mispricing factors related to the management (MGMT) and to the firm performance (PERF); Hou et al. (2018b) expected investment growth factor (EG); Daniel et al. (2018) short horizon earning surprise factor (PEAD) and long horizon financing factor (FIN); and labor share factor (LS). The intercepts and factor loadings are estimated over the full sample. The Newey-West adjusted t-statistics with 6-month lags are provided. The sample period is from January 1972 to December 2015.

	MKT	SMB	HML	CMA	RMW	UMD	Q_{ME}	Q_{IA}	Q_{ROE}	EG	MGMT	PERF	MIS	FIN	PEAD	LS
α	0.24	0.02	0.01	-0.03	0.11	-0.09	0.01	-0.02	0.14	0.38	0.17	0.20	0.10	0.26	0.50	0.31
t-stat	1.08	0.12	0.09	-0.37	1.11	-0.38	0.08	-0.23	1.36	3.31	1.26	0.96	0.75	1.49	5.41	1.55
β_{PC1}	-0.07	0.00	0.23	0.11	-0.07	-0.25	-0.06	0.09	-0.25	-0.06	0.16	-0.29	-0.06	0.12	-0.07	0.09
t-stat	-1.30	0.00	6.42	4.71	-2.74	-4.17	-2.45	5.63	-9.77	-2.30	4.89	-6.48	-2.31	2.41	-2.68	2.20
β_{PC2}	0.01	-0.03	0.02	-0.01	0.04	-0.03	-0.03	-0.01	0.02	0.01	0.02	0.00	-0.01	0.05	-0.01	-0.03
t-stat	1.01	-3.76	2.30	-2.22	4.98	-1.56	-3.16	-3.55	3.88	0.68	2.15	-0.15	-0.91	3.81	-1.64	-3.26
β_{PC3}	-0.32	-0.43	-0.01	-0.08	0.16	-0.59	-0.49	-0.04	0.00	-0.10	-0.08	-0.25	-0.28	0.06	-0.15	-0.22
t-stat	-4.01	-8.96	-0.15	-2.20	2.77	-6.11	-10.24	-1.42	0.11	-2.64	-1.29	-3.23	-5.92	0.62	-3.32	-3.02
β_{PC4}	-0.17	-0.02	-0.11	-0.16	-0.12	-0.48	-0.07	-0.24	-0.31	-0.21	-0.19	-0.31	-0.35	-0.25	-0.09	-0.01
t-stat	-2.39	-0.47	-2.09	-5.02	-3.79	-6.83	-1.88	-10.59	-10.56	-5.54	-3.76	-6.12	-9.32	-4.10	-3.00	-0.23
β_{PC5}	-0.26	0.04	0.00	0.00	-0.01	-0.16	0.02	-0.02	-0.10	-0.04	-0.02	-0.04	-0.06	-0.02	-0.03	0.03
t-stat	-8.08	2.44	-0.06	0.12	-1.10	-4.72	1.02	-1.89	-7.04	-2.95	-0.98	-1.13	-3.44	-0.72	-2.07	1.01
β_{PC6}	0.67	-0.26	-0.43	-0.21	0.06	0.19	-0.33	-0.27	0.04	-0.04	-0.29	0.47	0.15	-0.23	0.06	0.00
t-stat	6.57	-4.57	-7.82	-5.21	1.47	1.71	-5.70	-7.66	0.87	-0.85	-4.09	5.84	2.99	-2.95	1.14	-0.01
R^2	0.39	0.51	0.27	0.36	0.38	0.31	0.51	0.56	0.58	0.26	0.27	0.37	0.50	0.32	0.10	0.15

Table 1.23. Explaining various test portfolios with productivity factors: An expanded sample

This table presents the intercepts (α , % per month) and their t-statistics from time-series regressions of various portfolios on productivity factors, which are estimated from firms with a four-digit SIC code lower than 4900 (agriculture, mining, construction, and transportation), or between 5000 and 5999 (wholesale trade and retail trade), or between 7000 and 8999 (services). Test portfolios include 25 size and book-to-market sorted portfolios (Panel A), 25 size and operating profitability sorted portfolios (Panel B), 25 size and investment sorted portfolios (Panel C), 25 size and momentum sorted portfolios (Panel D), 25 size and idiosyncratic volatility sorted portfolios (Panel E), 30 Fama-French industry portfolios (Panel F), and 11 mispricing portfolios (Panel G). Factors include the 6 mimicking productivity portfolios constructed by full-sample principal components. Newey-West t-statistics with 6-month lags are provided. The sample period is from January 1972 to December 2015.

α (% per month)						t-statistics				
Panel A: 25 size and book-to-market sorted portfolios										
	Low BM	2	3	4	High BM	Low BM	2	3	4	High BM
Small	-0.13	0.37	0.22	0.41	0.49	-0.29	1.00	0.66	1.27	1.33
2	0.13	0.28	0.29	0.30	0.22	0.33	0.88	1.00	1.05	0.64
3	0.28	0.34	0.29	0.34	0.41	0.81	1.15	1.10	1.25	1.26
4	0.45	0.24	0.27	0.38	0.26	1.43	0.89	0.99	1.47	0.80
Big	0.38	0.22	0.14	-0.04	0.21	1.83	1.06	0.68	-0.13	0.79
Panel B: 25 size and operating profitability sorted portfolios										
	Low Op	2	3	4	High Op	Low Op	2	3	4	High Op
Small	0.12	0.34	0.24	0.25	0.15	0.28	1.03	0.73	0.72	0.37
2	0.14	0.16	0.26	0.33	0.32	0.39	0.52	0.90	1.07	0.93
3	0.29	0.29	0.28	0.25	0.42	0.84	1.09	1.06	0.87	1.33
4	0.38	0.32	0.28	0.38	0.31	1.22	1.18	1.04	1.42	1.08
Big	0.24	0.16	0.13	0.33	0.33	0.80	0.70	0.61	1.56	1.81
Panel C: 25 size and investment sorted portfolios										
	Low Inv	2	3	4	High Inv	Low Inv	2	3	4	High Inv
Small	0.43	0.42	0.36	0.23	-0.10	1.01	1.26	1.07	0.71	-0.25
2	0.23	0.27	0.30	0.35	0.12	0.62	0.93	1.09	1.14	0.33
3	0.33	0.35	0.31	0.38	0.33	1.05	1.34	1.14	1.33	0.97
4	0.28	0.28	0.30	0.39	0.46	0.89	1.11	1.16	1.46	1.43
Big	0.25	0.12	0.21	0.28	0.45	1.06	0.62	1.08	1.34	1.79
Panel D: 25 size and momentum sorted portfolios										
	Loser	2	3	4	Winner	Loser	2	3	4	Winner
Small	0.16	0.24	0.41	0.51	0.65	0.30	0.67	1.25	1.61	1.75
2	0.29	0.37	0.37	0.40	0.47	0.59	1.08	1.27	1.33	1.38
3	0.56	0.39	0.31	0.22	0.40	1.19	1.20	1.06	0.82	1.31
4	0.62	0.45	0.36	0.33	0.26	1.36	1.41	1.32	1.36	0.97
Big	0.46	0.43	0.12	0.14	0.12	1.11	1.55	0.57	0.74	0.53
Panel E: 25 size and idiosyncratic volatility sorted portfolios										
	Low Ivol	2	3	4	High Ivol	Low Ivol	2	3	4	High Ivol
Small	0.55	0.56	0.53	0.46	-0.32	2.10	1.68	1.29	0.96	-0.57
2	0.41	0.38	0.42	0.41	0.03	1.80	1.28	1.29	1.05	0.05
3	0.31	0.37	0.36	0.38	0.17	1.47	1.36	1.17	1.12	0.40
4	0.35	0.33	0.35	0.34	0.39	1.72	1.42	1.26	1.11	0.99
Big	0.15	0.16	0.16	0.23	0.51	0.94	0.90	0.73	0.92	1.61

α (% per month)					t-statistics				
Panel F: 30 Fama-French industry portfolios									
Agric	Food	Soda	Beer	Smoke	Agric	Food	Soda	Beer	Smoke
0.28	0.28	0.67	0.38	0.04	1.30	1.23	2.25	0.91	0.14
Toys	Fun	Books	Hshld	Clths	Toys	Fun	Books	Hshld	Clths
0.12	0.21	0.42	0.35	0.24	0.53	0.57	1.87	1.18	0.57
Hlth	MedEq	Drugs	Chems	Rubbr	Hlth	MedEq	Drugs	Chems	Rubbr
0.01	0.25	0.45	0.42	0.09	0.02	0.67	1.31	1.34	0.25
Txtls	BldMt	Cnstr	Steel	FabPr	Txtls	BldMt	Cnstr	Steel	FabPr
0.36	0.39	0.19	0.31	0.24	1.09	1.03	0.29	1.20	1.09
Mach	ElcEq	Autos	Aero	Ships	Mach	ElcEq	Autos	Aero	Ships
0.31	0.43	0.59	0.07	0.08	1.40	1.25	1.80	0.27	0.27
Guns	Gold	Mines	Coal	Oil	Guns	Gold	Mines	Coal	Oil
0.16	0.23	0.26	0.04	-0.04	0.58	0.82	0.77	0.15	-0.14
Panel G: 11 mispricing portfolios									
Acc	AG	CI	InvA	NOA	Acc	AG	CI	InvA	NOA
0.32	-0.03	0.18	0.05	0.19	1.96	-0.20	1.07	0.37	1.30
ISS	DIST	GP	Mom	OSCO	ISS	DIST	GP	Mom	OSCO
0.15	-0.07	0.33	0.06	0.24	1.12	-0.17	1.70	0.16	1.22
ROA					ROA				
0.20					0.91				

Table 1.24. Cross-sectional regressions of various factor models: An expanded sample

This table reports the coefficients (Coeff) and t-statistics (t-stat) from Fama-MacBeth regressions of various factor models. Test assets are 155 portfolios and the tested pricing factors: 25 size and book-to-market sorted portfolios, 25 size and operating profitability sorted portfolios, 25 size and investment sorted portfolios, 25 size and idiosyncratic volatility sorted portfolios, 30 Fama-French industry portfolios, and the tested pricing factors. Tested factor models are Fama and French (1993) 3-factor model (FF3), Fama and French (2015) 5-factor model (FF5), Fama and French (2015) 6-factor model (FF6), Hou et al. (2015) Q-factor model (HMZ), Hou et al. (2018b) q^5 -factor model (HMXZ), Stambaugh and Yuan (2017) mispricing factor model (SY), Daniel et al. (2018) behavioral factor model (DHS), and productivity-based model (TFP) estimated with firms with a four-digit SIC code lower than 4900 (agriculture, mining, construction, and transportation), or between 5000 and 5999 (wholesale trade and retail trade), or between 7000 and 8999 (services). The factor betas are computed over the full sample. All coefficients are multiplied by 100. The t-statistics are adjusted for errors-in-variables, following Shaiken (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 sample period is from January 1972 to December 2015.

	FF3		FF5		FF6		HXZ		HMXZ		SY		DHS		TFP	
	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	0.51	5.35	0.01	0.29	-0.07	-2.24	0.00	-0.03	-0.06	-1.10	-0.03	-0.44	0.30	2.43	0.22	1.58
γ_{MKT}	0.06	0.29	0.47	2.30	0.59	2.91	0.49	2.32	0.57	2.73	0.57	2.70	0.42	1.81		
γ_{SMB}	0.09	0.70	0.22	1.65	0.21	1.55										
γ_{HML}	0.24	1.65	0.07	0.53	0.28	2.10										
γ_{CMA}			0.29	2.52	0.26	2.29										
γ_{RMW}			0.43	4.01	0.27	2.75										
γ_{UMD}					0.73	3.72										
γ_{QME}							0.33	2.31	0.31	2.22						
γ_{QIA}							0.35	2.91	0.38	3.24						
γ_{QROE}							0.56	3.98	0.52	3.63						
γ_{EG}									0.64	4.29						
γ_{MISME}											0.32	2.39				
γ_{MGMT}											0.52	3.31				
γ_{PERF}											0.61	3.21				
γ_{FIN}													0.35	1.56		
γ_{PEAD}													0.38	2.25		
γ_{PC1}															0.62	2.42
γ_{PC2}															1.35	1.93
γ_{PC3}															-0.47	-1.64
γ_{PC4}															-1.78	-5.09
γ_{PC5}															0.63	1.069
γ_{PC6}															0.15	0.85
R^2	0.06		0.44		0.60		0.52		0.58		0.61		0.18		0.78	
(5 th , 95 th)	(0.03, 0.49)		(0.27, 0.59)		(0.44, 0.70)		(0.32, 0.63)		(0.40, 0.66)		(0.40, 0.68)		(0.03, 0.49)		(0.55, 0.80)	

Table 1.25. **Explaining productivity factors with other pricing factors: An expanded sample**

This table presents the excess returns (R^{EX}) and alphas of productivity factors, using full-sample estimation. Productivity factors are estimated from firms with a four-digit SIC code lower than 4900 (agriculture, mining, construction, and transportation), or between 5000 and 5999 (wholesale trade and retail trade), or between 7000 and 8999 (services). Alphas are computed from various factor models, including CAPM (α^{CAPM}), is the Fama and French (1993) 3 factor model (α^{FF3}), Carhart (1997) 4 factor model (α^{FF4}), Fama and French (2015) 5 factor model (α^{FF5}), Fama and French (2015) 6 factor model (α^{FF6}), Stambaugh and Yuan (2017) mispricing factor model (α^{SY}), Daniel et al. (2018) behavioral model (α^{DHS}), Hou et al. (2015) q -factor model (α^{HXZ}), and Hou et al. (2018b) q^5 model (α^{HMXZ}). R^2 is reported. All returns are multiplied with 100. Newey-West adjusted t-statistics with 6-month lags are provided in parentheses. The sample period is from January 1972 to December 2015.

Panel A: Full-sample estimation						
	FM1	FM2	FM3	FM4	FM5	FM6
R^{EX}	0.69 (4.42)	1.49 (1.82)	-0.44 (-2.24)	-1.78 (-5.19)	0.76 (1.19)	0.10 (0.96)
α^{CAPM}	0.71 (4.60)	1.73 (2.04)	-0.45 (-2.34)	-1.95 (-5.30)	1.39 (2.32)	-0.01 (-0.06)
R^2	0.00	0.02	0.00	0.04	0.17	0.16
α^{FF3}	0.52 (3.31)	1.07 (1.37)	-0.37 (-2.04)	-1.65 (-5.10)	0.74 (1.62)	0.04 (0.42)
R^2	0.08	0.09	0.47	0.11	0.52	0.19
α^{FF4}	0.57 (3.43)	0.69 (0.95)	-0.14 (-0.92)	-1.13 (-3.87)	0.16 (0.34)	-0.12 (-1.10)
R^2	0.08	0.10	0.53	0.23	0.56	0.28
α^{FF5}	0.50 (3.28)	-0.02 (-0.03)	-0.44 (-2.14)	-0.60 (-2.25)	-0.28 (-0.67)	-0.10 (-0.82)
R^2	0.10	0.22	0.50	0.51	0.63	0.26
α^{FF6}	0.55 (3.50)	-0.21 (-0.31)	-0.24 (-1.45)	-0.31 (-1.22)	-0.61 (-1.46)	-0.21 (-1.99)
R^2	0.10	0.23	0.56	0.56	0.65	0.33
α^{SY}	0.36 (2.07)	-0.90 (-1.18)	0.225 (1.57)	-0.03 (-0.09)	-1.52 (-3.43)	-0.41 (-4.32)
R^2	0.09	0.15	0.47	0.42	0.64	0.41
α^{DHS}	0.66 (3.55)	0.11 (0.16)	-0.48 (-1.79)	-0.68 (-2.43)	0.72 (1.22)	-0.35 (-2.98)
R^2	0.03	0.16	0.07	0.27	0.18	0.24
α^{HXZ}	0.81 (5.17)	-0.27 (-0.34)	-0.67 (-3.08)	0.07 (0.32)	-0.46 (-1.03)	0.00 (0.00)
R^2	0.19	0.14	0.52	0.70	0.61	0.20
α^{HMXZ}	0.74 (4.56)	-0.47 (-0.61)	-0.28 (-1.89)	0.20 (0.99)	-0.95 (-2.05)	-0.18 (-1.48)
R^2	0.19	0.15	0.59	0.70	0.62	0.25

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Chapter 2

Decoding the Pricing of Uncertainty

WITH ZHANHUI CHEN AND MICHAEL GALLMEYER

2.1 Introduction

Recent literature in economics emphasizes the role of economic uncertainty over business cycle (see, Bloom et al. (2007); Bloom (2009)). Many studies document that economic uncertainty is counter-cyclical and affects firm decisions including investment, hiring, payout, and so on. There are macroeconomic (macro) and microeconomic (micro) uncertainty. While macro uncertainty can be proxied by aggregate indices (e.g. VIX), micro uncertainty is represented by cross-sectional dispersion of micro-level variables, like productivity. However, this micro uncertainty is contaminated by macroeconomic uncertainty because firm-level productivity consists of systematic and idiosyncratic components. In this paper, we distinguish two components from productivity and examine the asset pricing implications of two different uncertainty measures. Empirically, we estimate the cross-sectional dispersion of total factor productivity (TFP) and show that it is the risk factor. Further, we decompose this total economic uncertainty into macro and micro uncertainty. We find that the macro uncertainty shock drives the movement of total uncertainty shock in both time-series and cross-section while the micro uncertainty shock is negligible. The uncertainty risk is inherited from the income inequality risk. Intuitively, when an agent has an idiosyncratic labor income shock

and cannot insure the income shock completely, he/she asks the risk premium on the income shock (Constantinides and Duffie (1996)). In this economy, the cross-sectional dispersion of income shock, income inequality, affects the pricing kernel. Since a firm faces its productivity first and then decides the labor hiring, the cross-sectional dispersion of productivity is closely related to income inequality. We construct the income inequality factor and show that the macro uncertainty factor explains the income inequality factor. Also, we find that the expected investment growth factor (EG) of Hou et al. (2018b) captures the productivity uncertainty risk since EG is the function of the cross-sectional dispersions of Tobin's q , cash-flow, and ROE change and the productivity uncertainty is significantly related to those three dispersions.

There are numerous uncertainty measures using many variables, including productivity, returns of financial assets, macroeconomic quantities, and even economic policy. They captures a different facet of uncertainty in the economy so they have their own economic and asset pricing implications. Recently, Bloom et al. (2018) suggest that micro uncertainty affects real economy via production decisions of firms by matching cross-sectional dispersion of total factor productivity (TFP). However, this micro uncertainty is confounded by macro uncertainty because firm productivity consists of systematic and idiosyncratic components. Based on this decomposition, we reconstruct macro and micro uncertainty by distinguishing systematic and idiosyncratic TFP and explore their roles from an asset pricing perspective.

We identify the cross-sectional standard deviations of TFP shock and the mimicking dispersion portfolios as follows. First, we estimate the firm-level total factor productivity (TFP) by following Olley and Pakes (1996) and Imrohoroglu and Tuzel (2014). Then, in each year, we calculate the cross-sectional standard deviation of TFP growth and define it as the total economic uncertainty. Further, we apply the principal component analysis (PCA) of Connor and Korajczyk (1987) to estimate the systematic TFP components. We identify six principal components to estimate the systematic TFP by following Chen and Kim (2018) and calculate the cross-sectional dispersion of systematic productivity (macro uncertainty). Then, we take the first-difference of these productivity dispersions and then

construct the mimicking dispersion factors by following Adrian et al. (2014). Our cross-sectional productivity dispersions are reasonably estimated. First, the negative correlation between total uncertainty and GDP growth confirms that the productivity uncertainty is counter-cyclical, consistent finding by Bloom et al. (2018). Also, it is positively correlated with the cross-sectional dispersion of stock returns. Further, the macro uncertainty captures most variations of the total uncertainty while the micro uncertainty does not. The correlation coefficient between macro uncertainty and total uncertainty is about 0.91 while that between micro uncertainty and total uncertainty is only -0.29. This implies that macro uncertainty tracks total uncertainty very well while micro uncertainty is not informative. Also, we find that the total uncertainty and the macro uncertainty have a significant correlation coefficient with the expected investment growth factor (EG) of Hou et al. (2018b). The magnitudes of correlation coefficients are 0.36 and 0.22, respectively.

We use the mimicking uncertainty portfolios to the asset pricing tests. First, the total uncertainty factor is significant across all different factor models. Its raw return is 0.65% per month (t-statistic=9.44). Since the abnormal returns of the total uncertainty factor are sizable and not explained by prevailing factor models, the total uncertainty factor captures a different fundamental risk from other pricing factors. Second, the macro uncertainty factor drives the significant pricing power of the total uncertainty factor. It explains the total uncertainty of about 82%. Also, the macro uncertainty factor has 0.55% per month (t-statistic=7.09) while the micro uncertainty factor has 0.94% per month (t-statistic=1.16). Abnormal returns of macro uncertainty factors are all significantly positive across all models. Also, in the cross-section, the macro uncertainty factor explains many different test portfolios and has a significant price of risk. Therefore, the macro uncertainty factor contains the important risk component of the total uncertainty factor.

Productivity uncertainty risk affects the pricing kernel via the income inequality channel. Constantinides and Duffie (1996) suggest that when a heterogeneous agent has an idiosyncratic labor income shock and cannot hedge the idiosyncratic income shock in a financial market, the cross-sectional dispersion of income shock affects the expected stock return in

equilibrium. The cross-sectional dispersion of income shock is closely related to the cross-sectional dispersion of productivity because the labor income distribution of the aggregate economy reflects the productivity distribution of the aggregate economy. To be specific, when the cross-sectional standard deviation of productivity increases, each firm faces very different productivity shock and then its employment decision is also very different from each other. This increases the cross-sectional dispersion of labor income shock at the aggregate economy. That is, income inequality contains the information of productivity dispersion. We use the income share from top 90th to 50th percentile of the income distribution from Piketty et al. (2018). Consistent with our prediction, the productivity uncertainty shock is positively correlated with the income inequality shock, with a correlation coefficient of 0.26. Mimicking income inequality factor is constructed in the same manner as the uncertainty factor. We find that the mimicking income inequality factor is significantly priced among many different assets. More importantly, the macro uncertainty factor fully explains the income inequality factor while the micro uncertainty factor does not capture the income inequality factor.

Lastly, we explore the rationale behind the significant connection between the productivity uncertainty and the expected investment growth (EG) factor of Hou et al. (2018b). Hou et al. (2018b) estimate EG factor by running Fama-MacBeth regression of the first-difference of asset growth against three predictors: Tobin's q , operating cash-flow, and the difference between ROE and four-quarter-lagged-ROE. Since the Fama-MacBeth regression coefficients capture the cross-sectional dispersion of three predictor variables and EG factor further captures the return spread of the sum of these cross-sectional dispersions weighted by the corresponding variables, we expect that EG factor shares the same risk with the cross-sectional productivity dispersion through the cross-sectional dispersions of three predictors. First, we show that the uncertainty factor explains EG factor while EG factor cannot fully explain the uncertainty factor. Second, we find that all cross-sectional dispersions of predictors are significantly correlated with the macro uncertainty. Overall, we confirm that EG factor contains the uncertainty risk via its regression coefficients which reflect the cross-sectional dispersions of predictors.

This paper contributes to the literature on economic uncertainty. The economic uncertainty, usually represented by the economic volatility, has received substantial attention recently. In the macroeconomics literature, Bloom et al. (2007) and Bloom (2009) suggest that the economic uncertainty makes firms to be more cautious about the future state so they postpone the investment decision, resulting in low investment in the aggregate economy. Although the economic consequences of economic uncertainty are well-documented, there are a few empirical measures. Bloom (2009) uses the VIX index as the aggregate uncertainty proxy. Bachmann et al. (2013) use the survey data to estimate economic uncertainty. Jurado et al. (2015) suggest the factor-based uncertainty by extracting key information from 132 macro-series including financial data. More recently, Bloom et al. (2018) find that the cross-sectional dispersion captures the economic uncertainty. Earlier asset pricing papers examine the impact of uncertainty on the financial market. Theoretically, the economic uncertainty has the first-order effect on an optimal investment decision (see Merton (1973); Campbell (1993); Campbell (1996); Bansal and Yaron (2004); Campbell et al. (2018)). Empirically, Ang et al. (2006) find that when a stock has a positive exposure on VIX index, its stock return is negatively priced. Similarly, G.Bali et al. (2017) show that a stock, which has positively sensitive to Jurado et al. (2015) uncertainty, predicts the negative stock return. Motivated by Bloom et al. (2018), we directly estimate the cross-sectional standard deviation, decompose it into macro and micro uncertainty, and test their asset pricing implications.

There have been several asset pricing models in empirical literature. After Fama and French (1993) three-factor model and Carhart (1997) four-factor models have been proposed, Fama and French (2015) suggest the five-factor model, including the market portfolio (MKT), the size factor (SMB), the value factor (HML), the investment factor (CMA), and the profitability factor (RMW). Further, Fama and French (2018) add the momentum (UMD) to Fama and French (2015) five-factor model. Also, Stambaugh and Yuan (2017) propose the mispricing factor model, including the market portfolio, the size factor, the mispricing factor related to a firm's management (MGMT), and the mispricing factor related to a firm's performance (PERF). Inspired by the production-based asset pricing, Hou et al. (2015) sug-

gest q -factor model, which has the market portfolio, the size factor (Q_{ME}), the investment factor (Q_{IA}), and the profitability factor (Q_{ROE}). Hou et al. (2018b) construct the expected investment growth factor (EG) and extend q -factor model by adding EG factor, which is called q^5 model.

We examine whether our productivity uncertainty factor is a significant macro risk factor by augmenting prevailing factor models with the uncertainty factor. Also, we test if the macro uncertainty marginally contributes to explain the return variations of many test assets in the cross-section. Moreover, we explore the connection between EG factor and the macro uncertainty factor and suggest that EG factor contains the uncertainty risk.

Also, this paper tabs the literature on income inequality. Income inequality in the United States has increased since the 1970s. Several papers find the increased income inequality using different data sources (see, e.g., Piketty and Saez (2003); Atkinson et al. (2011); Guvenen et al. (2014); Saez and Zucman (2016), Piketty et al. (2018)). Meanwhile, income inequality is considered an important risk factor. Constantinides and Duffie (1996) theoretically show that income inequality becomes an important risk factor when an agent receives the idiosyncratic labor income shock. Johnson (2012) empirically finds that income inequality risk has the negative price of risk in the cross-section. Chen and Yang (2019) document that the income inequality is one of the economic channels for the longevity risk and explains the momentum profits. Inspired by Constantinides and Duffie (1996), we indirectly show that income inequality is significantly priced. Since the income inequality reflects the productivity dispersion, the productivity uncertainty has the significant price of risk via the income inequality channel.

The rest of the paper proceeds as follows. Section 2.2 describes the data and procedures for estimating the cross-sectional dispersion of productivity. Section 2.3 presents the estimates of economic uncertainty factors. Section 2.4 describes the decomposition of the total uncertainty to the macro uncertainty and the micro uncertainty and tests the pricing power of both uncertainty over other prevailing pricing factors and test assets. Section 2.5 examines the income inequality channel. Section 2.6 explores the connection between economic

uncertainty and the expected investment growth factor. Finally, Section 2.7 concludes.

2.2 Estimating productivity uncertainty shock

The recent neoclassical theory stresses the role of economic uncertainty. Bloom et al. (2007) and Bloom (2009) theoretically show that the macro uncertainty shock enlarges firms' inaction range of labor hiring and investment decision because they are cautious about the future economic state with high uncertainty. More recently, Bloom et al. (2018) suggest the role of microeconomic uncertainty using the cross-sectional dispersion of establishment-level productivity and show that (1) it is strongly counter-cyclical and (2) it also has the similar economic impact as the macro uncertainty does. That is, the cross-sectional dispersion of productivity shock could be the risk pricing factor if it tracks the business cycle and a firm cannot hedge the micro uncertainty. In this section, we describe how to estimate the firm-level total factor productivity (TFP), the cross-sectional dispersion of TFP shock, and its mimicking productivity uncertainty factor.

2.2.1 Estimating firm-level total factor productivity and the cross-sectional dispersion of TFP

We estimate TFP by following Olley and Pakes (1996). Olley and Pakes (1996) estimate TFP by mitigating two endogenous issues. First, since input factors (e.g. labor and capital stock) are contemporaneously correlated, there is the simultaneity bias. They estimate the production function parameters for each input factor separately to address the simultaneity bias. The second endogenous problem is the selection bias. A firm's exit or entry decision depends on its productivity. Olley and Pakes (1996) assume TFP as the function of the survival probability and include that into 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; (3) investment includes the information about TFP. Imrohoroglu

and Tuzel (2014) apply Olley and Pakes (1996) to estimate firm-level TFP¹. We follow their estimation process with some modifications.

Assume the Cobb-Douglas production function:

$$Y_{it} = L_{it}^{\beta_L} K_{it}^{\beta_K} Z_{it} \quad (2.1)$$

where Y_{it} , L_{it} , K_{it} , and Z_{it} are value-added, labor, capital stock, and productivity of a firm i at time t . Productivity contains both systematic and idiosyncratic TFP components. Next, we scale the production function by its capital stock and take the logarithm at both sides. We scale the production function by the capital stock for three reasons. First, since TFP is the residual term, it is highly correlated with firm size. Second, the scaling avoids estimating the capital coefficients directly. Third, it mitigates the upward bias in the labor coefficient. Eq.(3.1) is rewritten as

$$\text{Log} \frac{Y_{it}}{K_{it}} = \beta_L \text{Log} \frac{L_{it}}{K_{it}} + (\beta_K + \beta_L - 1) \text{Log} K_{it} + \text{Log} Z_{it} \quad (2.2)$$

Denote $\text{Log} \frac{Y_{it}}{K_{it}}$, $\text{Log} \frac{L_{it}}{K_{it}}$, $\text{Log} K_{it}$, and $\text{Log} Z_{it}$ as yk_{it} , lk_{it} , k_{it} , and z_{it} . Also, let β_L and $(\beta_K + \beta_L - 1)$ as β_l and β_k . Rewrite Eq.(3.2) as follows:

$$yk_{it} = \beta_l lk_{it} + \beta_k k_{it} + z_{it}. \quad (2.3)$$

We can estimate the labor coefficient (β_l) and capital coefficient (β_k) using linear regressions. Then, the logarithmic TFP (z_{it}) is $y/k_{it} - \beta_l l/k_{i,t} - \beta_k k_{it}$. We estimate TFP with an extending window and TFP shocks can be computed as log growth rate. We define the cross-sectional standard deviation of log TFP growth as economic uncertainty. Further, we take the first-difference of the cross-sectional standard deviation of log TFP growth as total uncertainty shock (ΔUNC).

We use annual Compustat to estimate TFP for common stocks from NYSE, Amex, and

¹<http://www-bcf.usc.edu/~tuzel/TFPUUpload/Programs/>

Nasdaq. We include all firms except for financial and utility firms (four-digit SIC between 6000 - 6999 and between 4900 - 4999). Further, we exclude firms with assets or sales below \$1 million and the stock price lower than \$1 at the end of each year. The final sample period is from 1972 to 2016. See appendix 2.8.1 for more detail estimation.

2.2.2 Estimating macro and micro uncertainty

Here, we describe how to estimate macro and micro uncertainty as to our risk source. Following Herskovic et al. (2016), we decompose the aggregate TFP into systematic and idiosyncratic TFP via asymptotic principal component analysis of Connor and Korajczyk (1987). TFP estimates for N firms over time T , denoted as TFP_{NT} , can be decomposed into k principal components:

$$TFP_{NT} = B_{Nk} * PC_{kT} + \epsilon_{NT} \quad (2.4)$$

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

To estimate PC , we require the sample firms to have at least 5 years of TFP estimates and replace the missing observations to zero. However, when we estimate the sensitivity and the systematic TFP growth, we include the sample firms with more than 20 years of observations. We use higher requirement in order to estimate an accurate B_{Nk} ². Next, we choose six principal components ($k = 6$) by following Chen and Kim (2018). Chen and Kim (2018) find that (1) six principal components explain about 50% of log TFP growth variation; (2) there is the positive contemporaneous correlation between stock return and systematic TFP growth; and (3) only the volatility of systematic productivity predicts the expected stock return positively while that of idiosyncratic volatility cannot. These findings support

²Our results are not sensitive to the choice of criteria. Using 5 years to estimate the sensitivities has qualitatively similar results.

that six principal components are reasonable to estimate the systematic productivity shock.

After we estimate systematic TFP growth (idiosyncratic TFP growth), we calculate the cross-sectional standard deviation of systematic TFP growth (idiosyncratic TFP growth). Then, we take the first-difference of cross-sectional standard deviation for systematic TFP growth (idiosyncratic TFP growth), denoted as ΔUNC^{ma} (ΔUNC^{mi}).

