Fundamental Risk Sources and Pricing Factors

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Abstract

Neoclassical theory suggests that stocks exposed to common pricing factors must face common production risks. We estimate firm-level productivity shocks and decompose them into six aggregate risk components via asymptotic principal component analysis. We find that fundamental risks drive 13 of 15 prevailing pricing factors. First, we show that the fundamental shocks capture most factors proposed in the Fama-French six-factor model (Fama and French, 2018), the q-factor model (Hou et al., 2015), except the expected investment growth factor in the q^5 model (Hou et al., 2018). Second, we find that fundamental shocks explain most mispricing and behavioral factors (Stambaugh and Yuan, 2017; Daniel et al., 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 interpret this missing factor as the labor risk. Overall, the productivity-based model performs at least as well as the prevailing factor models.

JEL classification: E22, E23, E24, G11, G12

Keywords: productivity shocks, pricing factors, empirical asset pricing models

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Motivated by the failures of the Fama-French three-factor and Carhart four-factor models to account for many anomalies, several new factor models are suggested in the literature, from the risk or behavioral perspectives (Fama and French, 2015, 2018; Hou et al., 2015, 2018; Stambaugh and Yuan, 2017; Daniel et al., 2018). These models use asset prices to construct 15 pricing factors, based on various characteristics, and empirically perform well. However, often it is difficult to distinguish them. In this paper, we start with the common fundamental risks in firm productions and explore their asset pricing implications. This helps to trace the systematic risks behind prevailing pricing factors and also identify the factors missed in the existing models. Empirically, we identify six principal components of aggregate productivity shocks, which captures 13 of 15 prevailing factors. 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. (2018), correspond to the second to fourth productivity factors, 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). But, the productivity factors fail to capture the expected investment growth factor in Hou et al. (2018) and the short-horizon behavioral factor in Daniel et al. (2018). Moreover, we find that an important productivity factor, the first principal component, contain information not captured by the existing factors, e.g., a missing factor. We show that this missing factor captures the labor risks in the economy. Overall, the productivity-based model prices various test assets well and performs similarly to the q^5 model (Hou et al., 2018) and the behavioral model Daniel et al. (2018).

Why cares about fundamental risk sources? For example, given the large literature on empirical asset pricing models which propose various pricing factors and compute factor returns from asset prices, one might suggest we bypass fundamental risks and use those factor returns directly. The advantage of using fundamental risks is that the true systematic risks are from macroeconomic sources and asset risks arise endogenously from these fundamental risks. For example, this explains why stocks with similar characteristics like investment or profitability comove together. Also, fundamental risks help us distinguish different return-based factors, which are often hard to differentiate among competing models. In fact, different exposures to the multiple fundamental risks generate cross-sectional return variations.

Empirically, we identify the fundamental risk sources and their mimicking factor returns in three steps. We first estimate firm-level total factor productivity, following Olley and Pakes (1996) and İmrohoroğlu and Tüzel (2014). Second, we apply the asymptotic principal component analysis (Connor and Korajczyk, 1987; Chen et al., 2018) to estimate the systematic TFP components across all firms to identify fundamental risks. We identify six principal components of productivity shocks, which explain about 52% of total factor productivity across firms. We also validate such decompositions by showing that the systematic productivity factors predict stock returns while the idiosyncratic productivity is not priced. We find that the second productivity component traces the size factor in Fama and French (2015) and Hou et al. (2015), with a correlation coefficient of -0.24 and -0.25, respectively. The third productivity component captures the profitability factor in Fama and French (2015) and Hou et al. (2015), with a correlation coefficient of -0.48 and -0.42, respectively. The fourth productivity component captures the investment factor in Fama and French (2015) and Hou et al. (2015), with a correlation coefficient of 0.50 and 0.43, respectively. The fifth productivity component captures the momentum factor in Fama and French (2018), with a correlation coefficient of 0.35. The mispricing factor in Stambaugh and Yuan (2017) and the short-horizon behavioral factor in Daniel et al. (2018) are highly correlated with the sixth productivity component, with a correlation coefficient of -0.35 and -0.48, respectively.