2.2.3 Estimating mimicking uncertainty factors

We construct the mimicking portfolios to track the productivity uncertainty shock. One difficulty is that the frequency of productivity dispersion shock is annual. To construct the monthly mimicking portfolios, we follow Adrian et al. (2014) with the projection method. First, we project the cross-sectional dispersion shock (e.g. ΔUNC) onto a set of annual base asset returns:

$$\Delta UNC = \kappa_{0,UNC} + \kappa'_{x,UNC} X_{t,UNC}^a + u_t \quad (2.5)$$

where $X_{t,UNC}^a$ denotes the annual returns of some base assets in year t , and $\kappa_{0,UNC}$ and $\kappa'_{x,UNC}$ are the coefficients. In order to make the mimicking portfolio that tracks the information of economic uncertainty, we select the base assets from Hou et al. (2015) and Hou et al. (2018b). In Panel B of Table 2.1, we find that the annual correlation coefficient between total uncertainty shock (ΔUNC) and annual EG factor from Hou et al. (2018b) is significantly positive. Also, ΔUNC has moderate correlation coefficients with investment factors (0.16 for CMA and 0.19 for Q_{IA}) and the profitability factor (0.16 for RMW). To be specific, we include Hou et al. (2015) 18 size, investment, and profitability sorted portfolios (2 x 3 x 3) and Hou et al. (2018b) EG factor to extract the information of ΔUNC as much as possible. However, we can't include all 18 portfolios because using all 18 portfolios causes the multicollinearity problem. Also, because we only have 45 annual productivity dispersion shock, using all portfolios limits the degree of freedom for the projection regression. Therefore, we choose 4 of 18 portfolios. We start to project productivity dispersion shock onto all 18 portfolios and EG factor. Then, we choose the portfolios which have significant coefficients. The base

assets are as follows:

- $\Delta UNC = [\text{BLL}, \text{SML}, \text{BLM}, \text{BSH}, \text{EG}]$

For 4 portfolios except for the expected investment growth factor (EG), the first letter describes the size group, Small (S) or Big (B). The second letter describes the investment group, Low (L), Medium (M), or High (H). The third letter describes the profitability group, Low (L), Medium (M), and High (H). We use the same base assets to construct mimicking macro and micro uncertainty factors to avoid the arbitrariness. After we estimate $\kappa'_{x,PCn}$ at annual frequency, we normalize those coefficients: $\tilde{\kappa}'_{x,UNC} = \frac{\kappa_{x,UNC}}{|\Sigma \kappa_{x,UNC}|}$. The denominator is the sum of an absolute value of 5 coefficients. The normalized coefficients are $[0.08, -0.16, 0.41, -0.14, 0.81]'$. We find that the coefficient of EG factor is significantly positive and its magnitude is large. We further analyze the rationale behind this relationship in chapter 2.6. Overall, mimicking uncertainty portfolios track uncertainty shocks very well. The annual correlation coefficients between total uncertainty shock and its mimicking portfolio is about 35%. We construct the mimicking macro (micro) uncertainty factor in the similar manner and the correlation coefficient between the mimicking macro (micro) uncertainty portfolio and the macro (micro) uncertainty shock is 32% (31%). Last step is to make the mimicking uncertainty portfolios at monthly frequency, by multiplying the normalized coefficients and the monthly base asset returns,

$$\Delta UNC_t = \tilde{\kappa}'_{x,UNC} X_{t,UNC}^m \quad (2.6)$$

where X_t^m is the monthly returns of base assets from July t+1 to June t+2. When we construct the monthly mimicking uncertainty factor, we consider a 6-month reporting gap between uncertainty shock and stock return, following Fama and French (1993). That is, we estimate the annual portfolio weights ($\kappa'_{x,UNC}$) at the end of year t and multiply the weights with the monthly base asset returns from July t+1 to June t+2. In this paper, we will use the monthly mimicking portfolios for the rest of the asset pricing tests.

When we construct the mimicking uncertainty factor, we estimate the coefficients of base assets in full-sample. To avoid the look-ahead bias, we construct the mimicking uncertainty factor in the extending-window as a robustness test. The extending window starts from 1985 to have a sufficient number of observations. That is, the weights of the mimicking dispersion factor are estimated from 1972 to 1985 first, and we extend the estimation period up to 2016. To estimate the weights with enough degree of freedom for the extending-window, we use 4 base assets, as follows:

- $X_{t,UNC} = [\text{SML}, \text{BLM}, \text{BSH}, \text{EG}]$

2.3 Cross-sectional productivity dispersion

In this section, we first describe TFP and its economic uncertainty shock. We show that our uncertainty measures are reasonably estimated. Next, we test whether the productivity uncertainty shock is priced through the mimicking uncertainty factor.

2.3.1 Productivity uncertainty and Mimicking uncertainty factor

First, we examine the production function estimates. Labor coefficient (β_l) is 0.61 and capital coefficient (β_k) is 0.34. The estimates are similar to the numbers from Olley and Pakes (1996). Further, these estimates are consistent with neoclassical theory. For example, in Bloom et al. (2018), the labor coefficient is 2/3 and the capital coefficient is 1/3. During our sample period, the production technology is slightly decreasing return-to-scale, ($\beta_l + \beta_k = 0.94$).

Second, we directly compare our productivity uncertainty to that from Bloom et al. (2018). Bloom et al. (2018) show that the TFP uncertainty is strongly counter-cyclical. The correlation coefficient between TFP uncertainty from Bloom et al. (2018) and GDP growth is -0.45% from 1972 to 2011. Figure 1 shows the time-series pattern of our productivity uncertainty shocks and GDP growth. We apply HP-filter to all series. Similar to Bloom et al. (2018), total uncertainty (UNC) and macro uncertainty (UNC^{ma}) are counter-cyclical. For

example, both uncertainties spike at a Great recession while GDP growth (ΔGDP) drops. The correlation coefficient between UNC (UNC^{ma}) and ΔGDP is -0.27 (-0.25) as UNC^{mi} has only -0.04. We see that the productivity uncertainty is counter-cyclical and the macro uncertainty captures most of the variation of total uncertainty.

We note that there are three major differences between productivity uncertainty from Bloom et al. (2018) and our productivity uncertainty. First, their TFP is establishment-level while our TFP is firm-level. Second, they only cover manufacturing industries but our sample includes all firms except for finance and utility industries. Third, they estimate TFP following Foster et al. (2000). Even though there are some differences, overall our productivity uncertainty shares the strong counter-cyclical with Bloom et al. (2018). Moreover, in Figure 2, we plot the cross-sectional standard deviation of stock returns (RD) with productivity dispersions. Similar to productivity uncertainty, we decompose the stock return into systematic (RD^{sys}) and idiosyncratic (RD^{idio}) dispersions by regressing annual stock return on Carhart (1997) four-factor model. We use predicted stock return as a systematic stock return and a residual stock return as idiosyncratic stock return. After we decompose the stock return, then we calculate the cross-sectional standard deviation of stock returns for each year. Panel (a) and (b) of Figure 2 show that the total and macro productivity uncertainty track the cross-sectional return dispersions very well. For example, the correlation coefficients between UNC^{ma} and RD , RD^{sys} , and RD^{idio} are 0.63, 0.70, and 0.58 respectively. However, in Panel (c) of Figure 2, UNC^{mi} doesn't relate to the return dispersions. It only has -0.25, -0.33, and 0.09 for the corresponding return dispersions. These figures validate that our uncertainty measures are reasonably estimated.

Panel A of Table 2.1 shows that the log TFP growth (ΔTFP) has a mean of -0.01 and a standard deviation of 0.26. TFP growth varies over both cross-section and time-series. The next three rows present the descriptive statistics of productivity uncertainty shocks. Total TFP uncertainty shock (ΔUNC) has a mean of 0.00 with 0.03 standard deviation. Macro uncertainty shock (ΔUNC^{ma}) has more variation with 0.06 standard deviation while micro uncertainty shock (ΔUNC^{mi}) only has a standard deviation of 0.02. Income inequality shock

($\Delta Ineq$) is the first-difference of income share from the top 90 percentile to 50 percentile of the income distribution from Piketty et al. (2018). The sample period for the income inequality shock is from 1972 to 2014 because of data availability.

Panel B of Table 2.1 provides the annual correlation coefficients between productivity uncertainty shocks and prevailing pricing factors. We make a 6-month reporting gap between TFP uncertainty shocks and pricing factors. In this paper, we consider 11 pricing factors: (1) Six factors in Fama and French (2018), which are 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) Five factors from Hou et al. (2018b), 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) Univariate mispricing factor (MIS) from Stambaugh and Yuan (2017).

First, total uncertainty shock (ΔUNC) has a strong correlation coefficient with the expected investment growth factor (EG). The correlation between ΔUNC and EG is 0.36. We tackle this significant relationship in chapter 2.6. ΔUNC also has a significant correlation coefficients with MIS. The correlation coefficient is 0.31. This is not surprising because EG and MIS are highly correlated with 0.68. Hou et al. (2018a) find that their q^5 model subsumes the mispricing factors. The sample period for MIS ends in June 2016 while our full-sample period is up to June 2018. Therefore, we include EG into our base assets and examine the rationale behind strong correlation between ΔUNC and EG later. Second, we show that ΔUNC^{ma} is highly correlated with ΔUNC . The correlation coefficient between ΔUNC and ΔUNC^{ma} is 0.91, extremely high. This correlation indicates that macro uncertainty tracks total uncertainty very well and contains almost the same information. Also, ΔUNC^{ma} has pronounced correlation coefficients with EG and MIS, 0.22 and 0.22 respectively. Third, ΔUNC^{mi} has the different correlations from ΔUNC and ΔUNC^{ma} . ΔUNC^{mi} is not significantly correlated with ΔUNC . The magnitude of the correlation is only -0.29. Also, it does not have a strong correlation with EG while it has negatively correlated with size factors (SMB and Q_{ME}) and UMD, -0.31, -0.34, and -0.31 respectively. Overall, Panel B of Table

2.1 shows that ΔUNC^{ma} captures most of ΔUNC and both uncertainties have a significant relationship with EG factor.

Panel C of Table 2.1 presents the descriptive statistics of mimicking factors. ΔUNC has a mean of 0.65% per month with a standard deviation of 1.67% per month. Sharpe ratio of ΔUNC is 0.39. ΔUNC^{ma} has the sizable Sharpe ratio as well. On average, ΔUNC^{ma} has 0.55% per month with 1.74% per month of a standard deviation. Again, the monthly mimicking factor correlation between ΔUNC and ΔUNC^{ma} is 0.91. However, ΔUNC^{mi} has a very low Sharpe ratio, 0.06, because the standard deviation is 16.88% per month. The correlation between ΔUNC^{mi} and ΔUNC (ΔUNC^{mi}) is 0.07 (-0.02). This is consistent with the results from Panel B of Table 2.1, so Panel C further provides the evidence that our mimicking uncertainty factors are reasonably constructed by reflecting their correlation coefficients. Last, the mimicking income inequality factor ($\Delta Ineq$) has a sizable Sharpe ratio of 0.41 and it is significantly correlated with ΔUNC . The magnitude of the correlation coefficient is 0.43.

2.3.2 Productivity uncertainty risk

In this section, we formally test the mimicking uncertainty factor. We check whether the mimicking uncertainty factor is statistically significant on average. Further, we investigate it to see whether other pricing factor models explain the mimicking uncertainty factor.

Panel A of Table 2.2 reports the excess return of ΔUNC , its abnormal returns, and the sensitivities with respect to pricing factors, using the full sample period. We consider 8 factor models, including 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) mispricing factor model (SY), Hou et al. (2015) q -factor model (HXZ), and Hou et al. (2018b) q^5 model (HMXZ). First, the raw excess return is 0.65% per month (t-statistic=9.44) so the mimicking UNC factor is very significant over the sample period. Second, abnormal returns are still significant across different factor models. Moreover, the magnitude of abnormal

returns is stable from CAPM to HXZ. The lowest abnormal return is 0.45% per month (t-statistic=6.24) from SY and the highest abnormal return is from 0.66% per month (t-statistic=10.74) from FF3. Also, R^2 s are fairly low so the range of R^2 is from 0.06 to 0.35. Overall, the prevailing factor models from CAPM to HXZ do not explain the UNC factor. The last row reports the abnormal return from HMXZ and the abnormal return is 0.10% per month (t-statistic=3.09). Compared to previous factor models, HMXZ explains almost all variations of the UNC factor. Its R^2 is 0.82. The explanatory power increases by about 0.50 from R^2 of HXZ because EG increases the explanatory power. The coefficient of EG is 0.76 (t-statistic=35.01). Its magnitude and t-statistics are higher than any other coefficients. This is one piece of evidence that ΔUNC and EG contains similar fundamental risk.

To avoid the look-ahead bias, we use the extending-window estimation as a robustness check. Panel B of Table 2.2 presents the results. Overall, the extending-window estimation shows qualitatively similar results. Raw excess return is 0.77% per month (t-statistic=7.62). Alphas from other factor models except for HMXZ are from 0.38 to 0.77 and R^2 are from 0.00 to 0.32. However, q^5 model subsumes most of the time-series variation for ΔDIS . The abnormal return of HMXZ is 0.08% per month (t-statistic=1.80) and R^2 is 0.85. Also, the coefficient of EG is 0.89 (t-statistic=33.98).

Overall, Table 2.2 shows that productivity uncertainty is a significant risk factor. Moreover, the expected investment growth factor (EG) explains most of the productivity uncertainty variation.

2.4 Macro productivity uncertainty

Previously, we examine that the total productivity uncertainty (ΔUNC) is a significant risk factor and it is not explained by other pricing factors. Also, from Table 2.1, we see that the macro productivity uncertainty (ΔUNC^{ma}) is highly correlated with the total productivity uncertainty while micro productivity uncertainty (ΔUNC^{mi}) is not. In this section, we formally test whether ΔUNC^{ma} explains most of ΔUNC variations and whether

other factor models capture ΔUNC^{ma} . Further, we explore the ability of macro uncertainty to explain the return variations of test portfolios in the cross-section by running Fama-MacBeth two-pass regression.

2.4.1 Decomposing total uncertainty into macro and micro uncertainties

Panel A of Table 2.3 reports the time-series regression of ΔUNC against ΔUNC^{ma} and ΔUNC^{mi} . In Column (1), the coefficient of ΔUNC^{ma} from the simple linear regression is 0.51 (t-statistic=14.05) and R^2 is 0.82. This is not surprising because of the high correlation coefficients between ΔUNC and ΔUNC^{ma} , 0.91. In Column (2), we add ΔUNC^{mi} to the regression. The coefficient of ΔUNC^{mi} is 0.33 (t-statistic=3.05) while that of ΔUNC^{ma} is still 0.57 (t-statistic=14.87). Also, the explanatory power increases by only 0.03. Panel A of Table 2.3 suggests that the decomposition is reasonably estimated and ΔUNC^{ma} tracks ΔUNC very well.

Panel B of Table 2.3 shows the similar time-series regression but we replace productivity uncertainty factors to mimicking uncertainty factors. Regression results are similar to Panel A of Table 2.3. First, the coefficient of ΔUNC^{ma} is 0.84 (t-statistic=45.57). ΔUNC^{ma} explains 83% of ΔUNC variations. Even though we include ΔUNC^{mi} to the regression, its contribution to R^2 is very marginal. Overall, we see that macro uncertainty (ΔUNC^{ma}) captures most information of total uncertainty (ΔUNC) while the contribution of micro uncertainty (ΔUNC^{mi}) is negligible.

Panel C (D) of Table 2.3 presents the abnormal returns of ΔUNC^{ma} (ΔUNC^{mi}). We only report the abnormal returns and their t-statistics. In Panel C, we find that the raw return of ΔUNC^{ma} is 0.55% per month (t-statistic=7.09). Range of abnormal returns except for HMXZ are from 0.46% to 0.65%. Alphas from these factor models are quite stable. However, alpha from HMXZ is 0.18% per month (t-statistic=4.21). This seems that the pricing power of ΔUNC is inherited from ΔUNC^{ma} . Panel D shows the insignificant alphas of ΔUNC^{mi} . The raw return is 0.94% per month (t-statistic=1.16). Alpha from the market

model (CAPM) is only marginally significant.

Overall, Table 2.3 demonstrates that ΔUNC^{ma} is the main driver of ΔUNC variation. Further, only ΔUNC^{ma} is the risk factor while ΔUNC^{mi} is negligible.

2.4.2 Fama-MacBeth regression

Table 2.3 shows that ΔUNC^{mi} is the significant risk factor in time-series. Here, we explore the ability of ΔUNC^{ma} to explain many test assets in the cross-section by running Fama-MacBeth two-pass regression. Also, we see whether ΔUNC^{ma} has a significant price of risk in the cross-section. We use total of 35 test portfolios, including 6 size and book-to-market sorted portfolios, 6 size and investment sorted portfolios, 6 size and operating profitability sorted portfolios, 6 size and momentum sorted portfolios, 6 size and expected investment growth sorted portfolios, and 5 Fama-French industry portfolios. We download these portfolios from Kenneth French's website³. Following Lewellen et al. (2010), we add the pricing factors of tested factor models to test portfolios in order to restrict the price of risk to be equal to the average factor return.

We augment prevailing factor models with the mimicking macro uncertainty factor and compare those to prevailing factor models. 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), Stambaugh and Yuan (2017) mispricing factor model (SY), and Hou et al. (2015) q -factor model (HXZ). We do not extend Hou et al. (2018b) q^5 model (HMXZ) with our dispersion factor since EG and ΔUNC^{ma} are highly correlated. However, we compare q -factor model augmented with ΔUNC^{ma} to q^5 model in chapter 2.6. Augmented factor models are as follows:

- FF3+ ΔUNC^{ma} : $R_{it} = \gamma_0 + \gamma_{MKT}\hat{\beta}_{MKT,i} + \gamma_{SMB}\hat{\beta}_{SMB,i} + \gamma_{HML}\hat{\beta}_{HML,i} + \gamma_{UNC^{ma}}\hat{\beta}_{UNC^{ma},i} + \epsilon_{it}$
- FF4+ ΔUNC^{ma} : $R_{it} = \gamma_0 + \gamma_{MKT}\hat{\beta}_{MKT,i} + \gamma_{SMB}\hat{\beta}_{SMB,i} + \gamma_{HML}\hat{\beta}_{HML,i} + \gamma_{UMD}\hat{\beta}_{UMD,i} + \gamma_{UNC^{ma}}\hat{\beta}_{UNC^{ma},i} + \epsilon_{it}$

³<http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html>

- FF5+ ΔUNC^{ma} : $R_{it} = \gamma_0 + \gamma_{MKT}\hat{\beta}_{MKT,i} + \gamma_{SMB}\hat{\beta}_{SMB,i} + \gamma_{HML}\hat{\beta}_{HML,i} + \gamma_{CMA}\hat{\beta}_{CMA,i} + \gamma_{RMW}\hat{\beta}_{RMW,i} + \gamma_{UNC^{ma}}\hat{\beta}_{UNC^{ma},i} + \epsilon_{it}$
- FF6+ ΔUNC^{ma} : $R_{it} = \gamma_0 + \gamma_{MKT}\hat{\beta}_{MKT,i} + \gamma_{SMB}\hat{\beta}_{SMB,i} + \gamma_{HML}\hat{\beta}_{HML,i} + \gamma_{CMA}\hat{\beta}_{CMA,i} + \gamma_{RMW}\hat{\beta}_{RMW,i} + \gamma_{UMD}\hat{\beta}_{UMD,i} + \gamma_{UNC^{ma}}\hat{\beta}_{UNC^{ma},i} + \epsilon_{it}$
- HXZ+ ΔUNC^{ma} : $R_{it} = \gamma_0 + \gamma_{MKT}\hat{\beta}_{MKT,i} + \gamma_{Q_{ME}}\hat{\beta}_{Q_{ME},i} + \gamma_{Q_{IA}}\hat{\beta}_{Q_{IA},i} + \gamma_{Q_{ROE}}\hat{\beta}_{Q_{ROE},i} + \gamma_{UNC^{ma}}\hat{\beta}_{UNC^{ma},i} + \epsilon_{it}$
- SY+ ΔUNC^{ma} : $R_{it} = \gamma_0 + \gamma_{MKT}\hat{\beta}_{MKT,i} + \gamma_{MIS_{ME}}\hat{\beta}_{MIS_{ME},i} + \gamma_{MGMT}\hat{\beta}_{MGMT,i} + \gamma_{PERF}\hat{\beta}_{PERF,i} + \gamma_{UNC^{ma}}\hat{\beta}_{UNC^{ma},i} + \epsilon_{it}$

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 period. In the second stage, we run the cross-sectional regression of all test assets on the factor-loadings in each month and then estimate the time-series average of the price of risks. We adjust t-statistics for the errors-in-variables problem, 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 adjusted R^2 . To be specific, we bootstrap the time-series data of returns and factors by sampling with replacement to estimate the adjusted R^2 . We repeat these procedures 10,000 times and report the 5th and 95th percentiles of the sampling distribution.

Panel A of Table 2.4 reports the price of risks for each factor across different factor models. First, when we add the macro uncertainty factor to prevailing factor models, the augmented models explain the return variation in the cross-section. Augmented FF5, HXZ, and SY models have insignificant intercepts. For example, the pricing error (γ_0) decreases from 0.10% (t-statistic=4.83) of FF5 to 0.00% (t-statistic=-0.02) of FF5+ ΔUNC^{ma} . While γ_0 of HXZ is 0.09% (t-statistic=2.12), γ_0 of HXZ+ ΔUNC^{ma} is only 0.06% (t-statistic=1.15). Also, the mispricing factor model (SY) has a pricing error of 0.14% (t-statistic=2.53) but the augmented mispricing model has insignificant pricing error, 0.05% (t-statistic=0.83). This suggests that ΔUNC^{ma} plays an important role to explain the cross-sectional return variations among test portfolios. Second, we examine the price of risk for each factor. $\gamma_{UNC^{ma}}$ is from 0.39% to 0.66% across different augmented factor models. These price

of risks are quite close to the average factor returns, 0.55%. $\gamma_{UNC^{ma}}$ are stable across different augmented-factor models. We can infer that $\gamma_{UNC^{ma}}$ captures the different risk components from other prices of risks in Table 2.4. Third, we compare the adjusted R^2 between prevailing factor models and the corresponding augmented factor models. The adjusted R^2 increases from 0 to 0.18 by adding ΔUNC^{ma} . Bootstrap simulations further show that adding ΔUNC^{ma} to factor models contributes to improve the explanatory power.

In Panel B of Table 2.4, we replace ΔUNC^{ma} to ΔUNC^{mi} . It seems that ΔUNC^{mi} does not explain the return variation of test portfolios. When we compare prevailing factor models to ΔUNC^{mi} -augmented factor models, γ_0 doesn't change and it is still significant. For example, FF5 has 0.10% (t-statistic=4.83) of the abnormal return and FF5+ ΔUNC^{mi} still has 0.10% (t-statistic=4.90). All other augmented factor models have significant pricing errors as well. This is not surprising because the price of risks for ΔUNC^{mi} ($\gamma_{UNC^{mi}}$) are insignificant across all different augmented factor models. This is consistent results from Panel D of Table 2.3, which reports the insignificant mimicking micro uncertainty factor.

Since ΔUNC^{ma} tracks ΔUNC , we can replace ΔUNC^{ma} to ΔUNC . For the robustness test, we augment prevailing factor models with ΔUNC . Panel A of Table 2.14 reports the qualitatively similar results. γ_0 from the augmented FF5, HXZ, and SY models are insignificant. Also, γ_{UNC} are all significantly positive across different models and their magnitudes are close to the average factor return. To avoid the look-ahead bias, we report Fama-MacBeth regression using the extending-window estimation, following Ferson and Harvey (1999). Panel B of Table 2.14 reports the results. The sample period is from July 1986 to June 2018. We see that the regression results in the extending-window are similar. First, the intercepts become lower or insignificant after we augment prevailing factor models with ΔUNC . Second, γ_{UNC} is significantly positive across all augmented factor models. One may concern the look-ahead bias when we estimate the principal components because we use the full sample period. However, since the price of risk for ΔUNC in the extending window estimation is significantly positive and similar to the results using the full-sample estimation, we believe that the look-ahead bias does not drive our results.

For another robustness check, we extend prevailing factor models by adding both ΔUNC^{ma} and ΔUNC^{mi} instead of ΔUNC in Table 2.15. Across the augmented factor models, only $\gamma_{UNC^{ma}}$ are significantly positive while $\gamma_{UNC^{mi}}$ are insignificant. Further, we use the aggregate uncertainty (UNC^{agg}) to see its pricing power. We construct the mimicking aggregate uncertainty factor in the same manner to the mimicking macro uncertainty factor. We find that the aggregate uncertainty factor is positively priced but the overall pricing power is weaker than the macro uncertainty factor. See Appendix 2.8.2 for more details.

Overall, we conclude that ΔUNC improves the explanation power of prevailing factor models and its price of risk is significant in the cross-section. More importantly, ΔUNC^{ma} drives all the results of ΔUNC while ΔUNC^{mi} doesn't play any role.

2.4.3 Annual estimation using uncertainty factors

In the previous section, we examine the cross-sectional pricing power of ΔUNC and ΔUNC^{ma} by using their monthly mimicking portfolios and see that ΔUNC^{ma} drives the most of pricing power of ΔUNC . Although the monthly mimicking portfolio allows us to explore more comprehensive asset pricing tests in both time-series and cross-section, one may concern that the construction of the mimicking portfolio is arbitrary. Here, we evaluate the performance of various augmented factor models by having annual uncertainty factors directly in Fama-MacBeth two-pass regressions.

Table 2.6 reports the results from Fama-MacBeth regressions. To be consistent with Table 2.4, we use 29 test portfolios, including 6 size and book-to-market sorted portfolios, 6 size and investment sorted portfolios, 6 size and operating profitability sorted portfolios, 6 size and momentum sorted portfolios, and 5 Fama-French industry portfolios. We download these portfolios from Kenneth French's website⁴ and annualize the test assets and the pricing factors. We augment prevailing factor models with the macro uncertainty and compare those to prevailing factor models. Factor models are Fama and French (1993) three-factor model (FF3), Carhart (1997) four-factor model (FF4), Fama and French (2015) five-factor

⁴<http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html>

model (FF5), Fama and French (2018) six-factor model (FF6), Hou et al. (2015) q -factor model (HXZ), and Hou et al. (2018b) q^5 model (HMXZ). Again, we adjust t -statistics for the errors-in-variables problem, 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 adjusted R^2 and report the 5th and 95th percentiles of the sampling distribution. The sample period is from June 1974 to June 2018.

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 period. While prevailing pricing factors are contemporaneous with the test assets, the uncertainty factors are estimated at the end of the year and have a 6-month reporting gap. Also, to avoid the omitted factor problem, we estimate the sensitivities of uncertainty factors with Fama and French (2018) six factors and then use those sensitivities to estimate the price of risk in other Fama-French factor models. For example, we estimate the macro uncertainty sensitivities with Fama and French (2018) six factors. Next, we estimate Fama and French (1993) three factor sensitivities for each asset. Finally, we estimate the price of risks for both macro uncertainty and three factors together.⁵

Panel A of Table 2.6 reports the price of risks for each factor across different factor models. First, we recognize that $\gamma_{UNC^{ma}}$ is significantly priced. It varies from 4.99% to 5.79% per year across different augmented factor models. $\gamma_{UNC^{ma}}$ is stable and its magnitude is quite consistent with the average monthly mimicking portfolio, 0.55% per month. This further confirms that the monthly mimicking portfolio is well constructed. Second, we see that ΔUNC^{ma} improves model performance. For example, the pricing error (γ_0) decreases from 6.75% (t -statistics=1.84) of FF3 to 6.45% (t -statistics=1.36) of FF3+ ΔUNC^{ma} . Also, γ_0 decreases from 9.09% (t -statistics=2.05) of FF4 to 8.79% (t -statistics=1.60) of FF4+ ΔUNC^{ma} . Further, ΔUNC^{ma} increases the adjusted R^2 about 4%. Overall, these results echo the main findings of Table 2.4 using the monthly mimicking portfolio. That is, ΔUNC^{ma} has the important pricing power to explain various test assets.

⁵While this allows us to estimate the clean sensitivities for each factor, our results are qualitatively the same when we estimate the price of risk altogether.

In Panel B of Table 2.6, we replace ΔUNC^{ma} with ΔUNC^{mi} and reports the regression results. Consistent with the findings from Table 2.4, ΔUNC^{mi} does not have the significant price of risk except for $HXZ + \Delta UNC^{mi}$. The magnitude is negligible from -0.85% to -1.94% per year. The sign of the price of risk is negative although the sign of the mimicking portfolio is positive. This is because the sign of the mimicking portfolio is flipped by having the absolute sum of the portfolio weights in the denominator ($|\sum \kappa_{x,UNC}|$). That is, before we take the absolute value, the sum of the portfolio weights is negative.

Last, we run Fama-MacBeth regressions using total uncertainty factor (ΔUNC) in Table 2.17. We find qualitatively similar results. γ_{UNC} is significantly positive across different factor models. The magnitude is from 2.63% to 4.61% per year. It also helps to explain the pricing errors. Overall, the results using the macro uncertainty factor are consistent with the results using the monthly mimicking portfolios. Further, these results confirm that the macro uncertainty factor explains the various test assets with a significant price of risk while the micro uncertainty does not.

2.5 Inspecting the economic mechanism

So far, inspired by Bloom et al. (2018), we estimate the productivity uncertainty and show that it is an important and sizable risk factor. In this section, we explore the economic mechanism behind the previous results.

2.5.1 Income inequality risk

We suggest that an uncertainty shock affects the pricing kernel via an income inequality channel. Constantinides and Duffie (1996) extend the consumption-based CAPM with a heterogeneous income shock and show that the pricing kernel depends not only on the consumption growth but also the income inequality. Here, we show that income inequality is connected to the pricing kernel in the simple model of Constantinides and Duffie (1996). Consider an economy with a continuum of heterogeneous consumers, i , with homogeneous

power utility function, $\frac{C_{it}^{1-\gamma}}{1-\gamma}$, with the constant relative risk aversion, γ . Each agent is endowed with idiosyncratic labor income shock (ϵ_t^i) and this idiosyncratic income shock is not perfectly insured in the financial market. The pricing kernel ($M_{t,t+1}^i$) for each agent is as follows:

$$M_{t,t+1}^i = \left(\frac{C_{it+1}}{C_{it}}\right)^{-\gamma} \quad (2.7)$$

Following Constantinides and Duffie (1996), we assume that the individual consumption growth is as follows:

$$\frac{C_{it+1}}{C_{it}} = \frac{C_{t+1}}{C_t} \epsilon_{t+1}^i \quad (2.8)$$

where C_t is aggregate consumption in the economy. We further assume that $\log \epsilon_t^i$ is independent and individually distributed (i.i.d.) and follows the normal distribution with a mean of $-\frac{1}{2}\sigma_{y,t+1}^2$ and a standard deviation of $\sigma_{y,t+1}$. $\sigma_{y,t+1}$ is the cross-sectional standard deviation of income shock across heterogeneous agents and we can interpret this as income inequality. Since the income shock is i.i.d., the pricing kernel in the aggregate economy is as follows:

$$M_{t,t+1} = \exp\left[-\frac{\gamma(1+\gamma)}{2}\sigma_{y,t+1}^2\right]\left(\frac{C_{t+1}}{C_t}\right)^{-\gamma} \quad (2.9)$$

Eq.(2.9) shows that the pricing kernel depends not only the aggregate consumption growth, $\frac{C_{t+1}}{C_t}$, but also the cross-sectional dispersion of income shock, $\sigma_{y,t+1}^2$. The cross-sectional uncertainty directly affects the cross-sectional dispersion of income shock because the distribution of cross-sectional productivity links to the distribution of cross-sectional employment decisions and labor income. When a firm faces a systematic productivity shock at time t with a heterogeneous sensitivity, it decides its own optimal investment such as employment. Then, the distribution of labor income in the economy reflects the distribution of productivity shock in equilibrium. That is, the labor income inequality is the function of the productivity dispersion or the economic uncertainty.

To empirically establish the connection between the economic uncertainty and the cross-sectional income inequality, we estimate the first-difference of the income share from the

top 90 percentile to 50 percentile of the income distribution from Piketty et al. (2018). We focus on the income share of middle-income group from Piketty et al. (2018) for three reasons. First, Constantinides and Duffie (1996) assume that an individual agent has both a financial portfolio and a labor income, and he/she cannot perfectly hedge the labor income risk in the financial market. It is important to choose the representative group which has such a condition. Compared to middle-income group, the income group above the top 90 percentiles has a lot of financial assets while the income group below 50 percentiles rarely holds the financial assets⁶. Second, Piketty et al. (2018) construct the national income distribution by including comprehensive data such as tax, survey, and national accounts so the income distribution is consistent with macroeconomic quantities. Third, Piketty et al. (2018) provide both pre-tax and post-tax income distribution and we choose post-tax income distribution because individuals make their consumption decisions based on the final income. We download the income distribution data from Gabriel Zucman’s website⁷. The sample period is from 1972 to 2014 because of data availability.

Next, we examine whether income inequality shock is significantly priced. We construct the mimicking income inequality portfolios in the same manner as we construct the mimicking productivity uncertainty factors. We use the same base assets in the mimicking portfolio construction to avoid the arbitrariness. Then, we run Fama-MacBeth two-pass regression to see its price of risk. We use the same factor models as the factor models from Table 2.4 and augment those models with the income inequality factor ($\Delta Ineq$). Panel A of Table 2.7 reports the main results from Fama-MacBeth regressions using the full-sample estimation.

First, the income inequality-augmented factor models explain the test portfolios in the cross-section. For example, $\Delta Ineq$ reduces γ_0 of FF3, 0.29%, to 0.08% of FF3+ $\Delta Ineq$. Also, γ_0 of FF4+ $\Delta Ineq$ is 0.08% as γ_0 of FF4 is 0.10%. Other augmented factor models have quite similar intercepts to those from the prevailing factor models. Second, the prices of risks for $\Delta Ineq$, γ_{Ineq} , are significantly positive across different augmented factor models.

⁶Lettau et al. (2019) show that top 95% of stock wealth distribution owns 75% of stock market value. Also, Guvenen et al. (2014) find that the income share for 90% of income distribution is pro-cyclical because they own financial assets a lot. Therefore, we focus on the middle-income group as our representative agents.

⁷<http://gabriel-zucman.eu/usdina/>

For $FF5 + \Delta Ineq$, γ_{Ineq} is 0.94% (t-statistic=6.64). The range of γ_{Ineq} is from 0.70% to 0.94% and the magnitude of γ_{Ineq} is similar to the average factor return, 0.97%. This further confirms that income inequality risk is not captured by other prevailing factors. Third, for the robustness check, we run Fama-MacBeth regression in the extending-window estimation in Panel B of Table 2.7. The results are qualitatively similar. Income inequality has a significant price of risk across all different models and it improves to explain the cross-sectional return variations of test portfolios.

Overall, we identify that the productivity uncertainty may affect the pricing kernel through income inequality and find that the price of risk for income inequality is significant across many different test portfolios. In the next section, we dig the connection between income inequality and the uncertainty deeply.

2.5.2 Explaining income inequality risk with the uncertainty risk

We investigate the connection between income inequality risk and the productivity uncertainty risk. First, we estimate the correlation coefficient between the income inequality shock and the productivity uncertainty shock. The correlation coefficient is 0.26. Also, we estimate the correlation coefficient of the income inequality shock with macro (micro) uncertainty shock, 0.20 (0.07). Consistent with our prediction, income inequality is positively correlated with productivity uncertainty. This correlation confirms that the labor income distribution is closely affected by the productivity distribution and the income inequality of the middle-income group is counter-cyclical. More importantly, macro uncertainty is positively correlated with income inequality.

In order to examine the economic connection between the macro uncertainty and income inequality, we formally test whether the macro uncertainty factor explains the income inequality factor by running the time-series regression. Similar to Table 2.4, we augment prevailing factor models with the macro uncertainty factor. Panel A of Table 2.8 reports the regression results. Raw return of $\Delta Ineq$ is 0.97% per month (t-statistic=9.38). Among 7 augmented factor models, 5 augmented factor models have significant estimates of ΔUNC^{ma} .

For example, in HXZ, ΔUNC^{ma} has a regression coefficient of 0.39 with t-statistic=7.56. The intercept of this augmented factor model is -0.03% per month (t-statistic=-0.42). Other augmented factor models capture most of the income inequality variation over time. For augmented FF6, the intercept is only 0.21%, which is 22% of the income inequality factor. Next, we replace ΔUNC^{ma} to ΔUNC or ΔUNC^{mi} . Panel A of Table 2.18 reports the regression results using ΔUNC . ΔUNC -augmented factor models perform better than ΔUNC^{ma} -augmented factor models. Coefficients of ΔUNC are all significant across different models. Also, income inequality alphas are insignificant for FF5-, FF6-, SY-, and HXZ-augmented factor models. The abnormal returns are 0.09%, 0.07%, 0.05%, and -0.09%. Their t-statistics are 1.13, 0.91, 0.52, and -1.57 respectively. On the other hand, Panel A of Table 2.19 shows that ΔUNC^{mi} does not explain the income inequality factor. Across all ΔUNC^{mi} -augmented factor models, none of the intercepts are insignificant. This suggests that the macro uncertainty factor explains the income inequality risk while micro uncertainty doesn't.

Next, we test whether the income inequality factor explains the macro uncertainty factor in Panel B of Table 2.8. Examining Panel B of Table 2.8, we see that $\Delta Ineq$ cannot fully explain ΔUNC^{ma} . Raw return of ΔUNC^{ma} is 0.52% per month during the matched sample period. Across different augmented-factor models, $\Delta Ineq$ have the significant coefficients but the abnormal returns of ΔUNC^{ma} are still significantly positive and stable. Also, R^2 of augmented-factor models are relatively low from 0.06 to 0.36. When we replace ΔUNC^{ma} to ΔUNC , the main results are similar in Panel B of 2.18. These results suggest that macro uncertainty may better capture the cross-sectional dispersion risk than the income inequality measure does.

2.6 Interpreting the expected investment growth factor

When we construct the mimicking uncertainty factor, we include the expected investment growth factor (EG) from Hou et al. (2018b) because of the high correlation coefficients between them. Also, in Table 2.2 and Panel C of Table 2.3, only q^5 model explains most variations of productivity uncertainty factors. In this section, we examine how EG factor captures the variation of the productivity dispersion factor. First, we describe the EG factor construction by following Hou et al. (2018b). Then, we identify the economic linkage between EG factor and the productivity uncertainty factor. Also, we formally test which factor better explains another factor and the test portfolios. Lastly, we explore the connection between productivity uncertainty and the cross-sectional dispersion of each EG predictor.

2.6.1 Expected investment growth factor

From Cochrane (1991),

$$r_{it+1}^I \equiv \frac{X_{it+1} + (a/2)(I_{it+1}/A_{it+1})^2 + (1 - \delta)[1 + a(I_{it+1}/A_{it+1})]}{1 + a(I_{it}/A_{it})} \quad (2.10)$$

where r_t^I is the real-investment return of firm i at time t , X_{it} is the productivity, I_{it} is the investment, A_{it} is the capital stock (or asset), a is the cost parameter, and δ is the depreciation rate. Motivated by Eq.(2.10), Hou et al. (2015) suggest 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}). In Hou et al. (2018b), they further separate the nominator of (2.10) into the dividend yield, $X_{it+1} + (a/2)(I_{it+1}/A_{it+1})^2$, and the capital gain, $(1 - \delta)[1 + a(I_{it+1}/A_{it+1})]$, and construct the empirical risk factor capturing the capital gain component, which is the expected investment growth factor (EG). They suggest q^5 model by adding EG factor to q -factor model and show empirical success to explain many test portfolios and other pricing factors.

We replicate EG factor by following Hou et al. (2018b). Here, we describe the brief estimation process. To predict the expected future investment growth, they run Fama-MacBeth regression in the weighted least square with the market capitalization. Fama-MacBeth regression is as follows,

$$d\left(\frac{I_{it}}{A_{it}}\right) = \beta_0 + \beta_Q \log Q_{it-1} + \beta_{CoP} CoP_{it-1} + \beta_{dROE} dROE_{it-1} + \epsilon_{it} \quad (2.11)$$

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

$$E_t[dI_{it+1}/A_{it+1}] = \hat{\beta}_0 + \hat{\beta}_Q \log Q_{it} + \hat{\beta}_{CoP} CoP_{it} + \hat{\beta}_{dROE} dROE_{it} \quad (2.12)$$

.

After they estimate Eq.(2.12), they sort stocks on size and $E_t[dI_{it+1}/A_{it+1}]$ in 2-by-3 portfolios. Then, they construct the expected investment growth factor (EG), the difference between the average return of two high $E_t[dI_{it+1}/A_{it+1}]$ portfolios and the average return of two low $E_t[dI_{it+1}/A_{it+1}]$ portfolios, following Fama and French (1993). During our sample period, EG factor has a mean of 0.81% per month, a standard deviation of 2.02%, and Sharpe ratio of 0.40. Also, untabulated results show that the prevailing factor models cannot explain EG factor.

Why EG factor is highly correlated with productivity uncertainty factors? This is because the expected investment growth reflects the economic uncertainty. When we predict the future investment growth, the coefficients of Fama-MacBeth regression captures the cross-sectional variation of each predictor and those cross-sectional variations make the expected investment growth to share the same information of productivity dispersion factor. For example, consider only one predictor, $\log Q$, and assume the ordinary least square regression. Coefficient of Fama-MacBeth regression in each window is $\beta_Q = \frac{1}{120} \sum_{t-119}^t \beta_{Q,t}^{OLS}$ where $\beta_{Q,t}$

is Fama-MacBeth coefficient of $\log Q$ and $\beta_{Q,t}^{OLS}$ is the cross-sectional coefficient at time t . Further, $\beta_{Q,t}^{OLS}$ is equal to $\frac{cov(\log Q_{i,t-1}, d(\frac{I_{it}}{A_{it}}))}{var(\log Q_{i,t-1})}$ where $cov(x, y)$ is the covariance between x and y and $var(x)$ is the variance of x . Therefore, β_Q captures the average cross-sectional standard deviation of $\log Q$, $var(\log Q_{i,t-1})$, and $E_{it}[dI_{it+1}/A_{it+1}]$ is the function of average of cross-sectional dispersion of $\log Q$ weighted by $\log Q_{it}$. Then, EG factor captures the spread of the cross-sectional dispersion of $\log Q$ and further the productivity dispersion if the productivity dispersion and $\log Q$ dispersion are connected.

First, we formally test whether EG factor and macro uncertainty factor share the same fundamental risk in Table 2.9. In Panel A of Table 2.9, we present the time-series regression coefficients of EG factor against ΔUNC^{ma} -augmented factors. EG factor has 0.81% per month with t-statistic=8.77. The significant EG factor becomes insignificant when we control for the augmented-HXZ model. The abnormal return is 0.07% per month (t-statistic=1.25) and the regression coefficient of ΔUNC^{ma} is 0.80 (t-statistic=21.78). This is interesting results because EG factor cannot fully explain ΔUNC^{ma} in Panel C of Table 2.3. This shows that even though both EG factor and ΔUNC^{ma} share the same risk, ΔUNC^{ma} captures the uncertainty risk better. For other augmented factor models, ΔUNC^{ma} has all significant coefficients as well. Also, even though the abnormal returns of EG factor are significant, the magnitudes are small. For example, in the SY model, the intercept is 0.19% (t-statistic=2.77), which is 24% of EG factor. ΔUNC^{mi} takes the place of ΔUNC^{ma} in Panel B of Table 2.9. Any ΔUNC^{mi} -augmented factor models cannot capture the variation of EG factor. Further, the coefficients of ΔUNC^{mi} are insignificant in augmented CAPM, FF5, FF6, and HXZ models.

Table 2.21 reports the regression coefficients of ΔUNC to explain EG factor. In Panel A of Table 2.21, ΔUNC captures EG factor in augmented SY and HXZ model with insignificant intercepts, 0.07% (t-statistic=1.50) and 0.05% (t-statistic=1.22) respectively. Coefficients of ΔUNC are all significant. To avoid the look-ahead bias, we present the regression results in the extending-window estimation. In Panel B of Table 2.21, all ΔUNC -augmented factor models fully explains the EG factor. All abnormal returns of the augmented factor models

are from 0.01% to 0.08% and they are all insignificant.

Therefore, it seems that the EG factor and the macro uncertainty factor share the same fundamental risk. Further, the macro uncertainty factor can capture the EG factor while EG factor cannot explain all variations of the macro uncertainty factor.

2.6.2 Fama-MacBeth regression

In the previous section, we show that the productivity uncertainty explains EG factor while EG factor cannot capture the productivity uncertainty using time-series regression. Here, we compare two factors in the cross-section. Panel A of Table 2.4 reports the price of risk and the pricing error of Fama-MacBeth regression using the full-sample period. Factor models are Hou et al. (2018b) q^5 model (HMXZ), ΔUNC^{ma} -augmented HXZ model (HXZ+ ΔUNC^{ma}), and ΔUNC^{mi} -augmented HXZ model (HXZ+ ΔUNC^{mi}). First, the pricing error (γ_0) from HMXZ is 0.08% (t-statistic=1.66) while that from HXZ+ ΔUNC^{ma} is 0.06% (t-statistic=1.15). This shows that ΔUNC^{ma} explains the cross-sectional stock return variation a bit better than EG factor does. However, ΔUNC^{mi} does not play a role to explain γ_0 , 0.09% (t-statistic=2.10). Second, γ_{EG} is 0.75% (t-statistic=6.04) and $\gamma_{UNC^{ma}}$ is 0.56% (t-statistic=5.01). Both of price of risks are similar to their average factor return. In Panel B of Table 2.4, we estimate the price of risk using the extending-window betas. For ΔUNC^{ma} and ΔUNC^{mi} , we estimate the principal component using the full sample but we estimate the mimicking portfolios and their factor-loadings in the extending-window. Main results in Panel B are qualitatively similar. γ_0 from HMXZ is 0.11% (t-statistic=1.71) while that from HXZ+ ΔUNC^{ma} is 0.07% (t-statistic=0.97). Also, γ_{EG} and $\gamma_{UNC^{ma}}$ are 0.60% (t-statistic=3.87) and 0.72% (t-statistic=3.30) while $\gamma_{UNC^{mi}}$ is -0.25% (t-statistic=-0.17). For the robustness check, we replace ΔUNC^{ma} to ΔUNC in Table 2.22 and the results are similar to the results using ΔUNC^{ma} . Overall, EG factor and ΔUNC^{ma} have the similar contribution to HXZ model by explaining the test portfolios in the cross-section.

2.6.3 Cross-sectional dispersions of EG predictors

Previously, we describe how EG factor is constructed and show that the productivity uncertainty factor explains EG factor. In order for EG factor to capture the productivity uncertainty, the cross-sectional dispersion of three predictors should be significantly related to the uncertainty. Hou et al. (2018b) use three independent variables to predict future investment growth. They choose Tobin's q ($\log Q$), the operating cash-flow (CoP), and the first-difference of ROE ($dROE$). Theoretically, all three predictors are related to a firm's productivity. Tobin's q is a point where a firm's marginal profit is equal to its marginal cost in the production-based economy (see Hayashi (1982)). Also, operating cash flow and a change of ROE capture a firm's current profit and affect the investment in the next period. Since a firm observes its productivity shock first and decides the investment decision, the productivity shock should be linked to those variables.

If Fama-MacBeth regression estimates the coefficients of these predictors and those coefficients measure the cross-sectional variations, we expect that the productivity uncertainty is significantly correlated with the cross-sectional dispersion of three predictors. For each year, we calculate the cross-sectional standard deviation of each predictor. Also, we estimate the cross-sectional standard deviations of the first-differences of CoP and $\log Q$ to include only new information. Then, we run the time-series regression of the cross-sectional dispersions of predictors against UNC^{ma} in Panel A of Table 2.10.

First, UNC^{ma} explains the cross-sectional dispersion of three EG's predictors very well. For example, UNC^{ma} explains the cross-sectional dispersion of cash-flow (DIS_{COP}) with R^2 of 0.53. This suggests that UNC^{ma} is enough to explain the cross-sectional variation of cash-flow alone. Single regression coefficient is 0.25 (t-statistic=6.90). Also, UNC^{ma} explains the cross-sectional dispersions of Tobin's Q (DIS_Q) and ROE change (DIS_{dROE}). R^2 for DIS_Q and DIS_{dROE} are 0.43 and 0.41 respectively. Further, we see whether UNC^{ma} explains the latest information of cross-sectional dispersion of cash-flow (DIS_{dCOP}) and Tobin's Q (DIS_{dQ}). UNC^{ma} still explains the cross-sectional dispersion using the latest information. For example, using UNC^{ma} alone explains about 0.56 of the variation of

DIS_{dQ} . In Panel B of Table 2.10, we run the same regression using the micro uncertainty (UNC^{mi}). The regression results show that UNC^{mi} does not explain the cross-sectional dispersion of each predictor except for DIS_{dROE} . UNC^{mi} has the significant coefficient of 0.23 (t-statistic=2.10) in the regression of DIS_{dROE} . However, its R^2 is only 0.09.

Overall, Table 2.10 suggests that the macro uncertainty explains EG factor via the cross-sectional dispersions of predictors. Also, the micro uncertainty cannot capture the same fundamental risk of EG factor because it does not correlate with the cross-sectional dispersions of predictors. These results are consistent with our prediction, which is that the macro uncertainty reflects the same risk of EG factor via the cross-sectional dispersions of three predictors.

Next, we directly examine whether the cross-sectional dispersion of EG predictors are priced across various test assets. We run Fama-MacBeth regressions using first-differences of cross-sectional dispersion of EG predictors. Consistent with Hou et al. (2018b) q^5 model, we augment cross-sectional dispersions with Hou et al. (2015) q -factor model. Table 2.11 presents the regression results. ΔDIS_{COP} is significantly priced. The price of risk is 1.51% per year ($t=2.84$). Also, ΔDIS_Q is marginally priced. Its price of risk is 2.69% per year ($t=1.66$). However, ΔDIS_{dROE} is insignificant. This suggests that the pricing power of EG factor is driven by cross-sectional dispersion of operating cash flow and Tobin's Q, which are significantly linked to macro uncertainty.

Last, if macro uncertainty and EG factor share the same risk, test assets should have the same magnitude of exposures on both of them. Table 2.12 presents the cross-sectional regression of factor loadings of EG factor and the cross-sectional dispersion of EG predictors in Fama-MacBeth regressions against factor loadings of our uncertainty measures. In column (1), we find that factor loadings of total uncertainty explain those of EG factor about 68%. In Column (2), we replace total uncertainty to macro and micro uncertainty. Factor loadings of macro uncertainty significantly explains those of EG factor while those of micro uncertainty cannot explain the variation of factor loadings of EG factor additionally. Moreover, the coefficient of $\beta_{UNC^{ma}}$ is 1.07, which suggests that macro uncertainty capture the variations

of EG factors very well. Column (3) to (8) presents similar results replacing EG factor to cross-sectional dispersions of EG predictors. It seems that the factor loadings of ΔDIS_{COP} are significantly correlated to those of ΔUNC and ΔUNC^{ma} while ΔDIS_Q and ΔDIS_{dROE} have different exposures from them. Since EG factor and the cross-sectional dispersion of operating cash flow are priced and share similar exposure with macro uncertainty, macro uncertainty shares the same risk with EG factor.

2.6.4 Maximum squared Sharpe ratio

In Table 2.4, we use a set of test assets as the left-hand-side variables to study the pricing power of the macro and micro uncertainty factors. This left-hand-side approach is intuitive and widely used but the inferences of this approach depend on the choice of test assets. In this section, we use the right-hand-side approach following Barillas and Shanken (2017) and Fama and French (2018). 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 , assume a time-series regression of test assets (Π_i), which include nonfactor 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

$$Sh^2(a_i) = a_i' \Sigma_i^{-1} a_i \quad (2.13)$$

where Sh^2 denotes the maximum squared Sharpe ratio. Gibbons et al. (1989) show 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:

$$Sh^2(a_i) = Sh^2(\Pi_i, f_i) - Sh^2(f_i) \quad (2.14)$$

As Π_i and f_i include all competing factors, $Sh^2(\Pi_i, f_i)$ is independent of i . 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 , $Sh^2(f_i)$. The maximum squared Sharpe ratio can be computed from the tangent portfolio from prevailing pricing factors.

Table 2.13 reports the maximum squared Sharpe ratios for various models. For comparison, we use FF3, FF4, FF5, FF6, HXZ, and HMXZ. We couldn't use the SY model because of data availability. First, in Panel A of Table 2.13, ΔUNC^{ma} improves the maximum squared Sharpe ratio. The highest statistic is from ΔUNC^{ma} -augmented HMXZ factor model, followed by HXZ+ ΔUNC^{ma} and HMXZ. All of them have about 0.30. We see that both EG factor and ΔUNC^{ma} factor have the similar statistic. The rest of the factor models also have a higher maximum squared Sharpe ratio with ΔUNC^{ma} . Second, total uncertainty and the income inequality factors increase the maximum squared Sharpe ratio while the micro uncertainty factor does not contribute to increasing the maximum squared Sharpe ratio.

Overall, macro uncertainty is an important macroeconomic risk and its impact on the asset returns is independent of choosing the test assets. Further, EG factor reflects the macro uncertainty risk and has significant pricing power across various asset returns.

2.7 Conclusion

Motivated by Bloom et al. (2018), we start with the cross-sectional dispersion of firms' productivity and explore its asset pricing implications in both time-series and cross-section. Further, we estimate the macro uncertainty and show that it captures significant pricing power of the cross-sectional dispersion. We find that macro uncertainty has a significant price of risk and explains the stock return variations in the cross-section. The economic channel behind this pricing power is income inequality. In fact, income inequality reflects the cross-sectional dispersion of productivity because a firm's productivity is closely related to labor hiring. In particular, we explore the economic connection between the expected investment growth factor (EG) and the productivity dispersion by investigating the EG

factor construction. Since the expected investment growth is constructed by running Fama-MacBeth regression using Tobin's q , operating cash-flow, and the change of ROE, EG factor captures the sum of three predictors' cross-sectional dispersions multiplied with the corresponding predictors. We identify that the economic uncertainty shares the common risk sources with EG factor via three cross-sectional dispersions. Overall, the macro uncertainty is the important risk factor working through income inequality and EG factor captures this uncertainty risk.

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Figure 2.1. TFP dispersions and GDP growth

This figure plots the time series of total uncertainty (UNC), macro uncertainty (UNC^{ma}), and micro uncertainty (UNC^{mi}) against annual GDP growth in the United States. All series are standardized. The shaded areas are NBER recession periods.

Figure 2.2. TFP dispersions and 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 Carhart four-factor model. All series are standardized. The shaded areas are NBER recession periods.

Table 2.1. **Uncertainty factors: Descriptive statistics and relations with other pricing factors**

Panel A summarizes the annual log TFP growth (ΔTFP), the first-difference of cross-sectional standard deviation of TFP growth (total uncertainty, ΔUNC), systematic TFP growth (macro uncertainty, ΔUNC^{ma}), idiosyncratic TFP growth (micro uncertainty, ΔUNC^{mi}), and the first-difference of income inequality ($\Delta Ineq$), including the mean, standard deviation, percentiles, correlation with GDP growth ($\rho(GDP)$) and income inequality ($\rho(Ineq)$). We regress TFP growth on six principal components for each firm and define predicted (residual) TFP growth as systematic (idiosyncratic) TFP growth. Income inequality is the post-tax national income share from top 90th percentiles to 50th percentiles of the income distribution from Piketty et al. (2018). Panel B reports the annual time-series correlation coefficients between dispersions and pricing factors. The pricing factors include Fama and French (2015) market factor (MKT), size factor (SMB), value factor (HML), investment factor (CMA), and profitability factor (RMW); Carhart (1997) momentum factor (UMD); Hou et al. (2015) size factors (Q_{ME}), investment factor (Q_{IA}), and profitability factor (Q_{ROE}); Hou et al. (2018b) expected investment growth factor (EG); and Stambaugh and Yuan (2017) mispricing factor (MIS). Panel C presents the monthly mean (% per month), standard deviation (% per month, SD), Sharpe ratio (SR), and correlations for the mimicking dispersion and income inequality portfolios. The sample period of dispersions is from 1972 to 2016 while that of income inequality is from 1972 to 2014 because of the data availability. The sample period for pricing factors and factor-mimicking portfolios is from July 1973 to June 2018.

Panel A: TFP and uncertainty measures													
	Mean	SD	Min	Max	10%	25%	50%	75%	90%	AR(1)	$\rho(GDP)$	$\rho(Ineq)$	
ΔTFP	-0.01	0.26	-1.35	1.39	-0.29	-0.11	0.00	0.11	0.27	-0.09			
ΔUNC	0.00	0.03	-0.10	0.07	-0.03	-0.02	0.00	0.02	0.04	-0.18	-0.27	0.27	
ΔUNC^{ma}	0.00	0.06	-0.15	0.16	-0.05	-0.03	0.00	0.02	0.07	-0.34	-0.25	0.20	
ΔUNC^{mi}	0.00	0.02	-0.07	0.04	-0.02	-0.01	0.00	0.01	0.03	-0.29	-0.04	0.07	
$\Delta Ineq$	0.00	0.00	-0.01	0.01	0.00	0.00	0.00	0.00	0.00	-0.23	-0.29		
Panel B: Correlations between uncertainty measures and pricing factors													
	MKT	SMB	HML	CMA	RMW	UMD	Q_{ME}	Q_{IA}	Q_{ROE}	EG	MIS	ΔUNC	ΔUNC^{ma}
MKT	1.00												
SMB	0.10	1.00											
HML	-0.32	0.05	1.00										
CMA	-0.32	0.22	0.65	1.00									
RMW	-0.26	-0.06	0.40	0.24	1.00								
UMD	0.19	0.19	-0.25	-0.11	-0.05	1.00							
Q_{ME}	0.15	0.98	0.05	0.21	-0.13	0.26	1.00						
Q_{IA}	-0.27	0.19	0.63	0.91	0.28	-0.10	0.18	1.00					
Q_{ROE}	0.01	0.01	0.09	0.00	0.54	0.48	0.05	0.17	1.00				
EG	-0.15	0.17	0.11	0.26	0.35	0.32	0.16	0.28	0.45	1.00			
MIS	-0.26	-0.02	0.02	0.35	0.41	0.45	-0.03	0.34	0.45	0.68	1.00		
ΔUNC	-0.06	-0.02	0.09	0.16	0.16	-0.06	-0.03	0.19	0.04	0.36	0.31	1.00	
ΔUNC^{ma}	0.00	0.08	0.01	0.10	0.05	-0.02	0.07	0.11	-0.02	0.22	0.22	0.91	1.00
ΔUNC^{mi}	-0.09	-0.31	0.14	-0.08	0.09	-0.33	-0.34	0.01	0.05	-0.14	-0.18	-0.29	-0.49
Panel C: Statistics of monthly mimicking uncertainty and income inequality portfolios													
	Mean	SD	SR	ΔUNC	ΔUNC^{ma}	ΔUNC^{mi}							
ΔUNC	0.65	1.67	0.39										
ΔUNC^{ma}	0.55	1.74	0.32	0.91									
ΔUNC^{mi}	0.94	16.88	0.06	0.07	-0.02								
$\Delta Ineq$	0.97	2.37	0.41	0.43	0.17	0.30							

Table 2.2. **Explaining the total uncertainty factor with other pricing factors**

Panel A presents the abnormal returns and the factor-loadings of the mimicking uncertainty portfolio from various factor models, using full-sample period. Panel B shows similar results from the extending-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) mispricing factor model (SY), Hou et al. (2015) q -factor model (HXZ), and Hou et al. (2018b) q^5 model (HMXZ). 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 sample period for Panel A is from July 1973 to June 2018. The testing period for Panel B starts from July 1986.

Panel A: Full-sample estimation									
	α								
Raw	0.65								
t-stat	9.44								
	α	MKT						R^2	
CAPM	0.59	0.09						0.06	
t-stat	8.9	4.67							
	α	MKT	SMB	HML					R^2
FF3	0.66	0.11	-0.23	-0.07					0.24
t-stat	10.74	7.04	-9.52	-1.63					
	α	MKT	SMB	HML	UMD				R^2
FF4	0.59	0.13	-0.23	-0.04	0.09				0.28
t-stat	9.17	9.57	-9.42	-0.97	3.95				
	α	MKT	SMB	HML	CMA	RMW			R^2
FF5	0.59	0.13	-0.17	-0.08	-0.02	0.21			0.31
t-stat	7.96	8.27	-5.82	-1.98	-0.24	3.7			
	α	MKT	SMB	HML	CMA	RMW	UMD	R^2	
FF6	0.53	0.14	-0.17	-0.03	-0.06	0.20	0.08	0.35	
t-stat	7.73	9.69	-6.54	-0.85	-1.00	4.03	4.46		
	α	MKT	MIS_{ME}	MGMT	PERF				R^2
SY	0.45	0.18	-0.18	0.07	0.18				0.33
t-stat	6.24	11.35	-7.17	2.23	8.49				
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}				R^2
HXZ	0.55	0.13	-0.17	-0.12	0.21				0.33
t-stat	7.09	8.58	-5.47	-1.78	5.49				
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}	EG			R^2
HMXZ	0.10	0.20	-0.14	-0.32	-0.04	0.76			0.82
t-stat	3.09	19.68	-11.50	-13.13	-2.02	35.01			

Panel B: Extending-window estimation								
	α							
Raw	0.77							
t-stat	7.62							
	α	MKT						R^2
CAPM	0.77	0.01						0.00
t-stat	7.00	0.23						
	α	MKT	SMB	HML				R^2
FF3	0.77	0.02	-0.09	0.01				0.02
t-stat	7.44	0.65	-1.90	0.12				
	α	MKT	SMB	HML	UMD			R^2
FF4	0.67	0.05	-0.09	0.06	0.12			0.12
t-stat	6.74	1.97	-2.41	0.81	3.94			
	α	MKT	SMB	HML	CMA	RMW		R^2
FF5	0.60	0.08	-0.01	-0.13	0.20	0.27		0.14
t-stat	5.37	3.24	-0.20	-2.61	2.06	2.98		
	α	Mktrf	SMB	HML	CMA	RMW	UMD	R^2
FF6	0.55	0.10	-0.02	-0.06	0.15	0.25	0.10	0.21
t-stat	5.37	4.17	-0.48	-1.41	2.02	3.08	4.04	
	α	MKT	MIS_{ME}	MGMT	PERF			R^2
SY	0.38	0.15	0.02	0.22	0.21			0.32
t-stat	3.82	5.99	0.56	5.05	8.06			
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}			R^2
HXZ	0.59	0.07	0.00	0.08	0.25			0.15
t-stat	5.10	2.45	0.06	0.82	4.41			
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}	EG		R^2
HXMZ	0.08	0.15	0.02	-0.14	-0.03	0.89		0.85
t-stat	1.80	10.24	1.35	-5.12	-1.35	33.98		

Table 2.3. **Decomposing total uncertainty into macro and micro uncertainties**

Panel A presents the time-series regression of the aggregate uncertainty on the macro uncertainty (UNC^{ma}) and the micro uncertainty (UNC^{mi}). The aggregate uncertainty (UNC^{agg}) is the conditional standard deviation of a generalized autoregressive conditional heteroskedasticity GARCH (1,1) on aggregate TFP, obtained from Federal Reserve San Francisco. Panel B presents the time-series regression of total uncertainty (ΔUNC) on the macro uncertainty (ΔUNC^{ma}) and micro uncertainty (ΔUNC^{mi}). Panel C reports the time-series regression of the mimicking total uncertainty portfolio on mimicking macro uncertainty portfolio and micro uncertainty portfolio. Panel D reports the abnormal returns of the mimicking macro uncertainty portfolio (ΔUNC^{ma}) from various factor models. Panel E tabulates the abnormal returns of the mimicking micro uncertainty (ΔUNC^{mi}) from various 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), Hou et al. (2015) q -factor model (HXZ), Hou et al. (2018b) q^5 model (HMXZ), and Stambaugh and Yuan (2017) model (SY). From Panel B to Panel D, Newey-West adjusted t-statistics (t-stat) with 6-month lags are provided. The sample period is from July 1973 to June 2018.

Panel A: Regression of aggregate uncertainty against macro and micro uncertainty									
	(1)	(2)							
	UNC^{agg}	UNC^{agg}							
UNC^{ma}	0.20	0.20							
	(2.85)	(2.77)							
UNC^{mi}		-0.04							
		(-0.19)							
R^2	0.16	0.16							
Panel B: Regression of total uncertainty against macro and micro uncertainty									
	(1)	(2)							
	ΔUNC	ΔUNC							
ΔUNC^{ma}	0.51	0.57							
	(14.05)	(14.87)							
ΔUNC^{mi}		0.33							
		(3.05)							
R^2	0.82	0.85							
Panel C: Regression of mimicking uncertainty portfolios									
	(1)	(2)							
	ΔUNC	ΔUNC							
ΔUNC^{ma}	0.84	0.84							
	(45.57)	(49.17)							
ΔUNC^{mi}		0.01							
		(3.02)							
R^2	0.83	0.84							
Panel D: Abnormal return of macro uncertainty factor									
	Raw	CAPM	FF3	FF4	FF5	FF6	HXZ	HMXZ	SY
ΔUNC^{ma}	0.55	0.50	0.57	0.54	0.60	0.57	0.65	0.18	0.46
t-stat	7.09	6.64	7.96	7.33	7.23	7.00	7.81	4.21	5.78
Panel E: Abnormal return of micro uncertainty factor									
	Raw	CAPM	FF3	FF4	FF5	FF6	HXZ	HMXZ	SY
ΔUNC^{mi}	0.94	1.49	1.18	0.99	0.09	0.04	-1.11	-0.73	0.25
t-stat	1.16	1.87	1.53	1.40	0.13	0.06	-1.38	-1.04	0.33

Table 2.4. Cross-sectional regressions of macro- and micro- uncertainty-augmented factor models

Panel A reports Fama-MacBeth regressions of various factor models and those augmented with macro uncertainty portfolios (ΔUNC^{ma}), using the full-sample estimation. Panel B shows the similar results in the extending window estimation. Panel C presents Fama-MacBeth regressions of micro uncertainty (ΔUNC^{mi})-augmented factor models. Panel D shows the similar results in the extending window estimation. Test assets are 35 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, and 5 Fama-French industry portfolios. Tested factor models are Fama and French (1993) three-factor model (FF3), Carhart (1997) four-factor model (FF4), Fama and French (2015) five-factor model (FF5), Fama and French (2018) six-factor model (FF6), Hou et al. (2015) q -factor model (HMZ), and Stambaugh and Yuan (2017) model (SY). All coefficients are multiplied by 100. The t -statistics are adjusted for errors-in-variables, following Shanken (1992). The adjusted R^2 follows Jagannathan and Wang (1996). The 5th and 95th percentiles of the adjusted R^2 distribution from a bootstrap simulation of 10,000 times are reported in brackets. Sample period for Panel A and C (B and D) is July 1973 to June 2018 (July 1986 to June 2018).