Third, we construct the mimicking productivity factors for these six components, following Adrian et al. (2014). Then we test whether the productivity factors can explain the prevailing 15 pricing factors, as follows: (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. (2018), 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 component related to firms' performances ($PERF$); (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, except the expected investment growth factor (EG) and the short-horizon behavioral bias factor ($PEAD$). The mispricing factors in Stambaugh and Yuan (2017), though constructed from 11 anomalies, indeed capture the fundamental risks. We also show that productivity factors well explain more broad 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 portfolios, and 30 Fama-French industry portfolios. We further show that the productivity-based model provides the highest maximum squared Sharpe ratio among competing models. The productivity-based model delivers similar performance to that of the q^5 model (Hou et al., 2018) or the behavioral model Daniel et al. (2018).

On the other hand, we find that these prevailing 15 pricing factors can explain the second to sixth productivity factors. But the first productivity factor is missed by these pricing factors. We dig deeply to understand this missing factor. Empirically, we first show that labor productivity is an important part of total factor productivity and captured by the first productivity factor. Then, we construct the labor share portfolios, following Donangelo et al. (2018). We find that this labor sorted portfolios are not explained by the prevailing pricing factors as they capture mainly returns to the installed capital. But, the first productivity factor fully explains the labor sorted portfolios. Therefore, returns to installed labor appear to be missing in existing factor models while the first productivity factor tacks such labor risks.

This paper follows the tradition of production-based asset pricing literature, e.g., Cochrane (1991), Berk et al. (1999), Carlson et al. (2004), Zhang (2005), and Hou et al. (2015). Neoclassical theory links real investment returns to the stock returns and suggests that production shocks drive the stock return volatilities. This implies that rational pricing factors could be derived from various systematic productivity shocks. Our paper contributes to the literature by empirically constructing a productivity-based model.

Recently, several asset pricing models have been proposed in the empirical literature. The first type of models are based on rational risk factors. For example, motivated by the dividend discount model/surplus clean accounting, Fama and French (2015) construct a five-factor model, including a market factor (MKT), a size factor (SMB), a value factor (HML), an investment factor (CMA), and a profitability factor (RMW). Fama and French (2018) further add the momentum factor (UMD) to the five-factor model, i.e., 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 (MKT), a size factor (Q_{ME}), an investment factor(Q_{IA}), and a profitability factor (Q_{ROE}), where the investment and profitability factors are constructed differently from those in Fama and French (2015). Hou et al. (2018) add the expected investment growth factor (EG) to the q-factor model, i.e., a q^5 model. The second type of factor models suggests using 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 which are related to firms' management ($MGMT$ factor) and five anomalies that are related to firms' performances ($PERF$ factor). Daniel et al. (2018) propose a three-factor model, including a market factor, a factor related to long-horizon behavioral bias (FIN), and a factor related to short-horizon behavioral bias ($PEAD$). FIN is based on security issuance and repurchase, which measures managerial responses to the long-horizon behavioral bias. $PEAD$ derives 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, often it is difficult to evaluate these factors.[1] Our paper explores the fundamental risks possibly embedded or missed in these pricing models to understand these pricing factors. In a similar vein, Belo et al. (2018) show that factors other than installed physical capital are important determinants of firm values, suggesting the importance of recognizing the multiple risk sources in stock returns.

This paper also adds to the recent asset pricing literature on labor risks. Besides 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, 2016a,b), and search frictions in labor markets (Petrosky-Nadeau et al., 2018). For asset pricing purpose, labor can increase equity risks through the labor leverage channel (Danthine and Donaldson, 2002; Donangelo, 2014; Donangelo et al., 2018), or the insurance provided by the shareholders to workers (Marfè, 2016, 2017; Hartman-Glaser et al., 2017; Lettau et al., 2018). Different from 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 describes the data and empirical procedures of estimating systematic productivity factors. Section 2 presents the empirical estimates of productivity factors. Section 3 tests the pricing power of productivity factors over other prevailing pricing factors and test assets. Section 4 examines the explanatory power of productivity factors over mispricing portfolios in details. Section 5 identifies a productivity factor missed in the prevailing models and relates it to the labor risk. Finally, Section 6 concludes.

[1] Hou et al. (2018) provide some thoughtful discussions on the traditional covariance view, behavioral view, and investment CAPM perspective of factors. Empirically, Hou et al. (2018b) 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 premiums, and the mispricing factors in Stambaugh and Yuan (2017), but not the PEAD factor in Daniel et al. (2018).