Panel A: Augmented factor models with systematic TFP dispersion using the full-sample estimation																
	FF3		FF3+ ΔUNC^{ma}		FF4		FF4+ ΔUNC^{ma}		FF5		FF5+ ΔUNC^{ma}		FF6		FF6+ ΔUNC^{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
γ_0	0.31	6.09	0.11	2.53	0.10	4.64	0.02	0.78	0.10	4.83	-0.03	-1.77	0.09	5.06	-0.01	-0.72
γ_{MKT}	0.31	1.55	0.50	2.54	0.54	2.77	0.61	3.14	0.50	2.58	0.62	3.16	0.54	2.75	0.61	3.13
γ_{SMB}	0.21	1.60	0.23	1.75	0.22	1.71	0.25	1.90	0.27	2.08	0.30	2.29	0.26	2.00	0.30	2.28
γ_{HML}	0.18	1.35	0.31	2.33	0.28	2.12	0.39	2.97	0.10	0.78	0.24	1.81	0.21	1.59	0.28	2.15
γ_{CMA}									0.32	3.44	0.38	3.96	0.23	2.59	0.32	3.56
γ_{RMW}									0.20	1.93	0.32	3.07	0.17	1.69	0.30	2.87
γ_{UMD}					0.56	2.99	0.62	3.29			0.72	7.69	0.55	2.91	0.59	3.13
$\gamma_{UNC^{ma}}$	0.69		0.69	7.33			0.62	6.91			0.83		0.80		0.65	7.62
R^2	0.19		0.44		0.66		0.67		0.63		0.83		0.80		0.87	
(5 th , 95 th)	(0.00, 0.51)		(0.18, 0.71)		(0.46, 0.83)		(0.49, 0.81)		(0.37, 0.83)		(0.64, 0.91)		(0.63, 0.91)		(0.74, 0.93)	
Panel A (Continued)																
	HXZ		HXZ+ ΔUNC^{ma}		HMXZ		SY		SY+ ΔUNC^{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
γ_0	0.03	0.88	0.02	0.67	0.06	1.67	0.06	1.21	-0.01	-0.24						
γ_{MKT}	0.56	2.84	0.58	2.94	0.55	2.77	0.53	2.56	0.60	2.94						
γ_{QME}	0.39	2.85	0.38	2.77	0.38	2.75										
γ_{QIA}	0.31	2.93	0.31	2.95	0.31	2.92										
γ_{QROE}	0.56	4.10	0.46	3.32	0.39	2.83										
γ_{EG}					0.75	7.61										
γ_{MISME}							0.41	3.14	0.46	3.54						
γ_{MGMT}							0.54	3.73	0.63	4.35						
γ_{PERF}							0.58	3.05	0.60	3.13						
$\gamma_{UNC^{ma}}$			0.61	6.52					0.59	6.33						
R^2	0.62		0.86		0.84		0.73		0.85							
(5 th , 95 th)	(0.42, 0.77)		(0.70, 0.91)		(0.70, 0.90)		(0.55, 0.84)		(0.69, 0.90)							

Panel B: Augmented factor models with systematic TFP dispersion using the extending-window estimation

	FF3		FF3+ ΔUNC^{ma}		FF4		FF4+ ΔUNC^{ma}		FF5		FF5+ ΔUNC^{ma}		FF6		FF6+ ΔUNC^{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
γ_0	0.19	3.70	0.02	0.60	0.09	3.77	0.01	0.43	0.06	2.26	0.03	0.90	0.06	3.08	0.01	0.78
γ_{MKT}	0.50	2.13	0.67	2.93	0.61	2.73	0.68	2.99	0.60	2.67	0.64	2.85	0.61	2.73	0.65	2.87
γ_{SMB}	0.05	0.33	0.07	0.43	0.06	0.41	0.07	0.44	0.11	0.74	0.12	0.74	0.11	0.73	0.12	0.73
γ_{HML}	0.11	0.62	0.23	1.32	0.18	1.06	0.24	1.41	0.08	0.49	0.15	0.96	0.11	0.69	0.15	0.96
γ_{CMA}									0.28	2.15	0.22	1.71	0.21	1.82	0.23	1.98
γ_{RMW}									0.29	2.00	0.29	1.98	0.30	2.10	0.31	2.11
γ_{UMD}					0.49	2.03	0.49	2.02					0.48	2.02	0.48	1.96
$\gamma_{UNC^{ma}}$			0.93	5.17			0.93	5.66			0.86	5.08			0.92	5.79
R^2	0.21		0.65		0.39		0.67		0.63		0.87		0.67		0.88	
(5 th , 95 th)	(-0.01, 0.57)		(0.38, 0.80)		(0.32, 0.75)		(0.51, 0.84)		(0.33, 0.79)		(0.69, 0.91)		(0.52, 0.85)		(0.73, 0.93)	
Panel B (Continued)																
	HXZ		HXZ+ ΔUNC^{ma}		HMXZ		SY		SY+ ΔUNC^{ma}							
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat						
γ_0	0.05	0.99	0.03	0.56	0.08	1.89	0.13	2.00	0.16	2.69						
γ_{MKT}	0.62	2.76	0.65	2.87	0.60	2.64	0.53	2.21	0.50	2.06						
γ_{QME}	0.19	1.16	0.19	1.15	0.17	1.04										
γ_{QIA}	0.28	2.02	0.3	2.22	0.24	1.74										
γ_{QROE}	0.45	2.46	0.38	2.05	0.32	1.75										
γ_{EG}					0.63	4.96										
$\gamma_{MIS_{ME}}$							0.21	1.34	0.20	1.24						
γ_{MGMT}							0.45	2.45	0.42	2.34						
γ_{PERF}							0.55	2.16	0.46	1.80						
$\gamma_{UNC^{ma}}$			0.85	4.51					0.63	3.53						
R^2	0.54		0.72		0.73		0.56		0.66							
(5 th , 95 th)	(0.40, 0.80)		(0.65, 0.89)		(0.68, 0.91)		(0.52, 0.85)		(0.61, 0.89)							

Panel C: Augmented factor models with micro uncertainty using the full-sample estimation																		
	FF3+ ΔUNC^{mi}			FF4+ ΔUNC^{mi}			FF5+ ΔUNC^{mi}			FF6+ ΔUNC^{mi}			HXZ+ ΔUNC^{mi}			SY+ ΔUNC^{mi}		
	Coeff	t-stat		Coeff	t-stat		Coeff	t-stat		Coeff	t-stat		Coeff	t-stat		Coeff	t-stat	
γ_0	0.26	5.75		0.06	2.80		0.06	2.94		0.04	2.42		0.04	0.92		0.07	1.37	
γ_{MKT}	0.36	1.81		0.58	2.95		0.52	2.66		0.57	2.89		0.56	2.83		0.52	2.52	
γ_{SMB}	0.21	1.62		0.25	1.90		0.29	2.24		0.29	2.25							
γ_{HML}	0.18	1.33		0.32	2.45		0.12	0.93		0.23	1.78							
γ_{CMA}							0.39	4.11		0.29	3.28							
γ_{RMW}				0.62	3.28		0.28	2.75		0.26	2.55							
γ_{UMD}										0.60	3.18							
$\gamma_{Q_{ME}}$													0.39	2.87				
$\gamma_{Q_{IA}}$													0.32	3.09				
$\gamma_{Q_{ROE}}$													0.57	4.13				
$\gamma_{MISP_{ME}}$																0.41	3.15	
γ_{MGMT}																0.54	3.73	
γ_{PERF}																0.58	3.05	
$\gamma_{UNC^{mi}}$	0.73	1.00		0.90	1.24		0.87	1.20		0.88	1.22		0.88	1.21		0.91	1.21	
R^2	0.22			0.53			0.56			0.69			0.64			0.73		
(5 th , 95 th)	(0.07, 0.65)			(0.40, 0.79)			(0.40, 0.81)			(0.57, 0.86)			(0.50, 0.84)			(0.59, 0.88)		
Panel D: Augmented factor models with micro uncertainty using the extending-window estimation																		
	FF3+ ΔUNC^{mi}			FF4+ ΔUNC^{mi}			FF5+ ΔUNC^{mi}			FF6+ ΔUNC^{mi}			HXZ+ ΔUNC^{mi}			SY+ ΔUNC^{mi}		
	Coeff	t-stat		Coeff	t-stat		Coeff	t-stat		Coeff	t-stat		Coeff	t-stat		Coeff	t-stat	
γ_0	0.13	2.52		0.04	1.96		0.04	1.79		0.04	2.16		0.04	0.90		0.14	2.33	
γ_{MKT}	0.56	2.38		0.65	2.93		0.63	2.79		0.63	2.83		0.64	2.83		0.52	2.18	
γ_{SMB}	0.07	0.47		0.09	0.58		0.12	0.78		0.12	0.79							
γ_{HML}	0.13	0.82		0.17	1.05		0.12	0.75		0.13	0.79							
γ_{CMA}							0.23	1.80		0.22	1.91							
γ_{RMW}							0.30	2.08		0.30	2.14							
γ_{UMD}				0.49	2.06					0.47	1.94							
$\gamma_{Q_{ME}}$													0.18	1.09				
$\gamma_{Q_{IA}}$													0.28	2.10				
$\gamma_{Q_{ROE}}$													0.41	2.28				
$\gamma_{MISP_{ME}}$																0.22	1.43	
γ_{MGMT}																0.39	2.22	
γ_{PERF}																0.50	1.99	
$\gamma_{UNC^{mi}}$	-0.21	-0.15		-0.08	-0.05		-0.16	-0.11		-0.12	-0.08		-0.13	-0.09		-0.09	-0.06	
R^2	0.59			0.65			0.79			0.80			0.68			0.67		
(5 th , 95 th)	(0.06, 0.79)			(0.40, 0.87)			(0.45, 0.89)			(0.59, 0.92)			(0.51, 0.90)			(0.60, 0.92)		

Table 2.5. Cross-sectional regressions of non-tradable total uncertainty-augmented factor models

This table reports Fama-MacBeth regressions of various factor models and those augmented with non-tradable total uncertainty factor (ΔUNC) directly, using the full-sample estimation. Test assets are 35 portfolios, 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, and 5 Fama-French industry portfolios. Tested factor models are Fama and French (1993) three-factor model (FF3), Carhart (1997) four-factor model (FF4), Fama and French (2015) five-factor model (FF5), Fama and French (2018) six-factor model (FF6), Hou et al. (2015) q -factor model (HXZ), and Hou et al. (2018b) q^5 factor model (HMXZ). To avoid the omitted factor problem, we estimate the sensitivities of macro (micro) uncertainty with Fama and French (2018) six factors in the first stage and then use them in the second stage of other augmented factor models. We apply the similar estimation process to Hou et al. (2015) q -factor model. All test assets and the pricing factors are annualized. 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. Sample period is June 1974 to June 2018.

	FF3		FF3+ ΔUNC		FF4		FF4+ ΔUNC		FF5		FF5+ ΔUNC		FF6		FF6+ ΔUNC	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	10.79	2.94	9.51	1.33	12.65	2.70	11.40	1.53	-5.89	-1.01	-9.21	-0.97	4.12	1.00	-0.21	-0.03
γ_{MKT}	-3.21	-0.72	-2.07	-0.28	-4.87	-0.92	-3.77	-0.48	13.27	2.10	16.47	1.69	3.45	0.72	7.65	1.02
γ_{SMB}	3.59	2.07	3.33	1.90	3.50	2.01	3.26	1.86	3.43	1.97	3.24	1.84	3.32	1.92	3.17	1.81
γ_{HML}	2.63	1.17	3.94	1.61	3.22	1.38	4.40	1.77	0.33	0.14	1.36	0.52	2.20	0.99	2.84	1.20
γ_{CMA}									5.01	3.42	4.64	2.69	4.79	3.43	4.50	2.79
γ_{RMW}					10.67	4.70	10.04	4.36	3.88	2.12	5.18	2.34	2.42	1.44	3.77	1.97
γ_{UMD}							5.22	2.72					10.30	4.56	9.44	4.18
γ_{UNC}			5.66	3.02							6.48	2.75			5.71	2.81
R^2	0.29		0.44		0.65		0.79		0.50		0.73		0.69		0.87	
(5 th , 95 th)	(0.02, 0.69)		(0.12, 0.74)		(0.33, 0.85)		(0.44, 0.89)		(0.14, 0.78)		(0.27, 0.85)		(0.41, 0.87)		(0.54, 0.91)	
HMXZ																
	HXZ		HXZ+ ΔUNC		HMXZ		HMXZ		HMXZ		HMXZ		HMXZ		HMXZ	
	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	1.28	0.29	-4.42	-0.50	4.50	0.85										
γ_{MKT}	6.47	1.28	11.93	1.30	2.84	0.49										
γ_{QME}	4.08	2.24	3.81	1.99	3.39	1.84										
γ_{QIA}	3.16	1.67	4.53	1.63	4.52	2.16										
γ_{QROE}	6.58	3.88	7.00	2.95	5.60	2.97										
γ_{EG}					11.97	7.58										
γ_{UNC}			6.42	2.75												
R^2	0.57		0.79		0.92											
(5 th , 95 th)	(0.21, 0.84)		(0.40, 0.88)		(0.67, 0.93)											

Table 2.6. Cross-sectional regressions of non-tradable macro- and micro- uncertainty-augmented factor models

Panel A reports Fama-MacBeth regressions of various factor models augmented with non-tradable macro uncertainty factor (ΔUNC^{ma}) directly, using the full-sample estimation. Panel B presents Fama-MacBeth regressions of various factor models augmented with non-tradable micro uncertainty factor (ΔUNC^{mi}) directly. Test assets are 35 portfolios, 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, and 5 Fama-French industry portfolios. Tested factor models are Fama and French (1993) three-factor model (FF3), Carhart (1997) four-factor model (FF4), Fama and French (2015) five-factor model (FF5), Fama and French (2018) six-factor model (FF6), Hou et al. (2015) q -factor model (HXZ), and Hou et al. (2018b) q^5 factor model (HMXZ). To avoid the omitted factor problem, we estimate the sensitivities of macro (micro) uncertainty with Fama and French (2018) six factors in the first stage and then use them in the second stage of other augmented factor models. We apply the similar estimation process to Hou et al. (2015) q -factor model. All test assets and the pricing factors are annualized. 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. Sample period is June 1974 to June 2018.

Panel A: Augmented factor models with macro uncertainty using the full-sample estimation										
	FF3+ ΔUNC^{ma}		FF4+ ΔUNC^{ma}		FF5+ ΔUNC^{ma}		FF6+ ΔUNC^{ma}		HXZ+ ΔUNC^{ma}	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	9.53	1.47	11.46	1.68	-8.26	-0.95	1.23	0.19	-2.15	-0.29
γ_{MKT}	-1.97	-0.28	-3.71	-0.51	15.62	1.75	6.31	0.92	9.79	1.23
γ_{SMB}	3.43	1.96	3.36	1.92	3.27	1.86	3.19	1.83		
γ_{HML}	3.45	1.42	3.93	1.60	1.06	0.42	2.68	1.16		
γ_{CMA}					5.14	3.11	4.92	3.18		
γ_{RMW}					4.33	2.03	2.94	1.55		
γ_{UMD}			10.28	4.49			9.79	4.32		
γ_{QME}									3.77	2.00
γ_{QIA}									4.53	1.84
γ_{QROE}									6.51	3.01
$\gamma_{UNC^{ma}}$	8.87	2.82	7.99	2.46	9.89	2.42	8.67	2.45	9.50	2.40
R^2	0.37		0.73		0.63		0.79		0.69	
(5 th , 95 th)	(0.07, 0.73)		(0.39, 0.87)		(0.21, 0.82)		(0.48, 0.90)		(0.33, 0.86)	

Panel B: Augmented factor models with non-tradable micro uncertainty using the full-sample estimation											
	FF3+ ΔUNC^{mi}		FF4+ ΔUNC^{mi}		FF5+ ΔUNC^{mi}		FF6+ ΔUNC^{mi}		HXZ+ ΔUNC^{mi}		
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	
γ_0	10.62	2.70	12.50	2.66	-6.04	-1.00	3.93	0.93	3.63	0.67	
γ_{MKT}	-3.05	-0.65	-4.73	-0.89	13.40	2.07	3.62	0.74	3.94	0.66	
γ_{SMB}	3.58	2.07	3.49	2.01	3.41	1.96	3.30	1.90			
γ_{HML}	2.92	1.30	3.44	1.49	0.69	0.30	2.52	1.15			
γ_{CMA}					5.28	3.71	5.04	3.69			
γ_{RMW}					3.83	2.09	2.38	1.41			
γ_{UMD}			10.58				10.18	4.51			
γ_{QME}				4.67					4.06	2.20	
γ_{QIA}									5.12	2.70	
γ_{QROE}									3.98	2.11	
$\gamma_{UNC^{mi}}$	-0.91	-1.35	-0.73	-0.95	-0.99	-1.06	-0.91	-1.14	-2.40	-2.57	
R^2	0.28		0.64		0.50		0.69		0.69		
(5 th , 95 th)	(0.03, 0.71)		(0.36, 0.86)		(0.15, 0.80)		(0.45, 0.88)		(0.35, 0.87)		

Table 2.7. Cross-sectional regressions of income inequality-augmented factor models

Panel A reports Fama-MacBeth regressions of various factor models and those augmented with the mimicking income inequality portfolio ($\Delta Ineq$), using full-sample period. Test assets are 35 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, 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 (HMXZ), and Stambaugh and Yuan (2017) model (SY). Panel B shows similar results in the extending-window. All coefficients are multiplied by 100. The t -statistics are adjusted for errors-in-variables, following Shanken (1992). The adjusted R^2 follows Jagannathan and Wang (1996). The 5th and 95th percentiles of the adjusted R^2 distribution from a bootstrap simulation of 10,000 times are reported in brackets. The sample period is from July 1973 to June 2016. The testing period for Panel B starts from July 1986.

Panel A: Full-sample betas														
	FF3		FF3+ $\Delta Ineq$		FF4		FF4+ $\Delta Ineq$		FF5		FF5+ $\Delta Ineq$		FF6+ $\Delta Ineq$	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.32	5.95	0.02	0.74	0.07	3.28	0.03	1.34	0.05	2.44	0.05	2.22	0.04	2.15
γ_{MKT}	0.28	1.32	0.54	2.62	0.53	2.63	0.54	2.65	0.50	2.46	0.51	2.52	0.54	2.65
γ_{SMB}	0.20	1.48	0.29	2.16	0.23	1.73	0.29	2.14	0.28	2.12	0.28	2.13	0.28	2.13
γ_{HML}	0.20	1.46	0.24	1.70	0.36	2.66	0.26	1.92	0.14	1.04	0.24	1.78	0.25	1.86
γ_{CMA}									0.43	4.41	0.26	2.86	0.33	3.62
γ_{RMW}									0.29	2.67	0.22	2.03	0.26	2.46
γ_{UMD}					0.64	3.26	0.60	3.04			1.05	8.22	0.62	3.15
γ_{Ineq}			1.05	8.23			1.00	8.31			0.76		0.68	
R^2	0.16		0.75		0.50		0.75		0.57					
(5 th , 95 th)	(-0.01, 0.49)		(0.60, 0.84)		(0.34, 0.71)		(0.63, 0.85)		(0.37, 0.77)		(0.62, 0.86)		(0.51, 0.83)	(0.64, 0.87)
Panel A (Continued)														
	HXZ		HXZ+ $\Delta Ineq$		HMXZ		SY		SY+ $\Delta Ineq$					
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat				
γ_0	0.04	0.95	0.04	0.83	0.06	1.71	0.06	1.13	0.10	1.97				
γ_{MKT}	0.53	2.56	0.53	2.56	0.51	2.49	0.52	2.51	0.47	2.24				
γ_{QME}	0.38	2.71	0.36	2.57	0.37	2.59								
γ_{QIA}	0.34	3.16	0.33	3.10	0.34	3.11								
γ_{QROE}	0.57	4.01	0.46	3.22	0.41	2.89								
γ_{EG}					0.75	7.37								
γ_{MISME}							0.39	3.02	0.38	2.87				
γ_{MGMT}							0.53	3.64	0.43	2.98				
γ_{PERF}							0.62	3.23	0.59	3.07				
γ_{Ineq}			1.05	8.79					0.87	6.96				
R^2	0.62		0.73		0.82		0.73		0.75					
(5 th , 95 th)	(0.43, 0.78)		(0.59, 0.84)		(0.68, 0.89)		(0.55, 0.84)		(0.60, 0.86)					

Panel B: Extending-window betas

	FF3		FF3+ $\Delta Ineq$		FF4		FF4+ $\Delta Ineq$		FF5		FF5+ $\Delta Ineq$		FF6		FF6+ $\Delta Ineq$	
	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	0.19	3.52	0.05	1.40	0.10	3.78	0.02	0.73	0.05	1.99	0.07	2.56	0.06	2.94	0.05	2.61
γ_{MKT}	0.46	1.85	0.59	2.52	0.56	2.39	0.60	2.57	0.56	2.36	0.56	2.37	0.57	2.40	0.57	2.41
γ_{SMB}	0.03	0.15	0.08	0.49	0.04	0.23	0.09	0.52	0.09	0.57	0.09	0.58	0.09	0.56	0.10	0.58
γ_{HML}	0.13	0.72	0.19	1.03	0.19	1.13	0.18	1.03	0.10	0.59	0.16	0.96	0.12	0.75	0.15	0.93
γ_{CMA}									0.32	2.37	0.21	1.63	0.26	2.11	0.23	1.85
γ_{RMW}									0.31	2.04	0.30	1.95	0.32	2.14	0.31	2.03
γ_{UMD}					0.51	2.00	0.47	1.80					0.50	1.99	0.47	1.81
γ_{Ineq}			0.74	5.69			0.88	7.22			0.68	5.60			0.79	7.55
R^2	0.17		0.74		0.35		0.78		0.62		0.81		0.66		0.84	
(5 th , 95 th)	(-0.01, 0.55)		(0.67, 0.89)		(0.32, 0.74)		(0.70, 0.91)		(0.35, 0.80)		(0.70, 0.92)		(0.53, 0.85)		(0.73, 0.93)	

Panel B (Continued)

	HXZ		HXZ+ $\Delta Ineq$		HMXZ		SY		SY+ $\Delta Ineq$	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.05	1.07	0.09	1.88	0.09	1.90	0.12	1.93	0.17	2.85
γ_{MKT}	0.57	2.41	0.55	2.32	0.55	2.32	0.52	2.14	0.47	1.95
γ_{QME}	0.16	0.96	0.14	0.83	0.14	0.85				
γ_{QIA}	0.32	2.18	0.28	1.92	0.27	1.91				
γ_{QROE}	0.47	2.42	0.34	1.77	0.35	1.84				
γ_{EG}			0.61	4.62						
γ_{MISME}					0.19	1.19	0.19	1.16		
γ_{MGMT}					0.43	2.33	0.33	1.79		
γ_{PERF}					0.61	2.36	0.49	1.88		
γ_{Ineq}			0.71	5.98			0.69	6.12		
R^2	0.52		0.70		0.68		0.57		0.68	
(5 th , 95 th)	(0.41, 0.79)		(0.65, 0.89)		(0.65, 0.90)		(0.52, 0.90)		(0.65, 0.90)	

Table 2.8. **Explaining mimicking income inequality portfolio with macro uncertainty-augmented factor models**

Panel A presents the abnormal returns and the factor-loadings of mimicking income inequality portfolio ($\Delta Ineq$) from various macro uncertainty (ΔUNC^{ma})-augmented factor models, using full-sample period. Panel B shows the abnormal returns and the factor-loadings of mimicking macro uncertainty portfolio from various income inequality-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 sample period is from July 1973 to June 2018.

Panel A: Explaining income inequality using macro uncertainty factor									
	α							ΔUNC^{ma}	R^2
Raw	0.97								
t-stat	9.38								
	α	MKT						ΔUNC^{ma}	R^2
CAPM	0.80	0.24						0.07	0.23
t-stat	7.81	4.93						1.03	
	α	MKT	SMB	HML				ΔUNC^{ma}	R^2
FF3	0.60	0.24	0.19	0.22				0.22	0.35
t-stat	6.93	6.79	4.25	2.5				2.53	
	α	MKT	SMB	HML	UMD			ΔUNC^{ma}	R^2
FF4	0.48	0.28	0.18	0.27	0.16			0.18	0.43
t-stat	5.55	9.54	4.88	3.47	3.59			2.55	
	α	MKT	SMB	HML	CMA	RMW		ΔUNC^{ma}	R^2
FF5	0.26	0.34	0.28	-0.08	0.66	0.40		0.25	0.58
t-stat	2.9	14.61	6.23	-1.42	6.56	4.91		3.82	
	α	MKT	SMB	HML	CMA	RMW	UMD	ΔUNC^{ma}	R^2
FF6	0.21	0.35	0.27	-0.02	0.60	0.37	0.11	0.22	0.62
t-stat	2.46	17.03	7.01	-0.34	7.33	5.64	3.68	3.81	
	α	MKT	MIS_{ME}	MGMT	PERF			ΔUNC^{ma}	R^2
SY	0.19	0.39	0.29	0.42	0.22			0.07	0.56
t-stat	1.95	16.43	7.52	6.14	4.70			1.57	
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}			ΔUNC^{ma}	R^2
HXZ	-0.03	30.83	33.77	74.01	34.26			0.39	0.74
t-stat	-0.42	14.07	7.91	14.06	8.38			7.56	

Panel B: Explaining macro uncertainty using income inequality factor

	α									
Raw	0.52									
t-stat	6.57									
	α	MKT					$\Delta Ineq$	R^2		
CAPM	0.43	0.08					0.05	0.06		
t-stat	5.01	4.62					1.16			
	α	MKT	SMB	HML			$\Delta Ineq$	R^2		
FF3	0.44	0.05	-0.15	-0.13			0.14	0.16		
t-stat	5.65	2.86	-5.06	-4.12			3.41			
	α	MKT	SMB	HML	UMD			$\Delta Ineq$	R^2	
FF4	0.43	0.06	-0.15	-0.13	0.01			0.13	0.16	
t-stat	5.59	3.15	-5.06	-3.84	0.59			3.12		
	α	MKT	SMB	HML	CMA	RMW			$\Delta Ineq$	R^2
FF5	0.46	-0.01	-0.17	-0.01	-0.33	-0.04			0.25	0.22
t-stat	5.94	-0.34	-5.75	-0.27	-4.93	-0.76			3.99	
	α	Mktrf	SMB	HML	CMA	RMW	UMD	$\Delta Ineq$	R^2	
FF6	0.46	0.00	-0.17	-0.01	-0.33	-0.04	0.01	0.23	0.22	
t-stat	5.83	-0.14	-5.73	-0.11	-4.92	-0.75	0.66	3.88		
	α	MKT	MIS_{ME}	MGMT	PERF			$\Delta Ineq$	R^2	
SY	0.44	0.09	-0.13	-0.06	0.09			0.07	0.15	
t-stat	5.56	3.88	-4.01	-1.52	3.84			1.60		
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}			$\Delta Ineq$	R^2	
HXZ	0.44	-0.10	-0.27	-0.60	-0.13			0.50	0.36	
t-stat	7.12	-4.82	-9.04	-11.85	-4.06			8.83		

Table 2.9. **Explaining 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 full-sample period. 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 sample period is from July 1973 to June 2018.

Panel A: Full-sample estimation									
	α								
Raw	0.81								
t-stat	8.77								
	α	MKT							
CAPM	0.60	-0.23							ΔUNC^{ma} R^2
t-stat	7.93	-7							0.64 0.44
	α	MKT	SMB	HML					
FF3	0.53	-0.20	-0.06	0.16					
t-stat	7.59	-7.98	-2.11	2.64					
	α	MKT	SMB	HML	UMD				
FF4	0.42	-0.17	-0.06	0.21	0.15				
t-stat	6.59	-9.45	-2.64	3.96	4.74				
	α	MKT	SMB	HML	CMA	RMW			
FF5	0.29	-0.13	0.01	-0.05	0.47	0.31			
t-stat	4.01	-7.78	0.49	-1.22	5.96	5.68			
	α	MKT	SMB	HML	CMA	RMW	UMD	ΔUNC^{ma}	R^2
FF6	0.24	-0.11	0.00	0.01	0.40	0.28	0.11	0.66	0.72
t-stat	3.73	-8.54	0.17	0.43	7.24	6.97	5.97	17.23	
	α	MKT	MIS_{ME}	MGMT	PERF				
SY	0.19	-0.07	0.03	0.36	0.19				
t-stat	2.77	-4.28	1.28	9.15	6.51				
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}				
HXZ	0.07	-0.15	0.07	0.52	0.30				
t-stat	1.25	-9.82	3.00	11.38	10.47				

Panel B: Using idiosyncratic dispersion portfolio									
	α	MKT						ΔUNC^{mi}	R^2
CAPM	0.90	-0.16						0.01	0.17
t-stat	10.74	-6.16						1.51	
	α	MKT	SMB	HML				ΔUNC^{mi}	R^2
FF3	0.89	-0.12	-0.17	0.08				0.02	0.23
t-stat	11.01	-5.41	-4.58	1.19				2.17	
	α	MKT	SMB	HML	UMD			ΔUNC^{mi}	R^2
FF4	0.75	-0.09	-0.17	0.14	0.17			0.02	0.36
t-stat	9.40	-5.20	-5.58	2.43	4.65			2.15	
	α	MKT	SMB	HML	CMA	RMW		ΔUNC^{mi}	R^2
FF5	0.70	-0.07	-0.07	-0.08	0.32	0.34		0.00	0.37
t-stat	7.51	-3.49	-1.85	-1.41	3.19	3.94		0.81	
	α	Mktrf	SMB	HML	CMA	RMW	UMD	ΔUNC^{mi}	R^2
FF6	0.61	-0.06	-0.08	0.01	0.25	0.31	0.14	0.00	0.46
t-stat	7.38	-3.17	-2.44	0.20	3.45	4.65	5.46	0.75	
	α	MKT	MIS_{ME}	MGMT	PERF			ΔUNC^{mi}	R^2
SY	0.45	0.00	-0.04	0.34	0.25			0.01	0.50
t-stat	5.16	0.10	-1.50	7.75	7.60			1.85	
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}			ΔUNC^{mi}	R^2
HXZ	0.58	-0.10	-0.02	0.28	0.35			-0.01	0.43
t-stat	6.17	-4.63	-0.43	3.42	6.90			-1.34	

Table 2.10. Using uncertainty to explain the cross-sectional dispersions of EG predictors

In Panel A, first three columns ((1)-(3)) reports the coefficients, t-statistics, and R^2 from the time-series regression of each cross-sectional dispersion of EG predictor on 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}). Column (4) and (5) reports similar results using change of operating cash flows (DIS_{dCOP}) and Tobin's q (DIS_{dQ}). Panel B reports the similar results of the micro uncertainty (UNC^{mi}). The sample period is from 1972 to 2016.

Panel A: Using macro uncertainty						
	DIS_{COP}	DIS_Q	DIS_{dROE}	DIS_{dCOP}	DIS_{dQ}	
DIS^{sys}	0.25	0.88	0.37	0.33	1.16	
t-stat	6.90	5.69	5.48	2.04	7.39	
R^2	0.53	0.43	0.41	0.09	0.56	
Panel B: Using micro uncertainty						
	DIS_{COP}	DIS_Q	DIS_{dROE}	DIS_{dCOP}	DIS_{dQ}	
DIS^{idio}	0.16	-0.17	0.23	0.50	-0.68	
t-stat	1.13	-0.29	2.10	1.06	-1.03	
R^2	0.03	0.00	0.09	0.03	0.02	

Table 2.11. **Cross-sectional regressions of EG determinants-augmented factor models**

This table reports Fama-MacBeth regressions of Hou et al. (2015) q -factor model (HMZ) augmented with cross sectional dispersions of EG determinants, using the full-sample estimation. ΔDIS_{COP} is the first difference of the cross sectional dispersion of operating cash flow. ΔDIS_Q is the first difference of the cross sectional dispersion of Tobin's q . ΔDIS_{COP} is the first difference of the cross sectional dispersion of the change in return on equity. Test assets are 35 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, 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. Sample period is July 1973 to June 2018.

	HXZ+ ΔDIS_{COP}		HXZ+ ΔDIS_Q		HXZ+ ΔDIS_{dROE}	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	1.23	1.25	1.77	3.38	1.38	2.62
γ_{MKT}	6.31	2.32	6.01	2.31	6.37	2.45
$\gamma_{Q_{ME}}$	3.37	1.77	3.80	2.08	3.74	2.05
$\gamma_{Q_{IA}}$	2.55	0.93	2.30	1.31	2.30	1.35
$\gamma_{Q_{ROE}}$	7.77	3.77	5.40	3.25	6.38	3.92
$\gamma_{DIS_{COP}}$	1.51	2.84				
γ_{DIS_Q}			2.69	1.66		
$\gamma_{DIS_{dROE}}$					0.71	1.49
R^2	0.76		0.62		0.62	
(5 th , 95 th)	(0.38, 0.87)		(0.35, 0.85)		(0.30, 0.86)	

Table 2.12. **Examining factor loadings from various cross sectional dispersions**

This table presents the coefficients, t -statistics (t -stat), and R^2 of cross sectional regressions of factor loadings of EG factor and its determinants' cross sectional dispersions against those of total uncertainty (ΔUNC), macro uncertainty (ΔUNC^{ma}), and micro uncertainty (ΔUNC^{mi}). β_{EG} is the factor loading of EG factor. $\beta_{DIS_{COP}}$ is the factor loading of the first difference of the cross sectional dispersion of operating cash flow (ΔDIS_{COP}). β_{DIS_Q} is the factor loading of the first difference of the cross sectional dispersion of Tobin's q (ΔDIS_Q). $\beta_{DIS_{dROE}}$ is the factor loading of the first difference of the cross sectional dispersion of the change in return on equity (ΔDIS_{dROE}). We estimate factor loadings of each dispersion with Hou et al. (2015) q -factors. Test assets are 35 portfolios and tested pricing factors, including 35 portfolios, 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, and 5 Fama-French industry portfolios. The sample period is from June 1974 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}	0.76		1.85		0.01		-0.24	
t -stat	8.38		3.10		0.05		-0.39	
$\beta_{UNC^{ma}}$		1.07		3.79		-0.13		-1.03
t -stat		4.25		2.67		-0.3		-0.8
$\beta_{UNC^{mi}}$		-0.08		0.48		-0.04		0.47
t -stat		-1.50		1.62		-0.38		1.71
R^2	0.68	0.54	0.23	0.18	0.00	0.01	0.01	0.18

Table 2.13. Maximum squared Sharpe ratio

Panel A presents the maximum squared Sharpe ratio ($Sh^2(f)$) of the tangency portfolios constructed with pricing factors from prevailing factor models and macro-uncertainty (ΔUNC^{ma}) augmented factor models. Panel B reports the same estimates, using micro-uncertainty (ΔUNC^{mi}) augmented factor models. Panel C and D show the same estimates, using total uncertainty (ΔUNC) or income inequality augmented factor models, respectively. Factor models include Fama and French (1993) three-factor model (FF3), Carhart (1997) four-factor model (FF4), Fama and French (2015) five-factor model (FF5), Fama and French (2018) six-factor model (FF6), Hou et al. (2015) q -factor model (HXZ), and Hou et al. (2018b) q^5 model (HMXZ). The 5th and 95th percentiles of the $Sh^2(f)$ distribution from a bootstrap simulation of 10,000 times are reported in brackets. The sample period is from July 1973 to June 2018.

Panel A: Prevailing factor models and ΔUNC^{ma} augmented factor models							
	FF3	FF3+ ΔUNC^{ma}	FF4	FF4+ ΔUNC^{ma}	FF5	FF5+ ΔUNC^{ma}	
Sh2(f)	0.04	0.17	0.08	0.19	0.11	0.25	
(5 th , 95 th)	(0.02, 0.09)	(0.12, 0.24)	(0.05, 0.15)	(0.14, 0.28)	(0.08, 0.18)	(0.20, 0.35)	
	FF6	FF6+ ΔUNC^{ma}	HXZ	HXZ+ ΔUNC^{ma}	HMXZ	HMXZ+ ΔUNC^{ma}	
Sh2(f)	0.14	0.26	0.16	0.32	0.30	0.33	
(5 th , 95 th)	(0.10, 0.22)	(0.21, 0.37)	(0.11, 0.24)	(0.25, 0.44)	(0.23, 0.41)	(0.26, 0.45)	
Panel B: ΔUNC^{mi} augmented factor models							
	FF3+ ΔUNC^{mi}	FF4+ ΔUNC^{mi}	FF5+ ΔUNC^{mi}	FF6+ ΔUNC^{mi}	HXZ+ ΔUNC^{mi}	HMXZ+ ΔUNC^{mi}	
Sh2(f)	0.05	0.09	0.11	0.14	0.17	0.31	
(5 th , 95 th)	(0.03, 0.10)	(0.06, 0.16)	(0.08, 0.19)	(0.10, 0.22)	(0.12, 0.22)	(0.24, 0.43)	
Panel C: ΔUNC augmented factor models							
	FF3+ ΔUNC	FF4+ ΔUNC	FF5+ ΔUNC	FF6+ ΔUNC	HXZ+ ΔUNC	HMXZ+ ΔUNC	
Sh2(f)	0.24	0.25	0.28	0.28	0.31	0.32	
(5 th , 95 th)	(0.18, 0.32)	(0.19, 0.34)	(0.22, 0.38)	(0.23, 0.39)	(0.24, 0.41)	(0.25, 0.43)	
Panel D: $\Delta Ineq$ augmented factor models							
	FF3+ $\Delta Ineq$	FF4+ $\Delta Ineq$	FF5+ $\Delta Ineq$	FF6+ $\Delta Ineq$	HXZ+ $\Delta Ineq$	HMXZ+ $\Delta Ineq$	
Sh2(f)	0.17	0.18	0.18	0.19	0.19	0.31	
(5 th , 95 th)	(0.13, 0.25)	(0.13, 0.27)	(0.14, 0.27)	(0.14, 0.28)	(0.14, 0.28)	(0.25, 0.43)	

2.8 Appendices

2.8.1 TFP estimation

(1) Data

In order to estimate the total factor productivity (TFP), we have two main data sources: Annual Compustat and CRSP files. By matching Compustat and CRSP, we estimate TFP for public firms in the United States. The time period starts 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), depreciation, depletion and amortization (DPACT), employees (EMP), and staff expense (XLR).