1. Estimating systematic productivity shocks

Production-based asset pricing models directly relate stock returns with real investment returns, i.e., returns on investment of physical capital and labor. This implies that stock risks are inherited from production risks. Therefore, if stock returns depend on multiple rational pricing factors, firms' production must be subject to multiple systematic productivity shocks reflected in the pricing factors, and *vice versa* (See Appendix A for illustrations in a motivating model). In this section, we first estimate firm-level productivity. Then we identify systematic productivity shocks across firms and construct mimicking productivity factors.

1.1. Estimating firm-level total factor productivity

We follow Olley and Pakes (1996) to estimate TFP. Compared with the Sorrow residuals, Olley and Pakes (1996) address two issues. 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) mitigates this issue by specifying TFP as a function of the survival probability. Olley and Pakes (1996) assume: (1) productivity is a first-order Markov process; (2) capital is predetermined after productivity is observed; (3) investment contains the information on productivity. Recently, İmrohoroğlu and Tüzel (2014) apply Olley and Pakes (1996) to estimate firm level TFP. We follow their approach with some modifications.[2]

[2] Levinsohn and Petrin (2003) suggest another often 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. Olley and Pakes (1996) assume that investment contains the information on 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 investment is often lumpy. However, the firm level data of intermediate inputs (e.g., in Compustat) are often missing.

Assume the simple Cobb-Douglas production function:

$$Y_{it} = L_{it}^{\beta_L} K_{it}^{\beta_K} Z_{it} \tag{1}$$

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, 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 often highly correlated with the firm size. Second, this avoids estimating the capital coefficient directly. Third, there is an upward bias in labor coefficient, without scaling. Eq. (1) can be rewritten as

$$Log\frac{Y_{it}}{K_{it}} = \beta_L Log\frac{L_{it}}{K_{it}} + (\beta_K + \beta_L - 1)LogK_{it} + LogZ_{it} \tag{2}$$

Denote $Log\frac{Y_{it}}{K_{it}}$, $Log\frac{L_{it}}{K_{it}}$, $LogK_{it}$, and $LogZ_{it}$ as yk_{it}, lk_{it}, k_{it}, and z_{it}. Also, let β_L and $(\beta_K + \beta_L - 1)$ be β_l and β_k. Rewriting the above equation as follows:

$$yk_{it} = \beta_l lk_{it} + \beta_k k_{it} + z_{it} \tag{3}$$

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 $yk_{it} - \beta_l lk_{i,t} - \beta_k k_{it}$. We estimate TFP with a 5-year rolling window. TFP shocks can be computed as first-order autoregressive residuals by running regression of TFP in year t against TFP in year $t-1$.

We use annual Compustat data to estimate the total factor productivity (TFP) for all common stocks from NYSE/Amex/Nasdaq, applying the above procedures. We only include firms with four-digit SIC code lower than 4900. These firms are in agriculture, mining, manufacturing, construction, and transportation, which well fit the Cobb-Douglas production function. Also, we drop firms with asset or sales below $1 million or stock price lower than

\$1 at the end of each year. The sample starts from 1966, the rolling-window estimates are available from 1972 to 2015. See Appendix B for more details about TFP estimation.

1.2. 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:

$$TFP_{NT} = B_{Nk} * PC_{kT} + \epsilon_{NT} \tag{4}$$

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

Two issues remain while applying the asymptotic principal component over the TFP matrix (TFP). First, TFP matrix is unbalanced due to missing observations. Connor and Korajczyk (1987) address this issue by replacing those missing observations to 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) show that the main finding of Connor and Korajczyk (1987) is robust by using 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.[3] First, we show that the first six components capture about 52% of TFP across firms. Second, we find that there is a positive contemporaneous relationship between stock return and systematic TFP shocks. Third, we find that the volatility of systematic TFP growth positively predicts stock return. Fourth, we further show that the residual TFP, idiosyncratic TFP, has no predictability over stock returns. This validates the TFP decomposition.