We apply several filters to estimate the coefficients of labor and capital. We include common stocks listed at NYSE/Amex/Nasdaq. We exclude the financial firms and the utility firms (four-digit SIC between 6000 - 6999 and 4900 - 4999). Also, sample firms with sales or total assets less than \$1 million, or with negative employees, capital expenditure, and depreciation are deleted. Firms with value-added and material costs less than 0.01 are excluded as well. The stock price of each firm must be greater than \$1 at the end of the year. The labor expense ratio, which we will describe below, should be between 0 and 1. Finally, the sample firms should report their accounting information for 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 the price index for nonresidential private fixed investment (NIPA table 5.3.4 qtr line2). We obtain employees' earnings data from the Bureau of Labor Statistics (CES0500000030). Because this table reports weekly earnings for each month, we calculate 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 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, 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 wages 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 by following Imrohoroglu and Tuzel (2014). First, we compute the age of capital 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 the current year minus capital age. Finally, we take a 1-year lag for the capital stock to measure the available capital stock at the beginning of the period.

Investment (I_{it}) is capital expenditure deflated by the current fixed investment price index.

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

(3) TFP estimation

We follow Olley and Pakes (1996) to estimate the total factor productivity (TFP) because this is one of the robust ways of measuring production function parameters by 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 the TFP estimation process to avoid the selection bias. Imrohoroglu and Tuzel (2014) show how to estimate Olley and Pakes (1996) TFP using annual Compustat

and share their codes⁸. Our TFP estimation process is based on Imrohoroglu and Tuzel (2014) with some modifications.

We start from the simple Cobb-Douglas production technology.

$$Y_{it} = L_{it}^{\beta_L} K_{it}^{\beta_K} Z_{it} \quad (2.15)$$

where Y_{it} , L_{it} , K_{it} , and Z_{it} are value-added, labor, capital stock, and productivity 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 the labor coefficient without scaling. After scaled by the capital stock and transformed into logarithmic values, Eq.(3.9) is rewritten as

$$\text{Log} \frac{Y_{it}}{K_{it}} = \beta_L \text{Log} \frac{L_{it}}{K_{it}} + (\beta_K + \beta_L - 1) \text{Log} K_{it} + \text{Log} Z_{it}. \quad (2.16)$$

We define $\text{Log} \frac{Y_{it}}{K_{it}}$, $\text{Log} \frac{L_{it}}{K_{it}}$, $\text{Log} K_{it}$, and $\text{Log} Z_{it}$ 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.(3.10) as

$$yk_{it} = \beta_l lk_{it} + \beta_k k_{it} + z_{it}. \quad (2.17)$$

When facing the productivity shock (z_{it}) at t , a firm decides the optimal labor and the optimal investment. Because the productivity (z_{it}) is a state variable, the optimal investment (ik_{it}^*) is a function of the productivity (z_{it}). Olley and Pakes (1996) assume a monotonic relationship between the investment and productivity, so the productivity is a function of investment, i.e., $z_{it} = h(ik_{it})$. We assume that the function $h(ik_{it})$ is 3rd-order polynomials of ik_{it} .

⁸<http://www-bcf.usc.edu/~tuzel/TFPUUpload/Programs/>

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

$$y_{it} = \beta_l k_{it} + \beta_k k_{it} + \beta_0 + \beta_{ik} i k_{it} + \beta_{ik^2} i k_{it}^2 + \beta_{ik^3} i k_{it}^3 + year + \eta_j + \epsilon_{it} \quad (2.18)$$

where $h(ik_{it}) = \beta_0 + \beta_{ik} i k_{it} + \beta_{ik^2} i k_{it}^2 + \beta_{ik^3} i k_{it}^3$ and η_j is 4-digit SIC code to capture the differences of industrial technologies. From this stage, we estimate the labor coefficients, $\hat{\beta}_l$.

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

$$\begin{aligned} E_t(yk_{i,t+1} - \hat{\beta}_l k_{i,t+1} - \eta_j) &= \beta_k k_{i,t+1} + E_t(z_{i,t+1} | z_{i,t}, survival) \\ &= \beta_k k_{i,t+1} + g(z_{it}, \hat{P}_{survival,t}) \end{aligned} \quad (2.19)$$

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 3rd polynomials in investment rate, i/k . z_{it} is $\beta_0 + \beta_{ik} i k_{it} + \beta_{ik^2} i k_{it}^2 + \beta_{ik^3} i k_{it}^3$. 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:

$$TFP_{it} = \exp(yk_{it} - \hat{\beta}_l k_{i,t} - (\hat{\beta}_K + \hat{\beta}_l - 1)k_{it} - \eta_j) \quad (2.20)$$

. We estimate TFP growth as the first-difference of logarithmic TFP using a 5-year rolling window. TFP estimates are available from 1972 to 2016.

2.8.2 Cross-sectional regressions of dispersion-augmented factor models

In this subsection, we present Fama-MacBeth regression results using various uncertainty factors. For Table 2.14, we run Fama-MacBeth regressions using total uncertainty (ΔUNC) factors with various pricing factor models. As we mentioned, total uncertainty is priced

across all different factor models and improves the model performance in terms of R^2 in both full-time and extending-window estimation. Table 2.15 presents the similar results, replacing total uncertainty (ΔUNC) to macro uncertainty (ΔUNC^{ma}) and micro uncertainty (ΔUNC^{mi}). Consistent with the main findings, macro uncertainty is significantly priced across different models while micro uncertainty is not significant. Table 2.16 reports Fama-MacBeth regression results using aggregate uncertainty (UNC^{agg}). Similar to total uncertainty and macro uncertainty, aggregate uncertainty is significantly priced and help the prevailing factor models to explain the pricing errors. Table 2.17 shows that Fama-MacBeth regression using non-tradable total uncertainty shock. Although the frequency is annual, non-tradable total uncertainty is priced across different models. Moreover, the price of risk is from 5.48% per year to 6.31% per year, which are very sizable and similar to the size of mimicking portfolios.

2.8.3 Explaining mimicking income inequality portfolio with dispersion-augmented factor models

Table 2.18 and 2.19 present the time-series regressions of income inequality portfolio on total uncertainty-augmented and micro uncertainty-augmented factor models, respectively. Consistent with the main finding, total uncertainty helps prevailing factor models to explain the abnormal returns of income inequality portfolio while micro uncertainty cannot contribute to capturing the abnormal returns of income inequality portfolio.

2.8.4 Explaining mimicking expected investment growth factor with dispersion-augmented factor models

Table 2.20 examine the link between total uncertainty (UNC) and various cross-sectional dispersion of EG determinants. EG determinants include operating cash flows (COP), Tobin's q (Q), and first difference in ROE ($dROE$). Also, we use the first difference in operating cash flow ($dCOP$) and Tobin's q (dQ). After we calculate the cross-sectional standard devia-

tion of each variable, we regress those dispersions against total uncertainty. Total uncertainty explains cross-sectional dispersions of EG determinants very well.

2.8.5 Comparing q^5 model with dispersion-augmented q -model

Table 2.21 presents the time-series regressions of EG factor against total uncertainty-augmented factor models. Although EG factor has very significant raw returns, 0.81% per month ($t=8.77$), in the full-sample estimation, it becomes insignificant for SY and HXZ augmented factor models. The intercepts are 0.07 ($t=1.50$) and 0.05 ($t=1.22$), respectively. Panel B reports similar results using the extending-window estimation. The results are qualitatively the same.

2.8.6 Explaining the cross-sectional dispersion of EG predictors

Table 2.22 compares the Fama-MacBeth regression results of Hou et al. (2018b) q^5 model to Hou et al. (2015) q -model with total uncertainty (ΔUNC). By comparison, we can see that both EG factor and ΔUNC are significant and two models perform similarly in terms of R^2 . It seems that EG factor and total uncertainty share similar information.

Table 2.14. Cross-sectional regressions of various uncertainty-augmented factor models

Panel A reports the coefficients (Coeff) and t-statistics (t-stat) from Fama-MacBeth regressions of various factor models and total uncertainty (ΔUNC)-augmented factor models, computing the factor betas over the full sample. Test assets are 35 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, and 5 Fama-French industry portfolios. Tested factor models are Fama and French (1993) three-factor model (FF3), Carhart (1997) four-factor model (FF4), Fama and French (2015) five-factor model (FF5), Fama and French (2018) six-factor model (FF6), Hou et al. (2015) q -factor model (HMZ), and Stambaugh and Yuan (2017) model (SY). Panel B shows similar results in the extending-window. All coefficients are multiplied by 100. The t-statistics are adjusted for errors-in-variables, following Shanken (1992). The adjusted R^2 follows Jagannathan and Wang (1996). The 5th and 95th percentiles of the adjusted R^2 distribution from a bootstrap simulation of 10,000 times are reported in brackets. The sample period for Panel A is from July 1973 to June 2018. The testing period for Panel B starts from July 1986.

Panel A: Full-sample betas																
	FF3		FF3+ ΔUNC		FF4		FF4+ ΔUNC		FF5		FF5+ ΔUNC		FF6		FF6+ ΔUNC	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.31	6.09	-0.01	-0.22	0.10	4.64	0.00	0.17	0.10	4.83	0.00	0.06	0.09	5.06	0.01	1.05
γ_{MKT}	0.31	1.55	0.60	3.07	0.54	2.77	0.61	3.10	0.50	2.58	0.59	3.02	0.54	2.75	0.58	2.99
γ_{SMB}	0.21	1.60	0.28	2.16	0.22	1.71	0.28	2.15	0.27	2.08	0.29	2.27	0.26	2.00	0.29	2.26
γ_{HML}	0.18	1.35	0.31	2.31	0.28	2.12	0.33	2.46	0.10	0.78	0.26	1.99	0.21	1.59	0.27	2.06
γ_{CMA}									0.32	3.44	0.30	3.15	0.23	2.59	0.28	3.12
γ_{RMW}									0.20	1.93	0.28	2.64	0.17	1.69	0.27	2.60
γ_{UMD}					0.56	2.99	0.60	3.16			0.72	7.72			0.57	3.04
γ_{UNC}			0.83	8.14			0.75	9.17			0.87				0.69	8.94
R^2	0.19		0.80		0.66		0.82		0.63		0.87		0.80		0.87	
(5 th , 95 th)	(0.00, 0.51)		(0.58, 0.87)		(0.46, 0.83)		(0.66, 0.89)		(0.37, 0.83)		(0.72, 0.92)		(0.63, 0.91)		(0.75, 0.93)	
Panel A (Continued)																
	HXZ		HXZ+ ΔUNC		HMXZ		SY		SY+ ΔUNC							
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.03	0.88	0.04	1.22	0.06	1.67	0.06	1.21	0.03	0.67						
γ_{MKT}	0.56	2.84	0.56	2.83	0.55	2.77	0.53	2.56	0.55	2.69						
γ_{QME}	0.39	2.85	0.36	2.64	0.38	2.75										
γ_{QIA}	0.31	2.93	0.31	2.93	0.31	2.92										
γ_{QROE}	0.56	4.10	0.43	3.14	0.39	2.83										
γ_{EG}					0.75	7.61										
γ_{MISME}							0.41	3.14	0.48	3.70						
γ_{MGMT}							0.54	3.73	0.53	3.58						
γ_{PERF}							0.58	3.05	0.56	2.95						
γ_{UNC}			0.66	7.52					0.64	7.87						
R^2	0.62		0.85		0.84		0.73		0.87							
(5 th , 95 th)	(0.42, 0.77)		(0.70, 0.90)		(0.70, 0.90)		(0.55, 0.84)		(0.72, 0.91)							

Panel B: Extending-window betas

	FF3		FF3+ ΔUNC		FF4		FF4+ ΔUNC		FF5		FF5+ ΔUNC		FF6		FF6+ ΔUNC	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.19	3.70	0.05	1.38	0.09	3.77	0.01	0.41	0.06	2.26	0.06	2.33	0.06	3.08	0.04	2.33
γ_{MKT}	0.50	2.13	0.64	2.85	0.61	2.73	0.66	2.93	0.60	2.67	0.61	2.71	0.61	2.73	0.62	2.74
γ_{SMB}	0.05	0.33	0.10	0.60	0.06	0.41	0.10	0.64	0.11	0.74	0.12	0.74	0.11	0.73	0.12	0.75
γ_{HML}	0.11	0.62	0.19	1.11	0.18	1.06	0.19	1.09	0.08	0.49	0.16	0.96	0.11	0.69	0.15	0.93
γ_{CMA}									0.28	2.15	0.17	1.32	0.21	1.82	0.19	1.56
γ_{RMW}									0.29	2.00	0.29	1.99	0.30	2.10	0.30	2.08
γ_{UMD}							0.49	2.03	0.45	1.80			0.48	2.02	0.44	1.81
γ_{UNC}			0.70	5.87			0.86	8.33			0.66	6.01			0.78	8.58
R^2	0.21		0.73		0.39		0.79		0.63		0.83		0.67		0.86	
(5 th , 95 th)	(-0.01, 0.57)		(0.68, 0.90)		(0.32, 0.75)		(0.71, 0.91)		(0.33, 0.79)		(0.73, 0.93)		(0.52, 0.85)		(0.76, 0.94)	

Panel B (Continued)

	HXZ		HXZ+ ΔUNC		HMXZ		SY		SY+ ΔUNC	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.05	0.99	0.08	1.70	0.08	1.89	0.13	2.00	0.18	2.94
γ_{MKT}	0.62	2.76	0.6	2.67	0.60	2.64	0.53	2.21	0.48	2.01
γ_{QME}	0.19	1.16	0.16	0.97	0.17	1.04				
γ_{QIA}	0.28	2.02	0.26	1.94	0.24	1.74				
γ_{QROE}	0.45	2.46	0.34	1.87	0.32	1.75				
γ_{EG}					0.63	4.96				
γ_{MISME}							0.21	1.34	0.20	1.28
γ_{MGMT}							0.45	2.45	0.38	2.04
γ_{PERF}							0.55	2.16	0.45	1.71
γ_{UNC}			0.66	5.97					0.59	6.21
R^2	0.54		0.70		0.73		0.56		0.64	
(5 th , 95 th)	(0.40, 0.80)		(0.67, 0.90)		(0.68, 0.91)		(0.52, 0.85)		(0.67, 0.91)	

Table 2.15. Cross-sectional regressions of macro- and micro- uncertainty augmented factor models

Panel A reports Fama-MacBeth regressions of various factor models augmented with both macro- and micro- uncertainty factors, using the full-sample estimation. Panel B shows the similar results, using the extending-window estimation. Test assets are 35 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, and 5 Fama-French industry portfolios. Tested factor models are Fama and French (1993) three-factor model (FF3), Carhart (1997) four-factor model (FF4), Fama and French (2015) five-factor model (FF5), Fama and French (2018) six-factor model (FF6), Hou et al. (2015) q -factor model (HMZ), and Stambaugh and Yuan (2017) model (SY). All coefficients are multiplied by 100. The t -statistics are adjusted for errors-in-variables, following Shanken (1992). The adjusted R^2 follows Jagannathan and Wang (1996). The 5th and 95th percentiles of the adjusted R^2 distribution from a bootstrap simulation of 10,000 times are reported in brackets. Sample period for Panel A (Panel B) is from July 1973 to June 2018 (July 1986 to June 2018).

Panel A: Augmented factor models with macro- and micro- uncertainty in the full-sample estimation												
	FF3+ $\Delta UNC^{ma,mi}$		FF4+ $\Delta UNC^{ma,mi}$		FF5+ $\Delta UNC^{ma,mi}$		FF6+ $\Delta UNC^{ma,mi}$		HXZ+ $\Delta UNC^{ma,mi}$		SY+ $\Delta UNC^{ma,mi}$	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.08	2.04	0.01	0.30	-0.04	-1.88	-0.01	-0.86	0.04	1.28	-0.01	-0.24
γ_{MKT}	0.54	2.71	0.63	3.21	0.62	3.16	0.61	3.14	0.57	2.88	0.60	2.95
γ_{SMB}	0.23	1.72	0.25	1.90	0.30	2.30	0.30	2.29				
γ_{HML}	0.31	2.30	0.38	2.93	0.25	1.86	0.29	2.19				
γ_{CMA}					0.39	4.03	0.32	3.64				
γ_{RMW}					0.33	3.22	0.31	3.02				
γ_{UMD}			0.62	3.30			0.59	3.14				
γ_{QME}									0.37	2.69		
γ_{QIA}									0.32	3.07		
γ_{QROE}									0.44	3.20		
$\gamma_{MISP_{ME}}$											0.46	3.54
γ_{MGMT}											0.63	4.41
γ_{PERF}											0.60	3.12
$\gamma_{UNC^{ma}}$	0.68	7.30	0.62	6.88	0.71	7.68	0.65	7.59	0.56	6.14	0.59	6.34
$\gamma_{UNC^{mi}}$	0.91	1.25	0.96	1.32	0.97	1.33	0.94	1.30	0.89	1.23	1.00	1.34
R^2	0.45		0.68		0.84		0.87		0.88		0.85	
(5 th , 95 th)	(0.24, 0.78)		(0.54, 0.86)		(0.67, 0.92)		(0.77, 0.94)		(0.75, 0.94)		(0.71, 0.93)	

Panel B: Augmented factor models with macro- and micro- uncertainty in the extending window estimation

	FF3+ $\Delta UNC^{ma,mi}$		FF4+ $\Delta UNC^{ma,mi}$		FF5+ $\Delta UNC^{ma,mi}$		FF6+ $\Delta UNC^{ma,mi}$		HXZ+ $\Delta UNC^{ma,mi}$		SY+ $\Delta UNC^{ma,mi}$	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.02	0.59	-0.01	-0.30	0.03	1.02	0.01	0.76	0.02	0.39	0.16	2.80
γ_{MKT}	0.67	2.93	0.70	3.07	0.65	2.85	0.66	2.89	0.67	2.91	0.51	2.12
γ_{SMB}	0.08	0.49	0.09	0.55	0.11	0.73	0.12	0.74				
γ_{HML}	0.20	1.17	0.21	1.25	0.16	0.97	0.15	0.96				
γ_{CMA}					0.22	1.74	0.24	2.08				
γ_{RMW}					0.30	2.03	0.31	2.12				
γ_{UMD}			0.51	2.08			0.48	1.95				
γ_{QME}									0.20	1.22		
γ_{QIA}									0.31	2.36		
γ_{QROE}									0.38	2.06		
$\gamma_{MISF_{ME}}$											0.20	1.28
γ_{MGMT}											0.40	2.28
γ_{PERF}											0.45	1.79
$\gamma_{UNC^{ma}}$	0.96	5.40	0.96	5.87	0.86	5.13	0.91	5.65	0.87	4.99	0.67	4.05
$\gamma_{UNC^{mi}}$	-0.18	-0.12	-0.10	-0.07	-0.21	-0.15	-0.16	-0.11	-0.18	-0.12	-0.16	-0.11
R^2	0.75		0.78		0.90		0.91		0.78		0.72	
$(5^{th}, 95^{th})$	(0.50, 0.91)		(0.65, 0.93)		(0.73, 0.95)		(0.77, 0.96)		(0.70, 0.95)		(0.71, 0.95)	

Table 2.16. Cross-sectional regressions of aggregate uncertainty-augmented factor models

This paper reports Fama-MacBeth regressions of various factor models augmented with the mimicking aggregate uncertainty portfolio (UNC^{agg}), using full-sample period. Test assets are 35 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, and 5 Fama-French industry portfolios. Tested factor models are Fama and French (1993) three-factor model (FF3), Carhart (1997) four-factor model (FF4), Fama and French (2015) five-factor model (FF5), Fama and French (2018) six-factor model (FF6), Hou et al. (2015) q -factor model (HMZ), and Stambaugh and Yuan (2017) model (SY). All coefficients are multiplied by 100. The t-statistics are adjusted for errors-in-variables, following Shanken (1992). The adjusted R^2 follows Jagannathan and Wang (1996). The 5th and 95th percentiles of the adjusted R^2 distribution from a bootstrap simulation of 10,000 times are reported in brackets. The sample period is from July 1973 to June 2018.

	FF3+ UNC^{agg}		FF4+ UNC^{agg}		FF5+ UNC^{agg}		FF6+ UNC^{agg}		HXZ+ UNC^{agg}		SY+ UNC^{agg}	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.08	2.13	-0.01	-0.64	-0.05	-2.99	-0.03	-1.92	-0.04	-1.11	0.02	0.44
γ_{MKT}	0.55	2.76	0.66	3.38	0.64	3.30	0.64	3.29	0.66	3.32	0.58	2.82
γ_{SMB}	0.21	1.59	0.25	1.88	0.29	2.23	0.29	2.25				
γ_{HML}	0.21	2.03	0.38	2.92	0.20	1.47	0.27	2.07				
γ_{CMA}					0.39	4.07	0.30	3.37				
γ_{RMW}					0.31	2.96	0.28	2.69				
γ_{UMD}			0.64	3.38			0.61	3.22				
γ_{QME}									0.44	3.20		
γ_{QIA}									0.30	2.82		
γ_{QROE}									0.51	3.71		
γ_{MISME}											0.39	3.03
γ_{MGMT}											0.58	3.97
γ_{PERF}											0.58	3.08
$\gamma_{UNC^{agg}}$	0.88	2.24	0.91	2.31	0.99	2.51	0.93	2.38	0.94	2.37	0.84	2.07
R^2	0.35		0.64		0.75		0.82		0.79		0.78	
(5 th , 95 th)	(0.17, 0.67)		(0.50, 0.81)		(0.57, 0.87)		(0.72, 0.91)		(0.64, 0.88)		(0.62, 0.88)	

Table 2.17. Cross-sectional regressions of non-tradable total uncertainty-augmented factor models

This table reports Fama-MacBeth regressions of various factor models and those augmented with non-tradable total uncertainty factor (ΔUNC) directly, using the full-sample estimation. Test assets are 35 portfolios, 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, and 5 Fama-French industry portfolios. Tested factor models are Fama and French (1993) three-factor model (FF3), Carhart (1997) four-factor model (FF4), Fama and French (2015) five-factor model (FF5), Fama and French (2018) six-factor model (FF6), Hou et al. (2015) q -factor model (HXZ), and Hou et al. (2018b) q^5 factor model (HMXZ). To avoid the omitted factor problem, we estimate the sensitivities of macro (micro) uncertainty with Fama and French (2018) six factors in the first stage and then use them in the second stage of other augmented factor models. We apply the similar estimation process to Hou et al. (2015) q -factor model. All test assets and the pricing factors are annualized. 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. Sample period is June 1974 to June 2018.

	FF3		FF3+ ΔUNC		FF4		FF4+ ΔUNC		FF5		FF5+ ΔUNC		FF6		FF6+ ΔUNC	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	1.66	4.83	1.13	1.71	0.87	3.12	0.63	1.36	0.44	1.40	-0.08	-0.16	0.55	2.22	0.24	0.65
γ_{MKT}	6.10	2.39	6.45	2.48	7.03	2.76	7.13	2.76	6.95	2.72	7.30	2.82	7.06	2.76	7.22	2.80
γ_{SMB}	3.30	1.90	3.14	1.79	3.24	1.87	3.08	1.76	3.33	1.92	3.22	1.84	3.19	1.84	3.10	1.78
γ_{HML}	2.94	1.33	4.02	1.70	3.66	1.62	4.58	1.91	1.60	0.73	2.57	1.13	2.54	1.17	3.30	1.49
γ_{CMA}									4.79	3.63	4.69	3.24	4.57	3.48	4.42	3.11
γ_{RMW}					9.91	4.39	9.67	4.23	3.48	2.17	4.45	2.50	2.77	1.74	3.67	2.16
γ_{UMD}			5.80	2.98			5.48	2.77			6.31	3.14	9.55	4.26	9.24	4.11
γ_{UNC}	0.33		0.48		0.62		0.76		0.58		0.75		0.75		5.78	2.99
R^2	(0.06, 0.66)		(0.12, 0.74)		(0.34, 0.81)		(0.44, 0.89)		(0.27, 0.81)		(0.27, 0.85)		(0.50, 0.88)		0.90	
(5 th , 95 th)	HXZ		HXZ+ ΔUNC		HMXZ										(0.54, 0.91)	
	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	0.91	1.56	0.44	0.45	0.77	1.27										
γ_{MKT}	6.86	2.63	7.05	2.59	6.67	2.55										
γ_{QME}	3.94	2.16	3.65	1.92	3.48	1.88										
γ_{QIA}	3.48	1.87	4.12	1.59	4.73	2.33										
γ_{ROE}	6.62	4.08	6.77	3.27	6.16	3.43										
γ_{EG}					11.38	7.56										
γ_{UNC}			6.12	3.14												
R^2	0.61		0.80		0.92											
(5 th , 95 th)	(0.24, 0.83)		(0.40, 0.88)		(0.64, 0.92)											

Table 2.18. **Explaining mimicking income inequality portfolio with total uncertainty-augmented factor models**

Panel A presents the abnormal returns and the factor-loadings of mimicking income inequality portfolio ($\Delta Ineq$) from various total uncertainty (ΔUNC)-augmented factor models, using full-sample period. Panel B shows the abnormal returns and the factor-loadings of total uncertainty factor from various income inequality-augmented factor models, using full-sample period. 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 sample period is from July 1973 to June 2018.

Panel A: Explaining income inequality using total uncertainty-augmented factor models									
	α								
Raw	0.97								
t-stat	9.38								
	α	MKT						ΔUNC	R^2
CAPM	0.60	0.21						0.41	0.31
t-stat	6.83	4.3						3.41	
	α	MKT	SMB	HML				ΔUNC	R^2
FF3	0.28	0.18	0.31	0.24				0.69	0.50
t-stat	3.14	5.61	6.53	3.66				5.79	
	α	MKT	SMB	HML	UMD			ΔUNC	R^2
FF4	0.23	0.22	0.29	0.28	0.12			0.60	0.54
t-stat	2.77	7.59	7.28	4.63	3.25			6.38	
	α	MKT	SMB	HML	CMA	RMW		ΔUNC	R^2
FF5	0.09	0.28	0.35	-0.05	0.62	0.29		0.57	0.66
t-stat	1.13	13.2	8.69	-0.92	8.17	4.55		8.35	
	α	MKT	SMB	HML	CMA	RMW	UMD	ΔUNC	R^2
FF6	0.07	0.30	0.33	0.00	0.57	0.28	0.08	0.52	0.68
t-stat	0.91	15.14	9.44	-0.08	8.82	5.11	2.86	8.66	
	α	MKT	MIS_{ME}	MGMT	PERF			ΔUNC	R^2
SY	0.05	0.33	0.36	0.39	0.15			0.40	0.61
t-stat	0.52	14.20	10.06	6.35	3.70			6.13	
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}			ΔUNC	R^2
HXZ	-0.09	26.19	38.19	68.01	23.54			0.58	0.79
t-stat	-1.57	12.25	9.65	17.09	6.18			11.23	

Panel B: Explaining total uncertainty using inequality-augmented factor models

	α								
Raw	0.62								
t-stat	8.95								
	α	MKT					$\Delta Ineq$	R^2	
CAPM	0.37	0.03					0.24	0.16	
t-stat	4.55	1.72					5.43		
	α	MKT	SMB	HML			$\Delta Ineq$	R^2	
FF3	0.37	0.01	-0.28	-0.14			0.38	0.43	
t-stat	5.81	0.98	-13.07	-5.42			11.26		
	α	MKT	SMB	HML	UMD			$\Delta Ineq$	R^2
FF4	0.36	0.02	-0.28	-0.12	0.03			0.36	0.43
t-stat	5.74	1.73	-12.65	-4.79	1.63			10.39	
	α	MKT	SMB	HML	CMA	RMW	$\Delta Ineq$	R^2	
FF5	0.38	-0.02	-0.27	-0.04	-0.26	0.04	0.43	0.48	
t-stat	6.16	-1.20	-11.78	-1.06	-5.16	1.27	10.43		
	α	Mktrf	SMB	HML	CMA	RMW	UMD	$\Delta Ineq$	R^2
FF6	0.37	-0.01	-0.27	-0.02	-0.26	0.04	0.03	0.41	0.48
t-stat	6.06	-0.53	-11.73	-0.64	-5.14	1.41	1.66	9.66	
	α	MKT	MIS_{ME}	MGMT	PERF			$\Delta Ineq$	R^2
SY	0.38	0.06	-0.26	-0.05	0.11			0.29	0.41
t-stat	5.94	3.17	-10.86	-1.68	6.20			8.55	
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}			$\Delta Ineq$	R^2
HXZ	0.39	-0.07	-0.33	-0.46	0.01			0.59	0.56
t-stat	6.62	-4.60	-14.09	-11.65	0.19			13.91	

Table 2.19. **Explaining mimicking income inequality portfolio with micro uncertainty-augmented factor models**

Panel A presents the abnormal returns and the factor-loadings of income inequality factor ($\Delta Ineq$) from various micro uncertainty (ΔUNC^{mi})-augmented factor models, using full-sample period. Panel B shows the abnormal returns and the factor-loadings of micro uncertainty factor from various income inequality-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 sample period is from July 1973 to June 2018.

Panel A: Explaining income inequality using micro uncertainty-augmented factor models											
	α										
Raw	0.97										
t-stat	9.38										
	α	MKT					ΔUNC^{mi}	R^2			
CAPM	0.74	0.31					0.06	0.42			
t-stat	8.16	9.68					6.43				
	α	MKT	SMB	HML			ΔUNC^{mi}	R^2			
FF3	0.65	0.32	0.10	0.18			0.06	0.48			
t-stat	8.52	13.05	2.62	2.64			7.08				
	α	MKT	SMB	HML	UMD			ΔUNC^{mi}	R^2		
FF4	0.52	0.35	0.10	0.23	0.15			0.05	0.56		
t-stat	6.60	17.4	3.67	3.96	3.76			7.9			
	α	MKT	SMB	HML	CMA	RMW			ΔUNC^{mi}	R^2	
FF5	0.40	0.39	0.19	-0.08	0.57	0.31			0.04	0.63	
t-stat	4.91	18.41	5.08	-1.51	6.04	3.8			8.40		
	α	MKT	SMB	HML	CMA	RMW	UMD	ΔUNC^{mi}	R^2		
FF6	0.33	0.40	0.18	-0.01	0.51	0.29	0.12			0.04	0.68
t-stat	4.30	22.64	6.00	-0.26	7.19	4.39	3.81			9.49	
	α	MKT	MIS_{ME}	MGMT	PERF			ΔUNC^{mi}	R^2		
SY	0.21	0.44	0.22	0.39	0.20			0.05	0.67		
t-stat	2.48	20.71	7.62	7.54	5.27			10.23			
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}			ΔUNC^{mi}	R^2		
HXZ	0.25	0.35	0.24	0.58	0.30			0.03	0.71		
t-stat	3.14	16.43	5.38	8.89	6.50			5.52			

Panel B: Explaining micro uncertainty using income inequality-augmented factor models									
	α								
Raw	0.99								
t-stat	1.17								
	α	MKT					$\Delta Ineq$	R^2	
CAPM	-1.78	-1.90					3.94	0.29	
t-stat	-2.21	-8.32					10.08		
	α	MKT	SMB	HML			$\Delta Ineq$	R^2	
FF3	-1.69	-2.04	0.38	-0.42			3.97	0.30	
t-stat	-2.10	-9.79	1.04	-1.12			8.98		
	α	MKT	SMB	HML	UMD			$\Delta Ineq$	R^2
FF4	-1.54	-2.24	0.32	-0.69	-0.51			4.38	0.31
t-stat	-2.03	-10.74	0.96	-1.76	-1.90			8.54	
	α	MKT	SMB	HML	CMA	RMW	$\Delta Ineq$	R^2	
FF5	-1.64	-2.17	0.56	0.16	-1.52	0.63	4.10	0.32	
t-stat	-2.09	-9.27	1.43	0.40	-2.37	1.59	8.51		
	α	Mktrf	SMB	HML	CMA	RMW	UMD	$\Delta Ineq$	R^2
FF6	-1.49	-2.38	0.49	-0.10	-1.51	0.58	-0.48	4.51	0.34
t-stat	-2.02	-9.80	1.32	-0.23	-2.36	1.55	-1.83	7.90	
	α	MKT	MIS_{ME}	MGMT	PERF			$\Delta Ineq$	R^2
SY	-0.91	-2.82	-0.17	-1.60	-0.64			5.08	0.33
t-stat	-1.29	-10.57	-0.47	-3.83	-2.42			9.18	
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}			$\Delta Ineq$	R^2
HXZ	-0.91	-1.74	0.91	-0.07	1.09			3.10	0.32
t-stat	-2.30	-5.83	2.84	-0.10	2.84			5.90	

Table 2.20. Explaining the cross-sectional dispersions of EG predictors

First three columns ((1)-(3)) reports the coefficients, t-statistics, and R^2 from the time-series regression of each cross-sectional standard deviation of EG predictors on the total uncertainty level. (*UNC*). EG predictors are Operating cash flows (COP), Tobin's q (Q), and change in return on equity (dROE) respectively. Column (4) and (5) reports similar results using change of operating cash flows (dCOP) and Tobin's q (dQ). The sample period is from 1972 to 2016.

	(1)	(2)	(3)	(4)	(5)
	<i>DIS_{COP}</i>	<i>DIS_Q</i>	<i>DIS_{dROE}</i>	<i>DIS_{dCOP}</i>	<i>DIS_{dQ}</i>
<i>UNC</i>	0.34	1.12	0.53	0.32	1.4
t-stat	14.52	7.76	10.64	1.79	9.96
R^2	0.83	0.58	0.73	0.07	0.7

Table 2.21. **Explaining EG factor with total uncertainty-augmented factor models**

Panel A presents the abnormal returns and the factor-loadings of EG factor from various total uncertainty (ΔUNC)-augmented factor models, using full-sample period. Panel B shows similar results from the extending-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 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 sample period is from July 1973 to June 2018. The testing period for Panel B starts from July 1986.

Panel A: Full-sample estimation									
	α								
Raw	0.81								
t-stat	8.77								
	α	MKT						ΔUNC	R^2
CAPM	0.38	-0.26						0.91	0.68
t-stat	7.08	-9.59						14.39	
	α	MKT	SMB	HML			ΔUNC	R^2	
FF3	0.24	-0.25	0.08	0.16			1.00	0.74	
t-stat	4.34	-13.15	2.89	4.19			15.3		
	α	MKT	SMB	HML	UMD			ΔUNC	R^2
FF4	0.21	-0.23	0.06	0.18	0.09			0.94	0.77
t-stat	4.16	-14.89	3.01	5.75	4.28			18.79	
	α	MKT	SMB	HML	CMA	RMW	ΔUNC	R^2	
FF5	0.14	-0.20	0.10	0.00	0.34	0.14	0.96	0.80	
t-stat	2.74	-13.89	4	-0.07	6.7	3.83	22.44		
	α	MKT	SMB	HML	CMA	RMW	UMD	ΔUNC	R^2
FF6	0.13	-0.19	0.08	0.04	0.31	0.14	0.07	0.91	0.82
t-stat	2.64	-14.71	4.30	1.29	7.82	4.56	4.14	24.18	
	α	MKT	MIS_{ME}	MGMT	PERF			ΔUNC	R^2
SY	0.07	-0.15	0.12	0.29	0.10			0.85	0.82
t-stat	1.50	-10.21	6.40	10.33	4.43			21.97	
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}			ΔUNC	R^2
HXZ	0.05	-21.32	13.04	38.29	12.87			0.96	0.85
t-stat	1.22	-15.07	5.96	10.88	5.00			28.00	

Panel B: Extending-window estimation									
	α								
Raw	0.72								
t-stat	6.14								
	α	MKT						ΔUNC	R^2
CAPM	0.08	-0.21						1.00	0.86
t-stat	1.56	-10.83						15.48	
	α	MKT	SMB	HML				ΔUNC	R^2
FF3	0.06	-0.19	-0.05	0.12				0.99	0.89
t-stat	1.24	-14.08	-2.99	5.81				22.71	
	α	MKT	SMB	HML	UMD			ΔUNC	R^2
FF4	0.06	-0.18	-0.05	0.13	0.03			0.96	0.89
t-stat	1.22	-15.80	-3.04	6.34	1.64			25.99	
	α	MKT	SMB	HML	CMA	RMW		ΔUNC	R^2
FF5	0.03	-0.16	-0.02	0.06	0.09	0.12		0.93	0.90
t-stat	0.64	-13.18	-1.18	2.43	2.29	5.50		28.49	
	α	Mktrf	SMB	HML	CMA	RMW	UMD	ΔUNC	R^2
FF6	0.03	-0.15	-0.02	0.07	0.08	0.12	0.02	0.91	0.91
t-stat	0.64	-13.18	-1.32	3.24	2.33	6.02	1.69	31.15	
	α	MKT	MIS_{ME}	MGMT	PERF			ΔUNC	R^2
SY	0.01	-0.14	-0.02	0.17	0.04			0.90	0.89
t-stat	0.25	-10.41	-1.06	6.92	1.94			25.63	
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}			ΔUNC	R^2
HXZ	0.02	-0.16	-0.03	0.18	0.08			0.93	0.90
t-stat	0.43	-11.55	-1.76	5.37	3.72			25.89	

Table 2.22. **Comparing 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. (2018b) q^5 model and total uncertainty (ΔUNC)-augmented Hou et al. (2015) q -model, computing the factor betas over the full sample. Test assets are 29 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, and 5 Fama-French industry portfolios. Panel B shows similar results in the extending-window. All coefficients are multiplied by 100. The t-statistics are adjusted for errors-in-variables, following Shanken (1992). The adjusted R^2 follows Jagannathan and Wang (1996). The 5th and 95th percentiles of the adjusted R^2 distribution from a bootstrap simulation of 10,000 times are reported in brackets. The sample period for Panel A is from July 1973 to June 2018. The testing period for Panel B starts from July 1986.

Panel A: Full-sample betas				
	HMXZ		HXZ+ ΔUNC	
	Coeff	t-stat	Coeff	t-stat
γ_0	0.08	1.66	0.07	1.41
γ_{MKT}	0.52	2.63	0.53	2.69
$\gamma_{Q_{ME}}$	0.35	2.55	0.34	2.47
$\gamma_{Q_{IA}}$	0.30	2.80	0.29	2.77
$\gamma_{Q_{ROE}}$	0.36	2.61	0.41	2.94
γ_{EG}	0.75	6.04		
γ_{UNC}			0.64	5.73
R^2	0.82		0.81	
(5 th , 95 th)	(0.64, 0.90)		(0.60, 0.89)	

Panel B: Extending-window betas				
	HMXZ		HXZ+ ΔUNC	
	Coeff	t-stat	Coeff	t-stat
γ_0	0.11	1.71	0.10	1.72
γ_{MKT}	0.57	2.49	0.57	2.50
$\gamma_{Q_{ME}}$	0.15	0.86	0.13	0.78
$\gamma_{Q_{IA}}$	0.23	1.72	0.23	1.73
$\gamma_{Q_{ROE}}$	0.30	1.67	0.32	1.73
γ_{EG}	0.60	3.87		
γ_{UNC}			0.63	4.37
R^2	0.66		0.64	
(5 th , 95 th)	(0.60, 0.90)		(0.52, 0.88)	

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Chapter 3

Fundamental Tail Risk and Stock Return

WITH ZHANHUI CHEN

3.1 Introduction

In the literature, economic recession is characterized by negative first moment (mean) and positive second moment (volatility) (Bloom et al. (2007), Bloom (2009), and Bloom et al. (2018)). However, more recently, some papers stress the role of even higher moments of productivity shocks to characterize the economic state. Salgado et al. (2019) find out that fundamental skewness is procyclical across many countries including the United States. Further, they show that the right-tail skewness is procyclical while the left-tail skewness is counter-cyclical. That is, the recession has the third moment, skewness. In this paper, we estimate fundamental skewness by following Salgado et al. (2019) and explore its asset pricing implications. If the recession is characterized by fundamental skewness, we expect that the skewness shock endogenously affects the financial market. We estimate total factor productivity (TFP) and its cross-sectional skewness using TFP growth distribution. Further, we separate the right- and left-tail skewness. Then, we construct the mimicking skewness portfolios which track the fundamental skewness very well. Our main findings are as follows.

First, we find that the productivity skewness shock is a significant risk factor. Prevailing factor models cannot fully explain the skewness factor. Also, we show that the right-tail skewness drives the most of the pricing power of the skewness factor. In the cross-section, we find that the price of risk of skewness or the right-tail skewness is significantly positive across different factor models while that of the left-tail skewness is insignificant. Second, we explore the relationship between the skewness factor and the post-earnings-announcement-drift effect. From PEAD literature, we estimate two PEAD measures: Cumulative abnormal returns around earnings announcement date (ABR) and standardized unexpected earnings (SUE). Our skewness factors fully capture both ABR and SUE while prevailing factors cannot explain those. We expect that two PEAD measures share the same information, higher moment risk.

Fundamental skewness is a prevalent phenomenon across world-wide. Salgado et al. (2019) show that procyclical skewness in productivity, employment, and firm output exists over more than forty countries. Also, Guvenen et al. (2014) and Busch et al. (2018) document that the labor income distribution is negatively skewed in recessions. This negative skewness in the economy lowers the real economic output and hampers the effect of government policy. In the asset pricing perspective, we investigate the impact of fundamental skewness on stock returns. Also, we separate the skewness into the right- and left-tails and explore their implications.

Empirically, we identify the fundamental skewness from the cross-sectional skewness of firm-level productivity. First, we estimate the firm-level total factor productivity (TFP) by following Olley and Pakes (1996) and Imrohoroglu and Tuzel (2014). Then, in each year, we calculate the cross-sectional skewness of TFP growth and define it as the fundamental skewness. Following Salgado et al. (2019), we use Kelley skewness instead of using the conventional third-moment skewness. Kelley skewness has two advantages over the conventional measure. First, it avoids the existence of outliers and sample mean because Kelley skewness uses the percentile of TFP growth distribution. Second, we can easily decompose it into the right- and left-tail skewness. After we estimate the skewness measures, we take

the first-difference of those skewness measures and then construct the mimicking skewness portfolios by following Adrian et al. (2014). Our skewness measures are reasonably estimated. Consistent with Salgado et al. (2019), the skewness (the right-tail skewness) shock is procyclical. Meanwhile, the left-tail skewness is counter-cyclical. The correlation coefficient between the skewness (the right-tail skewness) shock and real GDP growth is 0.31 (0.19) while that between the left-tail skewness shock and real GDP is -0.27. Also, the skewness is positively correlated with ABR and SUE with 0.36 and 0.28. This confirms that there may be an economic link between the real economy and PEAD effect. The right-tail skewness also has the similar correlation coefficients, 0.27 and 0.29, while the left-tail skewness has the negligible correlation coefficients. From the correlation matrix, it seems that the right-tail skewness drives the main variation of the skewness. We further examine this relationship later.

We construct the mimicking skewness portfolios via the projection method. First, the mimicking skewness factor has a mean of 0.49% per month (t-statistic=6.77). Because the prevailing factor models cannot explain the mimicking skewness factor, we infer that the skewness factor reflects a different fundamental risk from other pricing factors. Second, the right- and left-tail skewness portfolios have 0.55% and -0.36% per month respectively. In the cross-section, we see that the skewness factor has a significant price of risk from various test assets. Further, when we separate the skewness factor into the right- and left-tail skewness, only the right-tail skewness has a significant price of risk. This suggests that the pricing power of the skewness factor comes from the right-tail skewness factor.

Last, we examine whether the skewness factor captures the information of the PEAD effect. We augment the prevailing factor models with the mimicking skewness factor and run the time-series regressions of ABR or SUE. Even though each of the PEAD factors cannot be fully explained by prevailing factors, the augmented factor models completely capture the variation of both ABR and SUE. Further, we replace the skewness factor to the right-tail skewness factor and find that the right-tail skewness factor drives the main pricing power of the skewness factor. We infer that the skewness risk may share the same fundamental risk

with PEAD anomaly from the significant pricing power of skewness factors against PEAD factors. In future research, we are going to explore the economic rationale behind this strong correlations.

This paper contributes to the literature on the high moments of the business cycle. Many papers have emphasized the role of uncertainty. Bloom et al. (2007) and Bloom (2009) suggest that the aggregate economic uncertainty lowers the aggregate investment and output. Also, Bloom et al. (2018) show that the micro uncertainty from the cross-sectional dispersion of productivity has a similar effect on the economy. In recent years, an even higher moment of economic shock has substantial attention. Guvenen et al. (2014) find that the labor income has the procyclical skewness and the left-tail skewness is strongly counter-cyclical while the variance (second moment) of labor income is acyclical, using a comprehensive data from the US Social Security Administration. Busch et al. (2018) also show that the labor income has asymmetric business cycle risk in the United States, Germany, and Sweden. They further show that in the recession the individual household fails to smooth the negative skewness shock and the social insurance is strongly needed. Salgado et al. (2019) show prevalent procyclical skewness across more than forty countries, including the United States. Further, they quantitatively show that the skewness shock drops the aggregate output, investment, employment, and consumption. Following Salgado et al. (2019), we measure the productivity skewness shock and examine its impact from the asset pricing perspective.

There have been many asset pricing papers studying the return skewness and its predictive power in the stock return. Theoretically, Brunnermeier and Parker (2004) design the preference for skewness or lottery-preference and show that an investor with such preference optimally chooses the stocks having skewed pay-off. Mitton and Vorkink (2007) extend the conventional mean-variance framework to the mean-variance-skewness framework and show that an investor with skewness preference bears the inefficient mean-variance portfolios. Barberis and Huang (2008) also document that the idiosyncratic skewness of stock return is priced based on the cumulative prospect theory because investors overweight the tails of stock return, resulting in mispricing. Empirically, Harvey and Siddique (2000) sug-

gest the co-skewness of stock return and show that it predicts the expected stock return. Chen et al. (2001) find that the heterogeneous opinions in the financial market generate the negative skewness under short-sale constraint condition. Inspired by Mitton and Vorkink (2007), Boyer et al. (2010) shows that the expected idiosyncratic skewness affects the expected stock return negatively. G.Bali et al. (2011) use the maximum daily return as a proxy for the lottery-stock and shows that the negative relationship between the maximum return and stock return next month. Conrad et al. (2012) show the significant negative relationship between risk-neutral skewness and stock return. Although the literature estimates the skewness from stock returns and links to the behavioral economic channel, we estimate the fundamental skewness from the accounting items and see its pricing power over the business cycle.

Also, this paper tabs the literature on the post-earnings-announcement-drift (PEAD) effect. PEAD has broad literature on both accounting and finance. After Ball and Brown (1968) and Bernard and Thomas (1989) document PEAD effect, there has been many papers. We use standardized unexpected earnings (SUE) from Foster et al. (1984). Chan et al. (1996) suggest several earnings momentum measures and show that these capture different information from the price momentum. Daniel et al. (2018) choose one of earnings momentum, the cumulative abnormal return (ABR), from Chan et al. (1996) and construct the behavioral factor model. Most of papers explain PEAD anomaly based on the mispricing (e.g. Chordia and Shivakumar (2005), Garfinkel and Sokobin (2006), Ng et al. (2008)). However, some authors explain PEAD anomaly based on the liquidity risk or the arbitrage risk. Sadka (2006) finds that the liquidity risk from intraday trading explains momentum and PEAD. Also, Mendenhall (2004) shows that extreme SUE portfolios have higher arbitrage risk. Compared to the literature, our paper tries to explain PEAD anomaly from a macroeconomic perspective with higher-moment fundamental shock.

The rest of the paper proceeds as follows. Section 3.2 describes the data and procedures of estimating the fundamental skewness shocks. Section 3.3 presents the estimates of productivity skewness shocks. Section 3.4 tests the pricing power of our productivity

skewness factors over other prevailing pricing factors and test assets. Section 3.5 explores the connection between the fundamental skewness and PEAD anomaly. Finally, Section 3.6 concludes.

3.2 Estimating productivity skewness shock

In the prior literature, the economic recession is characterized by the negative first-moment and the positive second moment (Bloom et al. (2007), Bloom (2009), and Bloom et al. (2018)). However, the recent papers pay attention to even higher-moment of fundamental shocks. Salgado et al. (2019) show that the third moment of productivity shock is procyclical across more than forty countries, including the United States. They further show that the right-tail of productivity shock is procyclical while the left-tail is counter-cyclical. Following Salgado et al. (2019), we estimate the cross-sectional skewness, right tail, and left tail of the productivity shock and examine their asset pricing implications. If the higher moment of productivity shock represents a certain economic state, we expect that the economic skewness is priced in the financial market. In this section, we describe how to estimate the firm-level total factor productivity (TFP), the cross-sectional skewness measures of TFP shock, and their mimicking skewness factors.

3.2.1 Estimating firm-level total factor productivity and Kelley skewness measure

We estimate TFP by following Olley and Pakes (1996). Olley and Pakes (1996) estimate TFP by mitigating two endogenous issues. First, since input factors (e.g. labor and capital stock) are contemporaneously correlated, there is the simultaneity bias. They estimate the production function parameters for each input factor separately to address the simultaneity bias. The second endogenous problem is the selection bias. A firm's exit or entry decision depends on its productivity. Olley and Pakes (1996) assume TFP as the function of the survival probability and include that into 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; (3) investment includes the information about TFP. Imrohoroglu and Tuzel (2014) apply Olley and Pakes (1996) to estimate firm-level TFP¹. We follow their estimation process with some modifications.

Assume Cobb-Douglas production function:

$$Y_{it} = L_{it}^{\beta_L} K_{it}^{\beta_K} Z_{it} \quad (3.1)$$

where Y_{it} , L_{it} , K_{it} , and Z_{it} are value-added, labor, capital stock, and productivity of a firm i at time t . Next, we scale the production function by its capital stock and take the logarithm at both sides. We scale the production function by the capital stock for three reasons. First, since TFP is the residual term, it is highly correlated with firm size. Second, the scaling avoids estimating the capital coefficients directly. Third, it mitigates the upward bias in the labor coefficient. Eq.(3.1) is rewritten as

$$\text{Log} \frac{Y_{it}}{K_{it}} = \beta_L \text{Log} \frac{L_{it}}{K_{it}} + (\beta_K + \beta_L - 1) \text{Log} K_{it} + \text{Log} Z_{it} \quad (3.2)$$

Denote $\text{Log} \frac{Y_{it}}{K_{it}}$, $\text{Log} \frac{L_{it}}{K_{it}}$, $\text{Log} K_{it}$, and $\text{Log} Z_{it}$ as yk_{it} , lk_{it} , k_{it} , and z_{it} . Also, let β_L and $(\beta_K + \beta_L - 1)$ as β_l and β_k . Rewrite Eq.(3.2) as follows:

$$yk_{it} = \beta_l lk_{it} + \beta_k k_{it} + z_{it}. \quad (3.3)$$

We can estimate the labor coefficient (β_l) and capital coefficient (β_k) using linear regressions. Then, the logarithmic TFP (z_{it}) is $y/k_{it} - \beta_l l/k_{i,t} - \beta_k k_{it}$. We estimate TFP with a 5-year rolling window and TFP shocks can be computed as first-order autoregressive residuals by running a regression of TFP in year t against TFP in year $t - 1$.

We define the cross-sectional skewness by following Salgado et al. (2019). They use Kelley

¹<http://www-bcf.usc.edu/tuzel/TFPUUpload/Programs/>

skewness (Kelley (1947)), which is as follows.

$$SK_t = \frac{P90_t - P50_t}{P90_t - P10_t} - \frac{P50_t - P10_t}{P90_t - P10_t} \quad (3.4)$$

where $P90_t$, $P50_t$, and $P10_t$ are 90th, 50th, and 10th percentiles of TFP growth distribution in year t . They prefer Kelley skewness to the conventional third-moment skewness for two reasons. First, Kelley skewness is less affected by the existence of outliers or the first-moment, mean. Kim and White (2004) compare several skewness measures including the conventional skewness and the skewness using percentiles. Because the conventional skewness might be distorted by the sample mean or the outliers, they find that the skewness using percentiles of distribution is insensitive to those. Further, Kelley skewness is between -1 and 1. Second, we can easily separate Kelley skewness into left- and right-tails. The first part of Eq.3.4 represents the right-tail of TFP growth distribution and the second part captures the left-tail of TFP growth distribution. Having separate skewness measures allows us to see which part of skewness shock drives the pricing power. Following Salgado et al. (2019), we define the right-tail skewness (RSK_t) as the differential between $P90_t - P50_t$ and the left-tail skewness (LSK_t) as the differential between $P50_t - P10_t$. Further, we take the first-difference of three skewness measures (ΔSK , ΔRSK , and ΔLSK respectively).

We use annual Compustat to estimate TFP for common stocks from NYSE, Amex, and Nasdaq. We include all firms except for financial and utility firms (four-digit SIC between 6000 - 6999 and between 4900 - 4999). Further, we exclude firms with assets or sales below \$1 million. The final sample period is from 1972 to 2016. See Online appendices for more detail estimation.

3.2.2 Estimating mimicking skewness factors

We construct the mimicking portfolios to track the productivity skewness shock. One difficulty is that the frequency of productivity shock is annual. To construct the monthly mimicking portfolios, we follow Adrian et al. (2014) and Chen and Yang (2019) with the

projection method. First, we project the skewness shock (e.g. ΔSK) onto a set of annual base asset returns:

$$\Delta SK = \kappa_{0,SK} + \kappa'_{x,SK} X_{t,SK}^a + u_t \quad (3.5)$$

where $X_{t,SK}^a$ denotes the annual returns of some base assets in year t , and $\kappa_{0,SK}$ and $\kappa'_{x,SK}$ are the coefficients. In order to make the mimicking portfolio that tracks the information of the skewness, we select the base assets based on its correlation coefficients with prevailing pricing factors. In Panel B of Table 3.1, we find that the annual correlation coefficients between the skewness (ΔSK) and annual Post-earning-announcement-drift factors are significantly positive (0.28 for SUE and 0.36 for ABR). Also, the skewness factor has some correlations with profitability factors (0.13 for RMW and 0.24 for Q_{ROE}). To be specific, we include Hou et al. (2015) 18 size, investment, and profitability sorted portfolios (2 x 3 x 3), Chan et al. (1996) ABR, and Foster et al. (1984) SUE to extract the information of ΔSK as much as possible. However, we can't include all 18 portfolios because using all 18 portfolios causes the multicollinearity problem. Also, because we only have 45 annual skewness shock, using all portfolios limits the degree of freedom for the projection regression. Therefore, we choose 4 of 18 portfolios. We start to project productivity dispersion shock onto all 18 portfolios, ABR, and SUE. Then, we choose the portfolios which have significant coefficients. The base assets are as follows:

- $\Delta SK = [\text{BMM}, \text{BSL}, \text{BLM}, \text{BML}, \text{ABR}, \text{SUE}]$

For 4 portfolios except for ABR and SUE factors, the first letter describes the size group, Small (S) or Big (B). The second letter describes the investment group, Low (L), Medium (M), or High (H). The third letter describes the profitability group, Low (L), Medium (M), and High (H). We use the same base assets to construct mimicking right- and left-tail skewness factors to avoid the arbitrariness. After we estimate $\kappa'_{x,PCn}$ at annual frequency, we normalize those coefficients: $\tilde{\kappa}'_{x,SK} = \frac{\kappa_{x,SK}}{|\Sigma \kappa_{x,SK}|}$. The denominator is the sum of the absolute value of 6 coefficients. The normalized coefficients are [0.02, -0.36, 0.13, 0.13, 0.13, 0.83, 0.26]'. We find that the coefficient of the ABR factor is positive and its magnitude is the

largest among the base assets. We further analyze the rationale behind this relationship in later research. Overall, mimicking skewness portfolios track skewness shock very well. The annual correlation coefficients between skewness shock and its mimicking portfolio is about 39%. We construct the mimicking right- (left-) tail skewness factor in the similar manner and the correlation coefficient between the mimicking right- (left-) tail skewness portfolio and the right- (left-) tail skewness shock is 0.36% (33%). The last step is to make the mimicking skewness portfolios at a monthly frequency, by multiplying the normalized coefficients and the monthly base asset returns,

$$\Delta SK_t = \tilde{\kappa}'_{x,SK} X_{t,SK}^m \quad (3.6)$$

where X_t^m is the monthly returns of base assets from July $t+1$ to June $t+2$. When we construct the monthly mimicking skewness factor, we consider a 6-month reporting gap between uncertainty shock and stock return, following Fama and French (1993). That is, we estimate the annual portfolio weights ($\kappa'_{x,SK}$) and multiply the weights with the monthly base asset returns from July $t+1$ to June $t+2$. In this paper, we will use the monthly mimicking portfolios for the rest of the asset pricing tests.

When we construct the mimicking skewness factor, we estimate the coefficients of base assets in full-sample. To avoid the look-ahead bias, we construct the mimicking skewness factor in the extending-window as a robustness test. The extending window starts from 1981 to have a sufficient number of observations. That is, the weights of the mimicking dispersion factor are estimated from 1972 to 1981 first, and we extend the estimation period up to 2016. To estimate the weights with enough degree of freedom for the extending-window, we use 5 base assets, as follows:

- $X_{t,SK} = [\text{BMM}, \text{BSL}, \text{BML}, \text{ABR}, \text{SUE}]$

3.3 Productivity skewness

In this section, we first describe TFP and its economic skewness shock. We show that our skewness measures are reasonably estimated. Next, we test whether the productivity skewness factor generates the sizable asset return.

First, we examine the production function estimates. Labor coefficient (β_l) is 0.61 and capital coefficient (β_k) is 0.34. The estimates are consistent with the estimates from Olley and Pakes (1996). Further, these estimates are consistent with neoclassical theory. For example, in Salgado et al. (2019), the labor share is 2/3 and the capital share is 1/3. During our sample period, the production technology is slightly decreasing return-to-scale, ($\beta_l + \beta_k = 0.94$).

Second, we investigate the business cyclicity of our skewness measures. Salgado et al. (2019) find that the productivity skewness is procyclical. Moreover, they show that the left-tail skewness is strongly counter-cyclical while the right-tail skewness is procyclical. We estimate the time-series correlation coefficients between skewness measures and real GDP growth. We download GDP growth from the NIPA table of Bureau of Economic Analysis (BEA). The correlation coefficient between productivity skewness and GDP growth is 0.31. Also, the right- and left-tail skewness have the correlation coefficients of 0.19 and -0.27. Consistent with the findings of Salgado et al. (2019), the skewness and the right-tail skewness are procyclical while the left-tail skewness is counter-cyclical.

Panel A of Table 3.1 shows that the log TFP growth (ΔTFP) has a mean of 0.01 and a standard deviation of 0.25. TFP growth varies over both cross-section and time-series. The next three rows present the descriptive statistics of productivity skewness shocks. Skewness shock (ΔSK) has a mean of 0.00 with 0.17 standard deviation. Right-tail skewness (ΔRSK) and left-tail skewness (ΔLSK) have lower variations with 0.06 standard deviations for each.

Panel B of Table 3.1 provides the annual correlation coefficients between productivity skewness shocks and prevailing pricing factors. We make a 6-month reporting gap between skewness shocks and pricing factors. In this paper, we consider 12 pricing factors: (1) Six factors in Fama and French (2018), which are 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) Five factors from Hou et al. (2018b), 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); (3) the cumulative abnormal return around the earnings announcement date (ABR) from Chan et al. (1996); and (4) Standardized unexpected earnings (SUE) from Foster et al. (1984). We download Fama and French (2018) six factors from Kenneth French’s website and estimate q^5 factors by following Hou et al. (2018b). For ABR and SUE, we choose a 1-month holding period, following Daniel et al. (2018). Also, we make pricing factors of ABR (SUE) by taking the difference between the average return of two high ABR (SUE) portfolios and the average return of two low ABR (SUE) portfolios after independently sorting stocks on size and ABR (SUE) by 2 x 3, following Fama and French (1993).

First, the skewness factor (ΔSK) has a strong correlation coefficient with ABR. The correlation between ΔSK and ABR is 0.36. Also, ΔSK has quite high correlation coefficients with SUE and UMD, 0.28 and 0.30, respectively. Since both ABR and SUE represent the post-earnings-announcement-drift (PEAD) effect and UMD is strongly related to PEAD literature, their higher correlation coefficients are not surprising.² Therefore, we include two PEAD measures, ABR and SUE, into our base assets and examine the rationale behind strong correlations later. Second, we show that both ΔRSK and ΔLSK are highly correlated with ΔSK but in the opposite direction. The correlation coefficient between ΔSK and ΔRSK (ΔLSK) is 0.82 (-0.85). Since ΔRSK is procyclical and ΔLSK is counter-cyclical, the opposite signs of the correlation with ΔSK make sense. Also, ΔRSK has pronounced correlation coefficients with ABR and SUE, 0.27 and 0.29 respectively while ΔLSK is correlated with only ABR (-0.24). Here, we have some clue that PEAD measures are closely related to productivity skewness, especially the right-tail skewness. Overall, Panel B of Table 3.1 shows that ΔRSK tracks ΔSK closely and both of them have a significant relationship

²Chan et al. (1996) use several measures for earnings momentum, including ABR and SUE. While most of PEAD literature use SUE, Daniel et al. (2018) construct the behavioral factor model, using ABR. Also, Chordia and Shivakumar (2006) show that earnings momentum explains price momentum.

with PEAD pricing factors.

Panel C of Table 3.1 presents the descriptive statistics of mimicking factors. ΔSK has a mean of 0.49% per month with a standard deviation of 1.59% per month. Sharpe ratio of ΔSK is 0.31. ΔRSK has the sizable Sharpe ratio as well. On average, ΔRSK has 0.55% per month with 1.87% per month of a standard deviation. The monthly mimicking factor correlation between ΔSK and ΔRSK is 0.66. ΔLSK has a mean of -0.36% per month with a standard deviation of 3.31%. Its correlation coefficient with ΔSK is strongly negative (-0.85). Overall, the correlation matrix of the mimicking portfolios follows that of the skewness measures. That is, Panel C further provides the evidence that our mimicking uncertainty factors are reasonably constructed by reflecting their correlation coefficients.

3.4 Examining the skewness and tail risk

In this section, we formally test the mimicking skewness factor. We check whether the mimicking skewness factor is statistically significant over time and whether other pricing factor models explain the mimicking uncertainty factor. Also, we explore the pricing power of the skewness factor by running Fama-MacBeth two-pass regressions with various test assets. Next, we decompose the skewness into right and left tails and see their pricing powers.

3.4.1 Pricing of skewness shock

Panel A of Table 3.2 reports the excess return of ΔSK , its abnormal returns, and the sensitivities with respect to pricing factors, using the full-sample period. We consider seven factor models, including 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), Hou et al. (2015) q -factor model (HXZ), and Hou et al. (2018b) q^5 model (HMXZ). First, the raw excess return is 0.49% per month (t-statistic=6.77) so the mimicking ΔSK factor is very significant over

the sample period. Second, the abnormal returns are still significant across different factor models. Moreover, the magnitude of abnormal returns is stable across all different factor models. The lowest abnormal return is 0.36% per month (t-statistic=5.28) from HMXZ and the highest abnormal return is from 0.60% per month (t-statistic=8.79) from FF3. Also, R^2 are fairly low. The range of R^2 is from 0.03 to 0.28. That is, the prevailing factor models do not explain ΔSK .

To avoid the look-ahead bias, we use the extending-window estimation as a robustness check. Panel B of Table 3.2 presents the results. The extending-window estimation shows qualitatively similar results. Raw excess return is 0.41% per month (t-statistic=5.40). Alphas from other factor models are from 0.29 to 0.51 and R^2 are from 0.06 to 0.32. Overall, Table 3.2 shows that productivity skewness is a significant risk factor, which is not captured by prevailing factor models.

Next, we examine the pricing power of the skewness factor in the cross-section. To be specific, we run Fama-MacBeth two-pass regression using various test portfolios. Also, we see whether ΔSK has a significant price of risk in the cross-section. We use total 160 test portfolios, including 25 size and book-to-market sorted portfolios, 25 size and investment sorted portfolios, 25 size and operating profitability sorted portfolios, 25 size and momentum sorted portfolios, 25 size and ABR sorted portfolios, 25 size and SUE sorted portfolios, and 10 Fama-French industry portfolios. We download these portfolios from Kenneth French's website³ except for ABR and SUE portfolios. Following Lewellen et al. (2010), we add the pricing factors of tested factor models to test portfolios in order to restrict the price of risk to be equal to the average factor return.

We augment prevailing factor models with the mimicking skewness factor and compare those to prevailing factor models. Factor models are Fama and French (1993) three-factor model (FF3), Carhart (1997) four-factor model (FF4), Fama and French (2015) five-factor model (FF5), Fama and French (2018) six-factor model (FF6), Hou et al. (2015) q -factor model (HXZ), and Hou et al. (2018b) q^5 model. Augmented factor models are as follows:

³<http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html>

- FF3+ ΔSK : $R_{it} = \gamma_0 + \gamma_{MKT}\hat{\beta}_{MKT,i} + \gamma_{SMB}\hat{\beta}_{SMB,i} + \gamma_{HML}\hat{\beta}_{HML,i} + \gamma_{SK}\hat{\beta}_{SK,i} + \epsilon_{it}$
- FF4+ ΔSK : $R_{it} = \gamma_0 + \gamma_{MKT}\hat{\beta}_{MKT,i} + \gamma_{SMB}\hat{\beta}_{SMB,i} + \gamma_{HML}\hat{\beta}_{HML,i} + \gamma_{UMD}\hat{\beta}_{UMD,i} + \gamma_{SK}\hat{\beta}_{SK,i} + \epsilon_{it}$
- FF5+ ΔSK : $R_{it} = \gamma_0 + \gamma_{MKT}\hat{\beta}_{MKT,i} + \gamma_{SMB}\hat{\beta}_{SMB,i} + \gamma_{HML}\hat{\beta}_{HML,i} + \gamma_{CMA}\hat{\beta}_{CMA,i} + \gamma_{RMW}\hat{\beta}_{RMW,i} + \gamma_{SK}\hat{\beta}_{SK,i} + \epsilon_{it}$
- FF6+ ΔSK : $R_{it} = \gamma_0 + \gamma_{MKT}\hat{\beta}_{MKT,i} + \gamma_{SMB}\hat{\beta}_{SMB,i} + \gamma_{HML}\hat{\beta}_{HML,i} + \gamma_{CMA}\hat{\beta}_{CMA,i} + \gamma_{RMW}\hat{\beta}_{RMW,i} + \gamma_{UMD}\hat{\beta}_{UMD,i} + \gamma_{SK}\hat{\beta}_{SK,i} + \epsilon_{it}$
- HXZ+ ΔSK : $R_{it} = \gamma_0 + \gamma_{MKT}\hat{\beta}_{MKT,i} + \gamma_{Q_{ME}}\hat{\beta}_{Q_{ME},i} + \gamma_{Q_{IA}}\hat{\beta}_{Q_{IA},i} + \gamma_{Q_{ROE}}\hat{\beta}_{Q_{ROE},i} + \gamma_{SK}\hat{\beta}_{SK,i} + \epsilon_{it}$
- HMXZ+ ΔSK : $R_{it} = \gamma_0 + \gamma_{MKT}\hat{\beta}_{MKT,i} + \gamma_{Q_{ME}}\hat{\beta}_{Q_{ME},i} + \gamma_{Q_{IA}}\hat{\beta}_{Q_{IA},i} + \gamma_{Q_{ROE}}\hat{\beta}_{Q_{ROE},i} + \gamma_{EG}\hat{\beta}_{EG,i} + \gamma_{SK}\hat{\beta}_{SK,i} + \epsilon_{it}$

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 period. In the second stage, we run the cross-sectional regression of all test assets on the factor-loadings in each month and then estimate the time-series average of the price of risks. We adjust t-statistics for the errors-in-variables problem, following Shanken (1992). We report the adjusted R^2 from Jagannathan and Wang (1996).