1.3. Estimating mimicking productivity factors

We construct the mimicking portfolios to track the principal components of TFP. One difficulty is that the frequency of TFP is annual. To construct the monthly mimicking portfolios, we follow Adrian et al. (2014). First, we project TFP principal component n, PC_n, onto a set of annual base asset returns:

$$PC_n = \kappa_{0,n} + \kappa'_{x,n} X^a_{t,n} + u_t, n = 1, 2, ..., 6 \tag{5}$$

where $X^a_{t,n}$ denotes the annual returns of some base assets in year t, $\kappa_{0,n}$ and $\kappa'_{x,n}$ are the coefficients. 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 asset-s. Second, to extract the information of productivity components as much as possible, 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, since using all 18 portfolios causes the multicollinearity problem, we only use 7 of these 18 portfolios. To choose the certain portfolios, we start to project each principal component onto all 18 portfolios, market portfolio, and the mispricing factor. Then, we choose portfolios which have significant coefficients. Ideally, we want to use the same base assets across all principal components to avoid arbitrariness, but using the same base assets causes the multicollinearity issues. To

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

avoid multicollinearity and to capture productivity-specific information, we change some of base assets for each principal component. The base assets for each principal component are as follows:

- $X_{t,1}$ = [MKT, MIS, SSL, BLM, BLH, BMH, BSL, SMH, BSH]
- $X_{t,2}$ = [MKT, MIS, SSL, BLM, BLH, BLL, BMH, BSL, SMH]
- $X_{t,3}$ = [MKT, MIS, SSL, BLM, BLL, BSL, SMH, BSH, SSH]
- $X_{t,4}$ = [MKT, MIS, SSL, BLM, BLH, BLL, BMH, BSL, SLM]
- $X_{t,5}$ = [MKT, MIS, SSL, BLM, BLH, BLL, BSL, SLM, SMH]
- $X_{t,6}$ = [MKT, MIS, SSL, BLM, SSM, BLH, BLL, BSL, 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., low (L), medium (M), or high (H). The third letter describes the profitability group, low (L), medium (M), and high (H). For example, SSL denotes the portfolio of stocks with small size, low investment, and low profitability. Overall, 4 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, 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 those coefficients: $\tilde{\kappa}'_{x,n} = \frac{\kappa_{x,n}}{|\Sigma\kappa_{x,n}|}$. The denominator is the sum of absolute value of 9 coefficients for each principal component. The last step is to compute the mimicking productivity portfolios at monthly frequency, by multiplying the normalized coefficients and the monthly base asset returns,

$$PC_{n,t} = \tilde{\kappa}'_{x,n} X_t^m \tag{6}$$

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, two look-ahead bias emerge. First, look-ahead bias occurs when we apply the principal component analysis over TFP matrix using the full sample. Second, look-ahed bias also occurs when constructing mimicking portfolios since the portfolio weights ($\kappa'_{x,n}$) are estimated in 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 from 2001 to allow for enough 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 enough degree of freedom for the extending-window case, we use 6 base assets only, as follows:

- $X_{t,1}$ = [MKT, MIS, BLL, BMH, SMH, BSH]
- $X_{t,2}$ = [MKT, MIS, BLL, BSL, SMH, BLM]
- $X_{t,3}$ = [MKT, MIS, SSL, BSL, SMH, BLM]
- $X_{t,4}$ = [MKT, MIS, SSL, BLH, SLM, BLM]
- $X_{t,5}$ = [MKT, MIS, BLL, BSL, SLM, SMH]
- $X_{t,6}$ = [MKT, MIS, SSL, BLM, BLL, BSL].

2. Productivity factors

In this section, we first describe our TFP estimates and its principal components. Then we show that these principal components reasonably capture firms' productivity shocks.

2.1. Productivity estimates and the mimicking portfolios

We first examine the production function estimated from Olley and Pakes (1996) and İmrohoroğlu and Tüzel (2014). The labor coefficients, (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) use 0.30 as the capital coefficient. The production function is slightly decreasing return to scale over the sample period.

Panel A of Table 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 how much 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 components explain 52% of log TFP growth and the marginal increment of R^2 decreases by adding more principal components.