Panel A of Table 3.3 reports the price of risks for each factor across different factor models. First, when we add the skewness factor to prevailing factor models, the augmented models improve the model performance in the cross-section. For example, the pricing error (γ_0) of FF3 is 0.70% with t-statistics of 5.92. However, γ_0 becomes 0.14 (t-statistic=2.48) in FF3+ ΔSK . Also, γ_0 of FF5 is 0.09% (t-statistic=2.13) but ΔSK -augmented FF5 has the insignificant pricing error, 0.06 (t-statistic=1.61). Since FF4, FF6, HXZ, and HMXZ already have the insignificant intercepts, we examine the adjusted R^2 between prevailing factor models and ΔSK -augmented factor models. The results show that adding ΔSK improves the explanatory power across prevailing factor models. R^2 of FF4 is 0.52 and it increases to 0.60 in FF4+ ΔSK . FF6 has R^2 of 0.62 while FF6+ ΔSK has higher R^2 , 0.69. The most striking improvement comes from FF3. R^2 increases by about 0.48 from FF3 to

FF3+ ΔSK . Second, we examine the price of risk of ΔSK . It is significantly positive across all models. γ_{SK} is from 0.33 to 0.60 across different factor models and the size of the price of risk is similar to the average of mimicking skewness factor, 0.49% per month. We can infer that γ_{SK} captures the different risk components from other prices of risks from Table 3.3. This suggests that ΔSK plays an important role to explain the cross-sectional return variations among test portfolios.

To avoid the look-ahead bias, we report Fama-MacBeth regression using the extending-window estimation, following Ferson and Harvey (1999). In Panel B of Table 3.3, we see that the results are similar to those from the full sample estimation. The price of risk for ΔSK is significantly positive across all models and its magnitude is similar to the time-series average of ΔSK in the extending window estimation. Also, the marginal improvement of R^2 is prevalent across different models. Overall, the skewness factor is a significant risk factor that isn't captured by prevailing factors.

3.4.2 Pricing of right- and left-tail skewness shock

Previously, we see that the skewness shock has an important role in explaining the various asset returns in the cross-section. This seems that the skewness shock is the significant pricing factor reflecting the macroeconomic risk. In this section, we further decompose the skewness shock into right- and left-tail skewness, following Salgado et al. (2019), and explore their pricing powers. We run Fama-MacBeth two-pass regression using the same test assets by replacing ΔSK to ΔRSK and ΔLSK .

We first replace ΔSK to ΔRSK only because Panel B of Table 3.1 shows that ΔRSK is very similar to ΔSK in terms of the correlation matrix. Panel A of Table 3.4 reports the regression results. Similar to ΔSK -augmented factor models, ΔRSK improves the model performance. For example, γ_0 of FF3+ ΔRSK is 0.09% (t-statistic=1.60) and its R^2 is 0.67. More importantly, γ_{RSK} is significantly positive across all factor models. The magnitude is from 0.50 (t-statistic=4.05) in HXZ+ ΔRSK to 0.70 (t-statistic=6.40) in FF4+ ΔRSK . Again, the price of risk for ΔRSK is close to its time-series average, 0.55% per month. Panel

B of Table 3.4 use the extending window estimation. The main findings of Panel B echoes the main results from the full-sample estimation. γ_{RSK} is significantly positive across all models and it is similar to the time-series average of ΔRSK , 0.44% per month. Untabulated results show that the time-series abnormal returns of ΔRSK are all significantly positive as well.

Next, we add both ΔRSK and ΔLSK to prevailing factor models in Table 3.5. Panel A of Table 3.5 presents the regression results, using the full sample estimation. Across all factor models, the price of risk for ΔLSK is insignificant. Its magnitude is from -0.12 to -0.27. That is, ΔLSK does not have an important role to explain the return variations of the test assets. These insignificant results are the same from Panel B of Table 3.5 when we use the extending-window estimation. Overall, it seems that the pricing power of ΔSK comes from ΔRSK . Although Salgado et al. (2019) pay more attention to the left-tail skewness, the right-tail skewness drives the main pricing power of the skewness shock.

3.4.3 Annual estimation using non-tradable skewness factor

So far, we examine the cross-sectional pricing power of ΔSK and ΔRSK by using their monthly mimicking portfolios and see that ΔRSK drives the most of pricing power of ΔSK . Although the monthly mimicking portfolios allow us to explore more comprehensive asset pricing tests in both time-series and cross-section, one may concern that the construction of the mimicking portfolio is arbitrary. Here, we evaluate the performance of various augmented factor models by having non-tradable skewness factors directly in Fama-MacBeth two-pass regressions.

Table 3.6 reports the results from Fama-MacBeth regressions. To be consistent with Table 3.3, we use 160 test portfolios and annualize the test assets and the tradable pricing factors. We augment prevailing factor models with each of non-tradable skewness measures and compare those to prevailing factor models. Again, we adjust t-statistics for the errors-in-variables problem, following Shanken (1992). We report the adjusted R^2 from Jagannathan and Wang (1996). The sample period is from June 1974 to June 2018.

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 period. While prevailing pricing factors are contemporaneous with the test assets, the skewness factors are estimated at the end of the year and have a six-month reporting gap.

Panel A of Table 3.6 reports the price of risks for ΔSK across different factor models. First, we recognize that γ_{SK} is significantly priced except for $FF6+\Delta SK$. Although it is very large in $FF3+\Delta SK$ and $FF4+\Delta SK$, γ_{SK} in other augmented models is quite stable. Moreover, the size of γ_{SK} from $FF6+\Delta SK$ (or $HMXZ+\Delta SK$) is 6.46% (8.38%) per year. That is, when the omitted pricing factors are controlled, the price of risk is quite similar to the size of mimicking skewness portfolio, which has 5.88% per year. This confirms that our projection method estimates the non-tradable skewness factor quite well. Panel B of Table 3.6 replaces ΔSK to ΔRSK . Again, the price of risk for ΔRSK is significantly priced over various portfolios. While ΔSK does not have the significant price of risk with $FF6$, γ_{RSK} is significantly positive across all factor models. Also, the magnitude of γ_{RSK} is consistent with the mimicking right-tail skewness portfolio. Last, we estimate the price of risk for ΔLSK . Although it is significantly negative in $FF3+\Delta LSK$ and $FF5+\Delta LSK$, γ_{LSK} becomes insignificant in the rest of the factor models. Overall, these results echo the main findings of the cross-sectional tests using the monthly mimicking skewness portfolios. That is, ΔSK and ΔRSK have the important pricing power to explain various test assets.

3.5 Explaining PEAD effects

In the previous section, inspired by Salgado et al. (2019), we estimate the productivity skewness shock and show that it is an important and sizable risk factor. Also, we confirm that our results are not driven by the arbitrary choice of the base assets in the projection method. However, it is important to explore the rationale behind the significant relationship between productivity skewness and two PEAD measures, ABR and SUE. In this section, we show that our skewness factor fully explains PEAD factors, ABR and SUE. Further, we

present that the right-tail skewness drives the explanation power of the skewness while the left-tail skewness cannot fully explain the return variations of those.

3.5.1 Explaining ABR with skewness factor

We construct the ABR factor following Chan et al. (1996). That is, we estimate the abnormal cumulative returns from 2 days before the earnings announcement date to 1 day after the earnings announcement date as follows,

$$ABR_{it} = \sum_{t-2}^{t+1} (r_{it} - r_{mt}) \quad (3.7)$$

where the earnings announcement date is $t=0$ and r_{mt} is the value-weighted market return. Then, we construct the ABR factor by following Fama and French (1993). It has 0.44% per month with a standard deviation of 1.5%. Untabulated results show that prevailing factor models cannot fully explain ABR factor. This is consistent with the findings of Daniel et al. (2018) and Hou et al. (2018c). Daniel et al. (2018) use the ABR factor to capture the short-horizon behavioral mispricing, an investor's inattention, and show that ABR factor has very significant abnormal returns. Hou et al. (2018c) further show that although Daniel et al. (2018) construct the ABR factor using 20th and 80th breakpoints, which are not the conventional breakpoint (30th and 70th breakpoints), when they reconstruct the ABR factor with the conventional breakpoint, the significant abnormal return still exists.

Here, we try to explain ABR using the skewness-augmented factor model. We run the time-series regressions to see whether ΔSK can capture the return variation of ABR. Factor models are 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), Hou et al. (2015) q -factor model (HXZ), and Hou et al. (2018b) q^5 model. Panel A of Table 3.7 presents the regression results. ABR has a mean of 0.44% per month (t-statistic=6.88). First, we see that the abnormal returns of ABR are all insignificant after we control for ΔSK . For example, α of CAPM is only 0.02% (t-

statistic=0.77). Also, FF6 and HMXZ have -0.02 (t-statistic=-0.65) and -0.04 (t-statistic=-1.23). More importantly, the factor-loadings of ΔSK are sizable with very high t-statistic. Across all models, the factor-loading is from 0.84 to 0.87 with a minimum t-statistic of 24.31. Further, R^2 is more than 0.75 across different models. This confirms that ΔSK captures the most of information from ABR. We see similar results from the extending-window estimation in Panel B of Table 3.7. Over the sample period, ABR still has significant excess returns, 0.39% (t-statistic=5.15). Similar to the results using the full-sample estimation, none of the intercepts from ΔSK augmented factor models are significantly positive. Some factor models such as FF3 have even slightly negative abnormal returns. The factor-loading of ΔSK and R^2 are very sizable. Also, we construct ABR-augmented factor models but these models cannot fully explain the abnormal returns of ΔSK .⁴

Next, we decompose ΔSK into ΔRSK and ΔLSK and see whether these two tail skewnesses explain ABR. First, Panel A of Table 3.8 presents the regression results using ΔRSK in the full sample estimation. ΔRSK augmented factor models fully capture the return variation of ABR. HMXZ model with ΔSK has the intercept of 0.07 (t-statistic=1.16). Other augmented models have significant abnormal returns but the magnitude is less than 0.15% per month. Second, the factor-loading of ΔRSK is from 0.46 to 0.57. The size of the factor-loading of ΔRSK is about 60% of that of ΔSK . This tells us that ΔRSK track ΔSK more than ΔLSK does. Panel B of Table 3.8 shows similar results. None of α is significant after we control for ΔRSK . Overall, ΔRSK explains ABR and drives the explanatory power of ΔSK .

In Panel C of Table 3.8, we replace ΔRSK to ΔLSK . Although ΔLSK has the significant factor-loadings, it fails to fully explain ABR. All of the intercepts from ΔLSK augmented factor models are significantly positive. The magnitude of the factor-loadings is from 0.38 to 0.41, which is 40% of the factor-loadings of ΔSK . We report the ΔLSK augmented model with the extending window estimation in Panel D of Table 3.8 and the

⁴We do not report these results because of the limited space. Although ABR captures the most of variations of ΔSK over time, the abnormal returns are still significant across all factor models. We can show the results upon request.

results are similar. Since ΔRSK tracks ΔSK and takes a larger part of the magnitude of the factor-loadings, we can expect that ΔRSK fully captures ABR. This is consistent with the correlation coefficients between skewness measures and ABR. From Panel B of Table 3.1, we see that the ΔRSK and ΔLSK have the correlation coefficients of 0.27 and -0.24 respectively. Since ΔRSK has a slightly higher correlation with ABR, the mimicking portfolio of ΔRSK has more explanatory power on ABR than that of ΔLSK has. We have the same analysis by augmenting prevailing factor models with ABR to explain either ΔRSK or ΔLSK . The results show that while ΔLSK loses its abnormal returns after we control for ABR, ΔRSK has the significant alphas across all models. This additionally confirms that ΔRSK tracks ΔSK and drives the pricing power.

3.5.2 Explaining ABR with skewness factor

In this section, we focus on the standardized unexpected earnings (SUE). In the literature, there are several ways to estimate SUE. In this paper, following Foster et al. (1984), we define SUE as follows,

$$SUE_{it} = \frac{Earnings_{it} - Earnings_{it-4}}{\sigma_{Earnings,t,t-7}} \quad (3.8)$$

where $\sigma_{Earnings,t,t-7}$ is the standard deviation of previous eight quarters of earnings. We construct SUE pricing factors following Fama and French (1993). Although the decile long-short portfolio of the univariate SUE sorting is fully explained by Carhart (1997) or Hou et al. (2015), the pricing factor of SUE has the significant abnormal returns even after we control for Fama and French (2018) six-factor model or Hou et al. (2018b) q^5 model.

We start to augment prevailing factors with ΔSK . Panel A of Table 3.9 presents the regression results. SUE has a mean of 0.64% per month (t-statistic=7.10). After we control for ΔSK , most of the abnormal returns disappear. For example, HXZ and HMXZ have the marginally significant alphas, 0.10 (t-statistic=1.79) and 0.10 (t-statistic=1.73) respectively. Other ΔSK augmented factor models explain the abnormal return quite well. The factor-loadings of ΔSK vary from 0.45 to 0.74 and they are very significant. In Panel B of Table

3.9, we use ΔSK in the extending window estimation and it has stronger results. From FF5, FF6, HXZ, and HMXZ, the intercepts are either insignificant or marginally significant. This is because the factor-loadings of ΔSK in the extending window have a bigger magnitude than those in the full sample estimation. While ΔSK improves the explanatory power of the prevailing factor to capture SUE, untabulated results show that SUE cannot fully capture the abnormal returns of ΔSK . It seems that even though ΔSK and SUE share the same information, ΔSK is a stronger pricing factor than SUE.

Last, we replace ΔSK to either ΔRSK and ΔLSK and report the regression results in Table 3.10. In Panel A, we examine whether ΔRSK explains SUE. Compared to ΔSK , using ΔRSK increases the explanatory power because HXZ and HMXZ now have the insignificant abnormal returns, 0.03 (t-statistic=0.67) and 0.04 (t-statistic=0.88). Factor-loadings of ΔRSK are from 0.63 to 0.92, which are higher than those of ΔSK . Panel B reports similar results in the extending window estimation. Also, the pricing power in Panel B is stronger than the pricing power of ΔSK . None of the alphas from SUE are significant. Next, we use ΔLSK to explain SUE. Panel C of Table 3.10 presents the results. The intercepts of SUE significantly survive in ΔLSK augmented factor models. This is not surprising since the factor-loadings of ΔLSK are quite small and some of them are even insignificant. For example, in FF4, the factor-loading of ΔLSK is 0.00 (t-statistic=0.01). Also, the factor-loading of ΔLSK in FF6 is only -0.02 (t-statistic=-0.54). We use ΔLSK in the extending window estimation in Panel D of Table 3.10 and the results are similar. All of the alphas are significantly positive and the factor-loadings of ΔLSK are smaller than those of ΔRSK . It seems that ΔLSK hampers the explanatory power of ΔSK but ΔRSK clearly explains SUE. This is consistent with their correlation coefficients between non-tradable skewness measures and SUE. In Panel B of Table 3.1, we see that ΔSK and ΔRSK have the correlation coefficients of 0.28 and 0.29 with SUE while ΔLSK only has a correlation of -0.12. Since our mimicking skewness portfolios are constructed to track their non-tradable factors, ΔRSK explains SUE completely while ΔLSK does not.

Overall, we show that productivity skewness and especially the right-tail skewness fully

explain two PEAD measures, ABR and SUE. This result casts doubt on the conventional mispricing interpretation of ABR and SUE. Since productivity skewness is strongly correlated with ABR and SUE, they may reflect the macroeconomic risk such as tail risk. In the next step, we will explore the economic mechanism and the rationale behind these strong correlations.

3.6 Conclusion

Motivated by Salgado et al. (2019), we construct the fundamental skewness shock from the cross-sectional productivity distributions and explore its asset pricing implications in both time-series and cross-section. Further, we separate the skewness into the right- and left-tail skewness and find that the right-tail skewness captures significant pricing power of the fundamental skewness. We show that the right-tail skewness has a significant price of risk and explains the stock return variations in the cross-section. Moreover, we explore the significant connection between PEAD pricing factors (ABR and SUE) and the fundamental skewness. We show that the skewness-augmented factor models fully explain ABR and SUE. Also, the right-tail skewness has similar results. It seems that there is an economic rationale behind this significant correlation. For the following work, we investigate the specific economic mechanism and show that PEAD reflects the macro risk over the business cycle.

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Table 3.1. **Skewness factors: Descriptive statistics and relations with other pricing factors**

Panel A summarizes the annual log TFP growth (ΔTFP), the first-difference of cross-sectional skewness of TFP growth (ΔSK), right-tail skewness (ΔRSK), and left-tail skewness (ΔLSK), including the mean, standard deviation, and percentiles. We define the cross-sectional skewness as Kelley skewness, $\frac{(P_{90} - P_{50}) - (P_{50} - P_{10})}{P_{90} - P_{10}}$ where P_{90} , P_{50} , and P_{10} are 90th, 50th, and 10th percentiles of the cross-sectional TFP growth distribution. Right (left)-tail skewness is $P_{90} - P_{50}$ ($P_{50} - P_{10}$). Panel B reports the annual time-series correlation coefficients between skewness measures and pricing factors. The pricing factors include Fama and French (2015) market factor (MKT), size factor (SMB), value factor (HML), investment factor (CMA), and profitability factor (RMW); Carhart (1997) momentum factor (UMD); Hou et al. (2015) size factors (Q_{ME}), investment factor (Q_{IA}), and profitability factor (Q_{ROE}); Hou et al. (2018b) expected investment growth factor (EG); Foster et al. (1984) standardized earnings surprises (SUE); and Chan et al. (1996) cumulative abnormal return (ABR). Panel C presents the monthly mean (% per month), standard deviation (% per month, SD), Sharpe ratio (SR), and correlations for the mimicking skewness portfolios. The sample period of dispersions is from 1972 to 2016. The sample period for pricing factors and factor-mimicking portfolios is from July 1973 to June 2018.

Panel A: TFP and its skewness measures														
	Mean	S.D.	Min	Max	10%	25%	50%	75%	90%	AR(1)				
ΔTFP	0.01	0.25	-1.31	1.28	-0.24	-0.09	0.01	0.11	0.27	0.07				
ΔSK	0.00	0.17	-0.37	0.67	-0.22	-0.07	0.01	0.08	0.15	-0.47				
ΔRSK	0.00	0.06	-0.18	0.23	-0.06	-0.02	0.00	0.03	0.06	-0.45				
ΔLSK	0.00	0.06	-0.25	0.19	-0.06	-0.02	0.01	0.02	0.05	-0.40				
Panel B: Correlations between TFP skewness and pricing factors														
	MKT	SMB	HML	CMA	RMW	UMD	Q_{ME}	Q_{IA}	Q_{ROE}	EG	SUE	ABR	ΔSK	ΔRSK
MKT	1.00													
SMB	0.10	1.00												
HML	-0.32	0.05	1.00											
CMA	-0.32	0.22	0.65	1.00										
RMW	-0.26	-0.06	0.40	0.24	1.00									
UMD	0.19	0.19	-0.25	-0.11	-0.05	1.00								
Q_{ME}	0.15	0.98	0.05	0.21	-0.13	0.26	1.00							
Q_{IA}	-0.27	0.19	0.63	0.91	0.28	-0.10	0.18	1.00						
Q_{ROE}	0.01	0.01	0.09	0.00	0.54	0.48	0.05	0.17	1.00					
EG	-0.15	0.17	0.11	0.26	0.35	0.32	0.16	0.28	0.45	1.00				
SUE	0.18	0.25	-0.08	0.00	0.05	0.66	0.31	0.12	0.74	0.44	1.00			
ABR	0.17	0.21	-0.04	0.17	-0.17	0.46	0.26	0.24	0.32	0.33	0.58	1.00		
ΔSK	0.06	-0.01	-0.09	0.04	0.13	0.30	0.03	0.08	0.24	0.23	0.28	0.36	1.00	
ΔRSK	-0.01	0.02	0.04	0.16	0.18	0.20	0.04	0.18	0.19	0.35	0.29	0.27	0.82	1.00
ΔLSK	0.03	0.07	0.10	0.10	-0.11	-0.22	0.04	0.04	-0.20	-0.08	-0.12	-0.24	-0.85	-0.50
Panel C: Statistics of monthly mimicking skewness														
	Mean	SD	SR	ΔSK	ΔRSK									
ΔSK	0.49	1.59	0.31											
ΔRSK	0.55	1.87	0.29	0.66										
ΔLSK	-0.36	3.31	-0.11	-0.85	-0.31									

Table 3.2. **Explaining the skewness factor with other pricing factors**

Panel A presents the abnormal returns and the factor-loadings of the mimicking skewness portfolio from various factor models, using full-sample period. Panel B shows similar results from the extending-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), Hou et al. (2015) q -factor model (HXZ), and Hou et al. (2018b) q^5 model (HMXZ). 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 sample period for Panel A is from July 1973 to June 2018. The testing period for Panel B starts from July 1982.

Panel A. Full-sample estimation									
	α								
Raw	0.49								
t-stat	6.77								
	α	MKT						R^2	
CAPM	0.53	-0.06						0.03	
t-stat	7.80	-2.47							
	α	MKT	SMB	HML					R^2
FF3	0.60	-0.09	-0.02	-0.16					0.11
t-stat	8.79	-4.14	-0.69	-4.85					
	α	MKT	SMB	HML	UMD				R^2
FF4	0.47	-0.06	-0.02	-0.11	0.15				0.28
t-stat	7.26	-3.48	-0.90	-3.35	7.94				
	α	MKT	SMB	HML	CMA	RMW			R^2
FF5	0.58	-0.08	-0.01	-0.18	0.05	0.02			0.12
t-stat	8.06	-3.89	-0.51	-4.43	0.77	0.54			
	α	MKT	SMB	HML	CMA	RMW	UMD	R^2	
FF6	0.48	-0.06	-0.02	-0.09	-0.03	-0.01	0.16	0.28	
t-stat	7.53	-3.53	-1.03	-2.30	-0.62	-0.43	7.78		
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}				R^2
HXZ	0.45	-0.06	0.04	-0.13	0.22				0.16
t-stat	6.12	-2.96	1.16	-2.60	5.06				
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}	EG			R^2
HMXZ	0.36	-0.05	0.04	-0.17	0.16	0.16			0.19
t-stat	5.28	-2.31	1.46	-3.23	3.18	3.12			

Panel B. Extending-window estimation								
	α							
Raw	0.41							
t-stat	5.40							
	α	MKT						R^2
CAPM	0.47	-0.08						0.06
t-stat	6.73	-2.88						
	α	MKT	SMB	HML				R^2
FF3	0.51	-0.10	-0.03	-0.12				0.11
t-stat	7.39	-4.07	-1.14	-3.25				
	α	MKT	SMB	HML	UMD			R^2
FF4	0.38	-0.06	-0.04	-0.06	0.16			0.32
t-stat	5.86	-3.12	-1.66	-1.79	7.96			
	α	MKT	SMB	HML	CMA	RMW		R^2
FF5	0.47	-0.08	-0.02	-0.16	0.07	0.07		0.12
t-stat	6.32	-3.49	-0.55	-4.38	1.18	1.61		
	α	Mktrf	SMB	HML	CMA	RMW	UMD	R^2
FF6	0.37	-0.05	-0.03	-0.06	0.00	0.02	0.16	0.32
t-stat	5.90	-2.90	-1.40	-1.67	-0.02	0.52	7.42	
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}			R^2
HXZ	0.37	-0.06	0.04	-0.08	0.21			0.18
t-stat	4.58	-2.51	0.96	-1.67	4.56			
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}	EG		R^2
HMXZ	0.29	-0.05	0.04	-0.12	0.17	0.13		0.20
t-stat	4.16	-2.13	1.15	-2.26	3.12	2.60		

Table 3.3. Cross-sectional regressions of various mimicking skewness-augmented factor models

Panel A reports the coefficients (Coeff) and t-statistics (t-stat) from Fama-MacBeth regressions of various factor models and mimicking skewness (ΔSK)-augmented factor models, computing the factor betas over the full sample. Test assets are 160 portfolios and the tested pricing factors, including 25 size and book-to-market sorted portfolios, 25 size and operating profitability sorted portfolios, 25 size and investment sorted portfolios, 25 size and momentum sorted portfolios, 25 size and ABR sorted portfolios, 25 size and SUE sorted portfolios, and 10 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 (HMXZ), and Hou et al. (2018b) q^5 model (HMXZ). Panel B shows similar results in the extending-window. All coefficients are multiplied by 100. The t-statistics are adjusted for errors-in-variables, following Shanken (1992). The adjusted R^2 follows Jagannathan and Wang (1996). The sample period for Panel A is from July 1973 to June 2018. The testing period for Panel B starts from July 1982.

Panel A: Full-sample betas														
	FF3		FF3+ ΔSK		FF4		FF4+ ΔSK		FF5		FF5+ ΔSK		FF6+ ΔSK	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.70	5.92	0.14	2.48	0.07	1.29	0.10	2.24	0.09	2.13	0.06	1.61	0.01	0.28
γ_{MKT}	-0.05	-0.20	0.51	2.47	0.60	2.92	0.56	2.75	0.51	2.51	0.58	2.87	0.63	3.12
γ_{SMB}	0.23	1.73	0.26	1.97	0.27	2.01	0.26	1.98	0.32	2.46	0.31	2.35	0.31	2.35
γ_{HML}	0.14	1.04	0.38	2.77	0.38	2.79	0.40	2.86	-0.01	-0.09	0.22	1.66	0.19	1.50
γ_{CMA}									0.47	4.56	0.30	3.21	0.31	3.40
γ_{RMW}					0.77	4.00	0.67	3.50	0.32	2.86	0.19	1.80	0.23	2.16
γ_{UMD}			0.60	5.09			0.52	6.15			0.47	4.39	0.71	3.71
γ_{SK}			0.60		0.52		0.60		0.50		0.69		0.62	3.21
R^2	0.16		0.60										0.51	6.18
Panel A (Continued)														
	HXZ		HXZ+ ΔSK		HMXZ		HMXZ+ ΔSK							
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat						
γ_0	0.06	0.94	0.07	1.57	0.06	1.20	0.13	3.13						
γ_{MKT}	0.56	2.66	0.56	2.78	0.57	2.81	0.52	2.58						
$\gamma_{Q_{ME}}$	0.43	3.12	0.38	2.77	0.43	3.08	0.39	2.79						
$\gamma_{Q_{IA}}$	0.31	2.69	0.42	3.97	0.32	2.84	0.40	3.78						
$\gamma_{Q_{ROE}}$	0.59	4.21	0.46	3.38	0.51	3.71	0.44	3.26						
γ_{EG}					0.62	3.98	0.43	3.34						
γ_{SK}			0.36	3.25			0.33	3.15						
R^2	0.62		0.67		0.63		0.66							

Panel B: Extending-window betas

	FF3		FF3+ ΔSK		FF4		FF4+ ΔSK		FF5		FF5+ ΔSK		FF6		FF6+ ΔSK	
	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	0.43	3.74	0.24	4.04	0.18	3.27	0.19	4.06	0.11	2.80	0.12	3.59	0.10	3.05	0.10	3.31
γ_{MKT}	0.36	1.39	0.54	2.34	0.63	2.80	0.60	2.71	0.67	3.04	0.66	3.01	0.69	3.21	0.68	3.13
γ_{SMB}	0.06	0.41	0.08	0.53	0.07	0.52	0.08	0.52	0.11	0.77	0.12	0.86	0.12	0.83	0.12	0.87
γ_{HML}	0.12	0.77	0.26	1.60	0.26	1.63	0.28	1.74	0.08	0.56	0.21	1.46	0.15	1.05	0.21	1.49
γ_{CMA}																
γ_{RMW}									0.35	2.74	0.24	2.04	0.26	2.33	0.25	2.23
γ_{UMD}					0.61	2.66	0.56	2.44	0.28	2.06	0.28	2.08	0.27	2.05	0.30	2.24
γ_{SK}			0.44	3.61			0.39	4.28			0.36	3.23			0.53	2.36
R^2	0.06		0.41		0.29		0.41		0.41		0.59		0.48		0.39	4.32

Panel B (Continued)

	HXZ		HXZ+ ΔSK		HMXZ		HMXZ+ ΔSK	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.20	3.05	0.22	4.67	0.19	3.34	0.21	4.58
γ_{MKT}	0.57	2.45	0.55	2.47	0.60	2.63	0.58	2.62
γ_{QME}	0.19	1.30	0.18	1.21	0.18	1.24	0.18	1.24
γ_{QIA}	0.39	2.84	0.38	2.94	0.37	2.82	0.34	2.67
γ_{QROE}	0.46	2.68	0.40	2.48	0.41	2.50	0.39	2.42
γ_{EG}					0.56	3.50	0.57	4.07
γ_{SK}			0.24	2.17			0.20	1.82
R^2	0.46		0.47		0.47		0.48	

Table 3.4. Cross-sectional regressions of mimicking right-tail skewness-augmented factor models

Panel A reports Fama-MacBeth regressions of mimicking right-tail skewness (ΔRSK) augmented factor models, using the full-sample estimation. Panel B shows the similar results in the extending window estimation. Test assets are 160 portfolios and the tested pricing factors, including 25 size and book-to-market sorted portfolios, 25 size and operating profitability sorted portfolios, 25 size and investment sorted portfolios, 25 size and momentum sorted portfolios, 25 size and ABR sorted portfolios, 25 size and SUE sorted portfolios, and 10 Fama-French industry portfolios. Tested factor models are Fama and French (1993) three-factor model (FF3), Carhart (1997) four-factor model (FF4), Fama and French (2015) five-factor model (FF5), Fama and French (2018) six-factor model (FF6), Hou et al. (2015) q -factor model (HXZ), and Hou et al. (2018b) q^5 model (HMXZ). All coefficients are multiplied by 100. The t-statistics are adjusted for errors-in-variables, following Shanken (1992). The adjusted R^2 follows Jagannathan and Wang (1996). Sample period for Panel A (Panel B) is July 1973 to June 2018 (July 1982 to June 2018).

Panel A: Full-sample betas												
	FF3+ ΔRSK		FF4+ ΔRSK		FF5+ ΔRSK		FF6+ ΔRSK		HXZ+ ΔRSK		HMXZ+ ΔRSK	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.09	1.60	0.07	1.43	0.06	1.62	0.04	1.31	0.07	1.38	0.12	2.76
γ_{MKT}	0.55	2.65	0.57	2.78	0.57	2.83	0.57	2.87	0.57	2.78	0.52	2.60
γ_{SMB}	0.28	2.09	0.28	2.08	0.30	2.31	0.30	2.31				
γ_{HML}	0.33	2.39	0.33	2.39	0.22	1.71	0.21	1.59				
γ_{CMA}					0.30	3.18	0.33	3.58				
γ_{RMW}					0.17	1.54	0.17	1.56				
γ_{UMD}			0.66	3.42			0.63	3.28				
γ_{QME}									0.39	2.78	0.39	2.79
γ_{QIA}									0.40	3.76	0.39	3.63
γ_{QROE}									0.43	3.15	0.41	3.01
γ_{EG}											0.44	3.23
γ_{RSK}	0.64	5.05	0.70	6.40	0.55	4.58	0.64	6.51	0.50	4.05	0.47	4.03
R^2	0.67		0.67		0.71		0.72		0.69		0.68	

Panel B: Extending-window betas													
	FF3+ ΔRSK		FF4+ ΔRSK		FF5+ ΔRSK		FF6+ ΔRSK		HXZ+ ΔRSK		HMXZ+ ΔRSK		
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	t-stat
γ_0	0.26	4.34	0.19	4.48	0.14	4.19	0.11	3.73	0.25	5.21	0.23	5.10	
γ_{MKT}	0.51	2.22	0.58	2.63	0.64	2.93	0.66	3.06	0.53	2.37	0.56	2.54	
γ_{SMB}	0.07	0.50	0.07	0.49	0.11	0.81	0.11	0.81					
γ_{HML}	0.26	1.53	0.27	1.73	0.21	1.46	0.21	1.47					
γ_{CMA}					0.24	2.00	0.26	2.31					
γ_{RMW}					0.27	2.02	0.29	2.20					
γ_{UMD}			0.56	2.46			0.54	2.39					
γ_{QME}									0.17	1.15	0.18	1.19	
γ_{QIA}									0.36	2.82	0.33	2.64	
γ_{QROE}									0.35	2.09	0.34	2.14	
γ_{EG}											0.54	3.71	
γ_{RSK}	0.46	3.28	0.43	3.94	0.35	2.82	0.39	3.78	0.28	2.11	0.24	1.96	
R^2	0.47		0.46		0.61		0.62		0.48		0.49		

Table 3.5. Cross-sectional regressions of mimicking right- and left-tail skewness-augmented factor models

Panel A reports Fama-MacBeth regressions of both mimicking right- and left-tail skewness (ΔRSK and ΔLSK) augmented factor models, using the full-sample estimation. Panel B shows the similar results in the extending window estimation. Test assets are 160 portfolios and the tested pricing factors, including 25 size and book-to-market sorted portfolios, 25 size and operating profitability sorted portfolios, 25 size and investment sorted portfolios, 25 size and momentum sorted portfolios, 25 size and ABR sorted portfolios, 25 size and SUE sorted portfolios, and 10 Fama-French industry portfolios. Tested factor models are Fama and French (1993) three-factor model (FF3), Carhart (1997) four-factor model (FF4), Fama and French (2015) five-factor model (FF5), Fama and French (2018) six-factor model (FF6), Hou et al. (2015) q -factor model (HXZ), and Hou et al. (2018b) q^5 model (HMXZ). All coefficients are multiplied by 100. The t-statistics are adjusted for errors-in-variables, following Shanken (1992). The adjusted R^2 follows Jagannathan and Wang (1996). Sample period for Panel A (Panel B) is July 1973 to June 2018 (July 1982 to June 2018).

Panel A: Full-sample betas

	FF3+ $\Delta R, LSK$		FF4+ $\Delta R, LSK$		FF5+ $\Delta R, LSK$		FF6+ $\Delta R, LSK$		HXZ+ $\Delta R, LSK$		HMXZ+ $\Delta R, LSK$	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.04	0.65	0.03	0.66	0.04	0.97	0.03	0.98	0.03	0.50	0.08	1.78
γ_{MKT}	0.60	2.88	0.60	2.95	0.59	2.95	0.59	2.94	0.61	2.98	0.57	2.81
γ_{SMB}	0.28	2.11	0.28	2.10	0.31	2.34	0.31	2.33				
γ_{HML}	0.35	2.54	0.34	2.50	0.24	1.81	0.21	1.63				
γ_{CMA}					0.29	3.07	0.32	3.55				
γ_{RMW}					0.17	1.57	0.17	1.60				
γ_{UMD}			0.67	3.45			0.62	3.22				
γ_{QME}									0.39	2.81	0.39	2.83
γ_{QIA}									0.42	3.94	0.41	3.78
γ_{QROE}									0.44	3.23	0.43	3.10
γ_{EG}											0.45	3.47
γ_{RSK}	0.63	4.99	0.7	6.25	0.5	4.36	0.61	6.2	0.46	4.07	0.44	3.92
γ_{LSK}	-0.12	-0.66	-0.16	-0.95	-0.2	-1.17	-0.27	-1.7	-0.13	-0.70	-0.13	-0.74
R^2	0.69		0.69		0.73		0.74		0.71		0.69	

Panel B: Extending-window

	FF3+ ΔR , LSK		FF4+ ΔR , LSK		FF5+ ΔR , LSK		FF6+ ΔR , LSK		HXZ+ ΔR , LSK		HMXZ+ ΔR , LSK	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.21	3.81	0.15	3.93	0.11	3.42	0.09	3.25	0.18	4.21	0.16	4.04
γ_{MKT}	0.56	2.44	0.62	2.82	0.67	3.08	0.68	3.18	0.59	2.68	0.62	2.84
γ_{SMB}	0.07	0.49	0.07	0.48	0.12	0.83	0.12	0.83				
γ_{HML}	0.26	1.68	0.27	1.76	0.22	1.51	0.21	1.50				
γ_{CMA}					0.25	2.13	0.26	2.40				
γ_{RMW}					0.27	2.04	0.29	2.22				
γ_{UMD}			0.58	2.56			0.55	2.42				
γ_{QME}									0.17	1.16	0.17	1.15
γ_{QIA}									0.39	3.08	0.36	2.78
γ_{QROE}									0.38	2.37	0.36	2.22
γ_{EG}											0.60	4.36
γ_{RSK}	0.48	3.59	0.45	4.14	0.36	3.02	0.39	3.9	0.29	2.60	0.28	2.49
γ_{LSK}	-0.25	-1.24	-0.17	-1.06	-0.16	-0.85	-0.2	-1.23	-0.12	-0.61	-0.02	-0.12
R^2	0.52		0.52		0.65		0.65		0.53		0.54	

Table 3.6. Cross-sectional regressions of non-tradable skewness-augmented factor models

Panel A reports Fama-MacBeth regressions of various factor models and those augmented with non-tradable skewness factor (ΔSK) directly, using the full-sample estimation. Panel B reports the similar results using non-tradable right-tail skewness (ΔRSK) factor directly. Panel C presents the similar results using non-tradable left-tail skewness (ΔLSK) factor directly. Test assets are 160 portfolios, including 25 size and book-to-market sorted portfolios, 25 size and operating profitability sorted portfolios, 25 size and investment sorted portfolios, 25 size and momentum sorted portfolios, 25 size and ABR sorted portfolios, 25 size and SUE sorted portfolios, and 10 Fama-French industry portfolios. Tested factor models are Fama and French (1993) three-factor model (FF3), Carhart (1997) four-factor model (FF4), Fama and French (2015) five-factor model (FF5), Fama and French (2018) six-factor model (FF6), Hou et al. (2015) q -factor model (HXZ), and Hou et al. (2018b) q^5 factor model (HMXZ). All test assets and the pricing factors are annualized. 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). Sample period is June 1974 to June 2018.

Panel A: Using Skewness factor																
	FF3		FF3+ ΔSK		FF4		FF4+ ΔSK		FF5		FF5+ ΔSK		FF6		FF6+ ΔSK	
	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	1.34	1.70	0.81	0.66	0.92	1.16	0.81	1.02	0.38	0.57	0.47	0.58	0.82	1.47	0.80	1.42
γ_{MKT}	6.39	2.40	7.39	2.63	7.13	2.67	7.29	2.75	7.18	2.74	7.46	2.80	7.02	2.70	7.06	2.72
γ_{SMB}	3.65	2.08	3.33	1.85	3.59	2.03	3.53	1.99	3.48	1.97	3.11	1.75	3.36	1.90	3.33	1.90
γ_{HML}	3.42	1.47	2.94	1.14	4.05	1.66	3.88	1.61	1.03	0.46	2.11	0.95	2.96	1.36	2.98	1.37
γ_{CMA}									5.27	3.96	5.17	3.77	4.58	3.49	4.60	3.51
γ_{RMW}									2.86	1.73	2.51	1.46	1.66	1.03	1.68	1.03
γ_{UMD}					11.20	4.80	11.12	4.77					10.75	4.62	10.74	4.62
γ_{SK}			22.67	3.04			7.96	1.65			20.78	2.96			6.46	1.49
R^2	0.35		0.56		0.69		0.69		0.52		0.63		0.75		0.75	
Panel A (Continued)																
	HXZ		HXZ+ ΔSK		HMXZ		HMXZ+ ΔSK									
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat								
γ_0	0.49	0.49	0.48	0.44	1.33	1.30	1.35	1.34								
γ_{MKT}	7.62	2.80	7.72	2.79	6.86	2.52	6.86	2.52								
γ_{QME}	4.31	2.33	4.29	2.30	3.58	1.94	3.63	1.97								
γ_{QIA}	3.58	1.84	4.42	2.44	4.50	2.36	4.68	2.59								
γ_{QROE}	6.69	4.14	6.32	3.80	6.59	3.94	6.48	3.87								
γ_{EG}					8.32	4.04	8.05	4.17								
γ_{SK}			13.16	2.32			8.38	1.73								
R^2	0.65		0.67		0.70		0.70									

Panel B: Using right-tail skewness

	FF3+ ΔRSK		FF4+ ΔRSK		FF5+ ΔRSK		FF6+ ΔRSK		HXZ+ ΔRSK		HMXZ+ ΔRSK	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	1.03	0.80	0.84	1.00	0.38	0.47	0.77	1.35	0.56	0.50	1.36	1.33
γ_{MKT}	6.88	2.42	7.22	2.69	7.35	2.76	7.09	2.72	7.55	2.73	6.82	2.50
γ_{SMB}	3.33	1.84	3.49	1.97	3.24	1.82	3.31	1.88				
γ_{HML}	3.53	1.33	3.99	1.61	2.26	1.02	3.09	1.42				
γ_{CMA}					5.13	3.74	4.60	3.51				
γ_{RMW}					3.22	1.80	1.85	1.13				
γ_{UMD}			10.94	4.69			10.67	4.59				
$\gamma_{Q_{ME}}$									4.25	2.28	3.67	2.00
$\gamma_{Q_{IA}}$									4.33	2.25	4.61	2.45
$\gamma_{Q_{ROE}}$									6.36	3.80	6.48	3.88
γ_{EG}											8.04	4.03
γ_{RSK}	8.67	3.23	3.90	2.49	7.49	3.15	3.10	2.06	5.11	2.74	3.58	2.49
R^2	0.56		0.70		0.62		0.75		0.69		0.70	

Panel C: Using left-tail skewness

	FF3+ ΔLSK		FF4+ ΔLSK		FF5+ ΔLSK		FF6+ ΔLSK		HXZ+ ΔLSK		HMXZ+ ΔLSK	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.82	0.77	0.96	1.21	0.42	0.55	0.83	1.47	0.46	0.44	1.32	1.29
γ_{MKT}	7.61	2.77	7.04	2.67	7.66	2.89	6.99	2.70	7.73	2.82	6.80	2.49
γ_{SMB}	3.56	2.00	3.60	2.03	3.21	1.82	3.37	1.91				
γ_{HML}	2.87	1.17	4.11	1.71	1.54	0.69	2.96	1.36				
γ_{CMA}					5.20	3.83	4.57	3.49				
γ_{RMW}					2.27	1.37	1.67	1.04				
γ_{UMD}			11.20	4.80			10.76	4.62				
$\gamma_{Q_{ME}}$									4.32	2.33	3.54	1.92
$\gamma_{Q_{IA}}$									3.72	2.00	4.41	2.33
$\gamma_{Q_{ROE}}$									6.58	4.07	6.69	3.99
γ_{EG}											8.54	4.41
γ_{LSK}	-5.59	-2.42	-0.13	-0.07	-4.9	-2.2	-0.28	-0.17	-1.45	-0.82	0.31	0.19
R^2	0.45		0.69		0.58		0.75		0.65		0.70	

Table 3.7. **Explaining ABR factor with skewness-augmented factor models**

Panel A presents the abnormal returns and the factor-loadings of ABR factor from various skewness (ΔSK)-augmented factor models, using full-sample period. Panel B shows similar results from the extending-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), Hou et al. (2015) q -factor model (HXZ), and Hou et al. (2018b) q^5 model (HMXZ). 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 sample period is from July 1973 to June 2018. The testing period for Panel B starts from July 1982.

Panel A: Full-sample estimation										
	α									
Raw	0.44									
t-stat	6.88									
	α	MKT					ΔSK	R^2		
CAPM	0.02	0.01					0.84	0.76		
t-stat	0.77	1.29					28.77			
	α	MKT	SMB	HML			ΔSK	R^2		
FF3	-0.02	0.03	0.00	0.06			0.87	0.77		
t-stat	-0.65	2.23	0.02	2.36			34.48			
	α	MKT	SMB	HML	UMD			ΔSK	R^2	
FF4	-0.02	0.03	0.00	0.07	0.02			0.84	0.77	
t-stat	-0.78	2.51	0	2.84	1.7			27.93		
	α	MKT	SMB	HML	CMA	RMW			ΔSK	R^2
FF5	-0.02	0.03	-0.01	0.03	0.08	-0.05			0.87	0.78
t-stat	-0.65	2.81	-0.79	0.95	2.38	-1.32			33.92	
	α	MKT	SMB	HML	CMA	RMW	UMD	ΔSK	R^2	
FF6	-0.02	0.03	-0.02	0.04	0.07	-0.05	0.02	0.84	0.79	
t-stat	-0.65	2.96	-0.95	1.38	2.25	-1.50	1.87	28.18		
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}			ΔSK	R^2	
HXZ	-0.01	0.02	0.01	0.07	-0.03			0.86	0.77	
t-stat	-0.29	1.99	0.24	2.70	-1.16			24.31		
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}	EG			ΔSK	R^2
HMXZ	-0.04	0.03	0.01	0.06	-0.05	0.07			0.85	0.77
t-stat	-1.23	2.69	0.35	1.98	-1.75	2.40			26.67	

Panel B: Extending-window estimation										
	α									
Raw	0.38									
t-stat	5.15									
	α	MKT						ΔSK	R^2	
CAPM	-0.04	0.04						0.97	0.84	
t-stat	-1.53	4.17						32.29		
	α	MKT	SMB	HML				ΔSK	R^2	
FF3	-0.06	0.04	0.02	0.02				0.98	0.84	
t-stat	-1.91	3.54	0.61	0.84				38.63		
	α	MKT	SMB	HML	UMD				ΔSK	R^2
FF4	-0.06	0.04	0.02	0.02	0.00				0.97	0.84
t-stat	-1.93	3.77	0.62	0.91	0.04				34.02	
	α	MKT	SMB	HML	CMA	RMW			ΔSK	R^2
FF5	-0.03	0.03	0.00	0.03	0.02	-0.08			0.98	0.85
t-stat	-0.94	2.77	-0.07	0.96	0.47	-1.96			38.48	
	α	Mktrf	SMB	HML	CMA	RMW	UMD	ΔSK	R^2	
FF6	-0.03	0.03	0.00	0.03	0.01	-0.08	0.00	0.98	0.85	
t-stat	-0.93	2.85	-0.09	1.09	0.46	-1.94	0.28	34.00		
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}				ΔSK	R^2
HXZ	-0.03	0.03	0.02	0.00	-0.06				1.00	0.85
t-stat	-0.78	2.41	0.51	0.12	-2.19				28.75	
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}	EG			ΔSK	R^2
HMXZ	-0.06	0.03	0.02	-0.01	-0.07	0.06			0.99	0.85
t-stat	-1.76	3.17	0.60	-0.59	-2.74	2.53			31.09	

Table 3.8. **Explaining ABR factor with right- and left-tail skewness augmented factor models**

Panel A presents the abnormal returns and the factor-loadings of ABR factor from various right-tail skewness (ΔRSK)-augmented factor models, using full-sample period. Panel B shows similar results from the extending-window estimation. Panel C reports the abnormal returns and the factor-loadings of ABR factor from various left-tail skewness (ΔLSK)-augmented factor models, using full-sample period. Panel D presents similar results from the extending-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), Hou et al. (2015) q -factor model (HXZ), and Hou et al. (2018b) q^5 model (HMXZ). 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 sample period is from July 1973 to June 2018. The testing period for Panel B starts from July 1982.

Panel A: Right-tail skewness using the full-sample estimation									
	α								
Raw	0.44								
t-stat	6.88								
	α	MKT					ΔRSK	R^2	
CAPM	0.12	0.05					0.53	0.37	
t-stat	1.92	4.13					10.29		
	α	MKT	SMB	HML			ΔRSK	R^2	
FF3	0.12	0.04	0.05	-0.05			0.54	0.39	
t-stat	1.96	2	1.07	-1.33			13.16		
	α	MKT	SMB	HML	UMD			ΔRSK	R^2
FF4	0.12	0.04	0.04	-0.03	0.07			0.46	0.42
t-stat	2.15	2.14	1.08	-1.09	2.34			7.64	
	α	MKT	SMB	HML	CMA	RMW	ΔRSK	R^2	
FF5	0.15	0.03	0.03	-0.05	0.02	-0.09	0.56	0.41	
t-stat	2.21	1.86	0.95	-1.25	0.38	-1.52	14.91		
	α	MKT	SMB	HML	CMA	RMW	UMD	ΔRSK	R^2
FF6	0.15	0.03	0.01	-0.02	0.00	-0.10	0.07	0.48	0.43
t-stat	2.57	1.88	0.67	-0.72	0.02	-1.85	2.90	9.60	
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}			ΔRSK	R^2
HXZ	0.13	0.04	0.05	-0.08	-0.01			0.57	0.39
t-stat	2.12	1.89	1.12	-1.91	-0.24			14.27	
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}	EG	ΔRSK	R^2	
HMXZ	0.07	0.04	0.06	-0.11	-0.04	0.12	0.55	0.41	
t-stat	1.16	2.74	1.26	-2.37	-0.98	2.33	13.63		

Panel B: Right-tail skewness using the extending-window estimation									
	α								
Raw	0.38								
t-stat	5.15								
	α	MKT						ΔRSK	R^2
CAPM	0.08	0.03						0.61	0.43
t-stat	1.58	2.26						13.66	
	α	MKT	SMB	HML				ΔRSK	R^2
FF3	0.07	0.03	0.04	0.01				0.62	0.44
t-stat	1.13	1.52	0.64	0.26				12.44	
	α	MKT	SMB	HML	UMD			ΔRSK	R^2
FF4	0.07	0.04	0.03	0.02	0.07			0.54	0.47
t-stat	1.21	1.91	0.61	0.67	2.20			7.28	
	α	MKT	SMB	HML	CMA	RMW		ΔRSK	R^2
FF5	0.09	0.03	0.00	0.00	0.09	-0.11		0.65	0.47
t-stat	1.32	1.45	0.10	-0.03	1.37	-1.56		17.37	
	α	Mktrf	SMB	HML	CMA	RMW	UMD	ΔRSK	R^2
FF6	0.09	0.03	-0.01	0.02	0.06	-0.12	0.07	0.57	0.49
t-stat	1.58	1.58	-0.23	0.65	1.00	-1.83	2.67	10.47	
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}			ΔRSK	R^2
HXZ	0.08	0.03	0.05	0.02	-0.03			0.64	0.45
t-stat	1.14	1.30	0.78	0.51	-0.71			14.25	
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}	EG		ΔRSK	R^2
HMXZ	0.00	0.04	0.05	-0.02	-0.08	0.14		0.63	0.47
t-stat	-0.02	2.15	0.91	-0.33	-1.51	2.93		14.77	
Panel C: Left-tail skewness using the full-sample estimation									
	α	MKT						ΔLSK	R^2
CAPM	0.27	0.06						-0.38	0.62
t-stat	6.01	3.98						-22.23	
	α	MKT	SMB	HML				ΔLSK	R^2
FF3	0.24	0.09	-0.06	0.07				-0.41	0.64
t-stat	5.83	5.90	-2.68	3.00				-22.88	
	α	MKT	SMB	HML	UMD			ΔLSK	R^2
FF4	0.19	0.09	-0.05	0.08	0.08			-0.37	0.69
t-stat	5.26	6.60	-3.31	5.17	6.29			-21.21	
	α	MKT	SMB	HML	CMA	RMW		ΔLSK	R^2
FF5	0.19	0.11	-0.06	-0.01	0.18	0.01		-0.41	0.67
t-stat	4.60	7.85	-3.42	-0.45	5.51	0.45		-23.84	
	α	Mktrf	SMB	HML	CMA	RMW	UMD	ΔLSK	R^2
FF6	0.17	0.11	-0.06	0.02	0.14	-0.01	0.08	-0.38	0.71
t-stat	4.67	8.28	-4.23	1.19	4.50	-0.51	6.05	-22.41	
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}			ΔLSK	R^2
HXZ	0.15	0.10	-0.02	0.15	0.07			-0.40	0.67
t-stat	3.43	6.49	-0.91	5.13	2.97			-21.07	
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}	EG		ΔLSK	R^2
HMXZ	0.10	0.11	-0.02	0.12	0.04	0.09		-0.39	0.68
t-stat	2.46	7.15	-0.80	4.10	1.38	3.01		-22.43	

Panel D: Left-tail skewness using the extending-window estimation									
	α	MKT						ΔLSK	R^2
CAPM	0.10	0.17						-0.62	0.94
t-stat	4.63	20.04						-43.07	
	α	MKT	SMB	HML				ΔLSK	R^2
FF3	0.10	0.18	-0.02	0.00				-0.62	0.94
t-stat	5.03	24.04	-2.72	0.20				-53.80	
	α	MKT	SMB	HML	UMD			ΔLSK	R^2
FF4	0.09	0.18	-0.02	0.01	0.02			-0.60	0.94
t-stat	4.54	23.75	-2.70	0.99	3.09			-58.81	
	α	MKT	SMB	HML	CMA	RMW		ΔLSK	R^2
FF5	0.08	0.18	-0.02	-0.02	0.04	0.02		-0.62	0.94
t-stat	4.13	25.83	-2.25	-1.99	2.54	2.28		-55.60	
	α	Mktrf	SMB	HML	CMA	RMW	UMD	ΔLSK	R^2
FF6	0.07	0.18	-0.02	-0.01	0.03	0.02	0.02	-0.60	0.94
t-stat	4.10	26.12	-2.46	-1.01	1.95	1.42	2.59	-62.95	
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}			ΔLSK	R^2
HXZ	0.07	0.18	-0.02	0.01	0.03			-0.61	0.94
t-stat	3.83	24.01	-2.64	1.20	2.57			-57.48	
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}	EG		ΔLSK	R^2
HMXZ	0.07	0.18	-0.02	0.01	0.02	0.01		-0.61	0.94
t-stat	3.57	24.22	-2.63	0.90	2.06	0.83		-55.27	

Table 3.9. Explaining SUE factor with skewness-augmented factor models

Panel A presents the abnormal returns and the factor-loadings of SUE factor from various skewness (ΔSK)-augmented factor models, using full-sample period. Panel B shows similar results from the extending-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), Hou et al. (2015) q -factor model (HXZ), and Hou et al. (2018b) q^5 model (HMXZ). 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 sample period is from July 1973 to June 2018. The testing period for Panel B starts from July 1982.

Panel A: Full-sample estimation									
	α								
Raw	0.64								
t-stat	7.1								
	α	MKT					ΔSK	R^2	
CAPM	0.26	0.03					0.74	0.31	
t-stat	3.13	1.36					7.92		
	α	MKT	SMB	HML			ΔSK	R^2	
FF3	0.36	0.04	-0.18	-0.09			0.68	0.39	
t-stat	4.95	1.51	-3.26	-1.82			9.37		
	α	MKT	SMB	HML	UMD			ΔSK	R^2
FF4	0.34	0.05	-0.19	-0.06	0.19			0.45	0.51
t-stat	5.51	2.65	-2.74	-1.21	5.69			7.04	
	α	MKT	SMB	HML	CMA	RMW	ΔSK	R^2	
FF5	0.23	0.07	-0.11	-0.16	0.11	0.29	0.67	0.48	
t-stat	3.23	3.32	-2.98	-3.14	1.46	5.74	9.32		
	α	MKT	SMB	HML	CMA	RMW	UMD	ΔSK	R^2
FF6	0.24	0.08	-0.12	-0.09	0.03	0.26	0.17	0.46	0.58
t-stat	3.91	3.86	-3.16	-1.88	0.50	3.73	6.13	7.08	
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}			ΔSK	R^2
HXZ	0.10	0.07	-0.02	-0.02	0.52			0.45	0.70
t-stat	1.79	4.26	-0.65	-0.51	15.91			9.64	
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}	EG	ΔSK	R^2	
HMXZ	0.10	6.81	-1.68	-2.17	51.76	0.00	0.45	0.70	
t-stat	1.73	4.65	-0.63	-0.51	14.84	0.09	9.52		

Panel B: Extending-window estimation									
	α								
Raw	0.53								
t-stat	5.66								
	α	MKT						ΔSK	R^2
CAPM	0.19	0.03						0.78	0.34
t-stat	2.32	1.45						7.77	
	α	MKT	SMB	HML					
FF3	0.24	0.04	-0.15	-0.07					
t-stat	3.21	1.48	-2.44	-1.38					
	α	MKT	SMB	HML	UMD				
FF4	0.23	0.06	-0.17	-0.04	0.17				
t-stat	3.54	2.69	-2.23	-0.71	4.24				
	α	MKT	SMB	HML	CMA	RMW			
FF5	0.10	0.08	-0.06	-0.13	0.01	0.33			
t-stat	1.33	3.54	-1.63	-3.05	0.09	6.59			
	α	Mktrf	SMB	HML	CMA	RMW	UMD	ΔSK	R^2
FF6	0.11	0.09	-0.07	-0.07	-0.05	0.31	0.16	0.48	0.59
t-stat	1.75	4.10	-2.12	-1.79	-0.88	4.48	4.65	6.35	
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}				
HXZ	0.03	0.09	0.00	-0.06	0.51				
t-stat	0.45	5.18	0.12	-1.49	13.90				
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}	EG			
HMXZ	0.07	0.09	0.00	-0.04	0.54	-0.08			
t-stat	1.20	5.18	0.04	-0.85	14.50	-2.28			

Table 3.10. **Explaining SUE factor with right- and left-tail skewness augmented factor models**

Panel A presents the abnormal returns and the factor-loadings of SUE factor from various right-tail skewness (ΔRSK)-augmented factor models, using full-sample period. Panel B shows similar results from the extending-window estimation. Panel C reports the abnormal returns and the factor-loadings of SUE factor from various left-tail skewness (ΔLSK)-augmented factor models, using full-sample period. Panel D presents the similar results from the extending-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), Hou et al. (2015) q -factor model (HXZ), and Hou et al. (2018b) q^5 model (HMXZ). 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 sample period is from July 1973 to June 2018. The testing period for Panel B starts from July 1982.

Panel A: Right-tail skewness using the full-sample estimation									
	α								
Raw	0.64								
t-stat	7.1								
	α	MKT					ΔRSK	R^2	
CAPM	0.05	0.14					0.92	0.57	
t-stat	0.71	6.37					15.95		
	α	MKT	SMB	HML			ΔRSK	R^2	
FF3	0.17	0.12	-0.09	-0.16			0.87	0.63	
t-stat	2.68	5.43	-2.54	-3.79			19.44		
	α	MKT	SMB	HML	UMD			ΔRSK	R^2
FF4	0.17	0.12	-0.11	-0.12	0.12			0.72	0.68
t-stat	2.89	5.41	-2.55	-2.95	4.36			12.21	
	α	MKT	SMB	HML	CMA	RMW	ΔRSK	R^2	
FF5	0.11	0.13	-0.04	-0.17	-0.02	0.21	0.84	0.68	
t-stat	1.85	6.87	-1.39	-4	-0.28	5.82	17.47		
	α	MKT	SMB	HML	CMA	RMW	UMD	ΔRSK	R^2
FF6	0.12	0.12	-0.06	-0.11	-0.05	0.20	0.12	0.70	0.72
t-stat	2.20	6.79	-2.08	-2.65	-0.94	4.52	6.19	15.63	
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}			ΔRSK	R^2
HXZ	0.03	0.12	0.02	-0.13	0.43			0.63	0.81
t-stat	0.67	8.84	0.89	-4.05	14.68			18.27	
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}	EG	ΔRSK	R^2	
HMXZ	0.04	0.11	0.02	-0.13	0.43	-0.02	0.63	0.81	
t-stat	0.88	8.95	0.87	-3.74	14.09	-0.55	18.32		

Panel B: Right-tail skewness using the extending-window estimation									
	α								
Raw	0.53								
t-stat	5.66								
	α	MKT						ΔRSK	R^2
CAPM	0.08	0.08						0.90	0.56
t-stat	1.16	4.10						15.56	
	α	MKT	SMB	HML				ΔRSK	R^2
FF3	0.10	0.09	-0.11	-0.01				0.87	0.59
t-stat	1.46	4.01	-3.27	-0.16				17.01	
	α	MKT	SMB	HML	UMD			ΔRSK	R^2
FF4	0.09	0.10	-0.13	0.01	0.13			0.71	0.65
t-stat	1.39	4.65	-2.84	0.32	4.22			9.69	
	α	MKT	SMB	HML	CMA	RMW		ΔRSK	R^2
FF5	0.00	0.13	-0.04	-0.08	0.06	0.26		0.81	0.65
t-stat	0.00	6.15	-1.70	-2.28	0.94	6.81		14.11	
	α	Mktrf	SMB	HML	CMA	RMW	UMD	ΔRSK	R^2
FF6	0.01	0.13	-0.06	-0.04	0.00	0.25	0.12	0.66	0.71
t-stat	0.15	6.10	-2.32	-1.07	0.00	5.29	5.55	12.48	
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}			ΔRSK	R^2
HXZ	-0.05	0.13	0.02	0.00	0.43			0.61	0.81
t-stat	-1.10	7.74	0.79	-0.10	14.58			15.81	
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}	EG		ΔRSK	R^2
HMXZ	-0.01	0.12	0.01	0.02	0.45	-0.07		0.61	0.81
t-stat	-0.31	7.89	0.75	0.49	14.07	-2.41		16.65	
Panel C: Left-tail skewness using the full-sample estimation									
	α	MKT						ΔLSK	R^2
CAPM	0.58	0.02						-0.13	0.04
t-stat	6.49	0.63						-1.92	
	α	MKT	SMB	HML				ΔLSK	R^2
FF3	0.70	0.01	-0.20	-0.17				-0.10	0.17
t-stat	8.14	0.45	-3.35	-2.91				-2.05	
	α	MKT	SMB	HML	UMD			ΔLSK	R^2
FF4	0.55	0.03	-0.20	-0.11	0.26			0.00	0.42
t-stat	7.11	1.48	-2.72	-2.16	8.53			0.01	
	α	MKT	SMB	HML	CMA	RMW		ΔLSK	R^2
FF5	0.54	0.06	-0.13	-0.25	0.16	0.32		-0.12	0.28
t-stat	5.98	2.56	-2.66	-4.06	1.63	5.73		-2.77	
	α	Mktrf	SMB	HML	CMA	RMW	UMD	ΔLSK	R^2
FF6	0.45	0.05	-0.13	-0.13	0.02	0.25	0.24	-0.02	0.49
t-stat	6.15	2.60	-2.94	-2.39	0.29	3.40	8.17	-0.54	
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}			ΔLSK	R^2
HXZ	0.27	0.06	-0.01	-0.05	0.60			-0.06	0.61
t-stat	4.05	2.97	-0.27	-1.03	15.56			-2.27	
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}	EG		ΔLSK	R^2
HMXZ	0.24	0.06	0.00	-0.07	0.58	0.06		-0.05	0.61
t-stat	3.59	3.37	-0.17	-1.40	14.12	1.18		-1.98	

Panel D: Left-tail skewness using the extending-window estimation									
	α	MKT						ΔLSK	R^2
CAPM	0.46	0.04						-0.20	0.06
t-stat	4.60	1.00						-1.89	
	α	MKT	SMB	HML				ΔLSK	R^2
FF3	0.51	0.04	-0.18	-0.13				-0.18	0.16
t-stat	5.95	1.26	-2.53	-2.09				-2.13	
	α	MKT	SMB	HML	UMD			ΔLSK	R^2
FF4	0.42	0.03	-0.19	-0.06	0.25			0.00	0.39
t-stat	5.41	1.19	-2.32	-1.18	7.31			0.06	
	α	MKT	SMB	HML	CMA	RMW		ΔLSK	R^2
FF5	0.31	0.10	-0.07	-0.21	0.04	0.39		-0.20	0.31
t-stat	3.72	4.00	-1.57	-3.73	0.50	7.22		-3.08	
	α	Mktrf	SMB	HML	CMA	RMW	UMD	ΔLSK	R^2
FF6	0.28	0.07	-0.09	-0.10	-0.05	0.32	0.23	-0.03	0.50
t-stat	3.97	3.05	-2.21	-2.17	-0.78	4.33	6.28	-0.58	
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}			ΔLSK	R^2
HXZ	0.16	0.09	0.01	-0.09	0.59			-0.08	0.62
t-stat	2.44	4.10	0.40	-1.77	14.17			-2.23	
	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}	EG		ΔLSK	R^2
HMXZ	0.19	0.09	0.01	-0.07	0.61	-0.05		-0.09	0.62
t-stat	2.78	4.02	0.34	-1.47	14.09	-1.13		-2.28	

3.7 Appendices

3.7.1 TFP estimation

(1) Data

In order to estimate the total factor productivity (TFP), we have two main data sources: Annual Compustat and CRSP files. By matching Compustat and CRSP, we estimate TFP for public firms in the United States. The time period starts from 1965 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), depreciation, depletion and amortization (DPACT), employees (EMP), and staff expense (XLR).

We apply several filters to estimate the coefficients of labor and capital. We include common stocks listed at NYSE/Amex/Nasdaq. We exclude the financial firms and the utility firms (four-digit SIC between 6000 - 6999 and 4900 - 4999). Also, sample firms with sales or total assets less than \$1 million, or with negative employees, capital expenditure, and depreciation are deleted. Firms with value-added and material costs less than 0.01 are excluded as well. The labor expense ratio, which we will describe below, should be between 0 and 1. Finally, the sample firms should report their accounting information for 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 the price index for nonresidential private fixed investment (NIPA table 5.3.4 qtr line2). We obtain employees' earnings data from the Bureau of Labor Statistics (CES0500000030). Because this table reports weekly earnings for each month, we calculate 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 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, 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 wages 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 by following Imrohoroglu and Tuzel (2014). First, we compute the age of capital 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 the current year minus capital age. Finally, we take a 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 deflated by the current fixed investment price index.

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

(3) TFP estimation

We follow Olley and Pakes (1996) to estimate the total factor productivity (TFP) because this is one of the robust ways of measuring production function parameters by 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. Imrohoroglu and Tuzel (2014) show how to estimate Olley and Pakes (1996) TFP using annual Compustat

and share their codes⁵. Our TFP estimation process is based on Imrohoroglu and Tuzel (2014) with some modifications.

We start from the simple Cobb-Douglas production technology.

$$Y_{it} = L_{it}^{\beta_L} K_{it}^{\beta_K} Z_{it} \quad (3.9)$$

where Y_{it} , L_{it} , K_{it} , and Z_{it} are value-added, labor, capital stock, and productivity 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 the labor coefficient without scaling. After scaled by the capital stock and transformed into logarithmic values, Eq.(3.9) is rewritten as

$$\text{Log} \frac{Y_{it}}{K_{it}} = \beta_L \text{Log} \frac{L_{it}}{K_{it}} + (\beta_K + \beta_L - 1) \text{Log} K_{it} + \text{Log} Z_{it}. \quad (3.10)$$

We define $\text{Log} \frac{Y_{it}}{K_{it}}$, $\text{Log} \frac{L_{it}}{K_{it}}$, $\text{Log} K_{it}$, and $\text{Log} Z_{it}$ 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.(3.10) as

$$yk_{it} = \beta_l lk_{it} + \beta_k k_{it} + z_{it}. \quad (3.11)$$

When facing the productivity shock (z_{it}) at t , a firm decides the optimal labor and the optimal investment. Because the productivity (z_{it}) is a state variable, the optimal investment (ik_{it}^*) is a function of the productivity (z_{it}). Olley and Pakes (1996) assume a monotonic relationship between the investment and productivity, so the productivity is a function of investment, i.e., $z_{it} = h(ik_{it})$. We assume that the function $h(ik_{it})$ is 4th-order polynomials of ik_{it} .

⁵<http://www-bcf.usc.edu/~tuzel/TFPUUpload/Programs/>

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

$$y_{it} = \beta_l l k_{it} + \beta_k k_{it} + \beta_0 + \beta_{ik} i k_{it} + \beta_{ik^2} i k_{it}^2 + \beta_{ik^3} i k_{it}^3 + \beta_{ik^4} i k_{it}^4 + year + \eta_j + \epsilon_{it} \quad (3.12)$$

where $h(ik_{it}) = \beta_0 + \beta_{ik} i k_{it} + \beta_{ik^2} i k_{it}^2 + \beta_{ik^3} i k_{it}^3 + \beta_{ik^4} i k_{it}^4$ and η_j is 4-digit SIC code to capture the differences of industrial technologies. From this stage, we estimate the labor coefficients, $\hat{\beta}_l$.

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

$$\begin{aligned} E_t(y k_{i,t+1} - \hat{\beta}_l l k_{i,t+1} - \eta_j) &= \beta_k k_{i,t+1} + E_t(z_{i,t+1} | z_{i,t}, survival) \\ &= \beta_k k_{i,t+1} + g(z_{it}, \hat{P}_{survival,t}) \end{aligned} \quad (3.13)$$

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 4th-order polynomials in investment rate, i/k . z_{it} is $\beta_0 + \beta_{ik} i k_{it} + \beta_{ik^2} i k_{it}^2 + \beta_{ik^3} i k_{it}^3 + \beta_{ik^4} i k_{it}^4$. 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:

$$TFP_{it} = \exp(y k_{it} - \hat{\beta}_l l k_{i,t} - (\hat{\beta}_K + \hat{\beta}_l - 1) k_{it} - \eta_j) \quad (3.14)$$

. We estimate TFP shocks as first-order autoregressive residuals by running a regression of TFP in year t against TFP in year $t-1$. TFP estimates are available from 1972 to 2016.

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