In Panel B of Table 1, we report the annual correlation coefficients between productivity components and other pricing factors. In the main context, we consider 15 prevailing pring factors, either risk based and 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. (2018) 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. (2018) 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 the management, MGMT. Another mispricing is related to the 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 score.[4] (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). PEAD derives limited attention and underreaction to earnings information. FIN is based on security issuance and repurchase, which measures managerial responses to the long-horizon behavioral bias.[5]

First, we note that none of pricing factors have strong correlation with the first productivity component (PC1) except for the momentum factor (UMD) and the short-horizon behavioral factor (PEAD). However, the correlation between PC1 and UMD is -0.28 while the correlation between PC1 and PEAD is -0.22. These two correlations are driven by one extreme observation in 2009.[6] When we exclude the observation in 2009, the correlations become 0.17 and 0.16.[7]. Given the fact that the first productivity component is the most important factor in capturing the aggregate productivity shocks, it is surprising that all pricing factors do not capture this component. Second we see that PC2 to PC5 have strong correlations with those 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 similar relationship with the expected investment growth factor (EG). The third productivity component (PC3) has the pronounced pattern 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 component (PC4) is positively correlated with the investment factors (CMA and Q_{IA}). The magnitude of its correlation with CMA (Q_{IA}) is 0.50 (0.43). The fifth productivity principal component (PC5) and the

[4]http://finance.wharton.upenn.edu/ stambaug/

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

[6]In 2009, PC1 increases dramatically because of the financial crisis.

[7]We exclude the observation in 2009 for other productivity factors but their correlations are stable.

momentum factor (UMD) are positively correlated, with a correlation coefficient of 0.35. The sixth productivity component has significant correlation with the mispricing factor (MIS) and 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.

Panel C of Table 1 reports the mean, standard deviation (S.D.), Sharpe ratio (SR), and the 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 the pairwise correlation coefficients across the mimicking factors are not very sizable, this alleviates the multicollinearity concern.

2.2. Validating productivity decomposition

Table 2 further validates the productivity decomposition. We compute the systematic and idiosyncratic parts of TFP, using the six principal components. For each firm, we run the time-series regression of TFP growth on six principal components. Then, we use the predicted TFP growth as the systematic TFP growth and the residuals as the idiosyncratic TFP growth. İmrohoroğlu and Tüzel (2014) find that the contemporaneous correlation between stock returns and 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 the Panel A of Table 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.

Next, we examine whether the idiosyncratic productivity shocks are priced to further validate our productivity decomposition. From the asset pricing perspective, we expect that only systematic productivity shocks are priced because firms cannot hedge against the systematic uncertainty. We compute the standard deviation of log TFP growth ($\sigma_{\Delta TFP}$), systematic TFP growth ($\sigma_{\Delta TFP_{sys}}$), and the 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 fewer than 5 firms. In Panel B of Table 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 take logrithm on the standard deviations. Model (1) shows that the total TFP volatilities are positively correlated with 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 stock returns while the idiosyncratic TFP volatility is marginally significant only. We further control for asset growth (AG) and cashflow (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. We see that idiosyncratic TFP volatility becomes insignificant while systematic TFP volatility remains significantly positive in Model (3). Turning to the return volatilities, in Models (4) and (5), we run panel regression 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. Models (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 2 confirm that our TFP estimate and its decomposition reasonably captures common risk sources.

3. Asset pricing tests

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

Panel B of Table 1 shows that PC2-PC5 are highly correlated with those prevailing pricing factors. In this subsection, we formally test whether productivity factors can capture those pricing factors. We use the six mimicking productivity factors and the empirical asset pricing model is as follows:

$$R_{i,t} = \alpha_i + \beta_{PC1,i} PC1_t + \beta_{PC2,i} PC2_t + \beta_{PC3,i} PC3_t + \beta_{PC4,i} PC4_t + \beta_{PC5,i} PC5_t + \beta_{PC6,i} PC6_t + \epsilon_{i,t} \tag{7}$$

where $R_{i,t}$ is the excess return of asset i in month t, $PC1$ to $PC6$ are the returns of the mimicking productivity factors at month t. 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 3 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 controlling for six mimicking productivity portfolios. This suggests that these 13 pricing factors share common fundamental risk sources. There are only 2 pricing factors having the significant alphas. The expected investment growth factor (EG) in Hou et al. (2018) 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 controlling 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.[8]

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

Turning to the factor loadings, we recognize that our mimicking portfolios track their principal 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.[9] The fifth mimicking productivity factor is significantly priced for the momentum factor (UMD), with a factor loading of 1.07 (t=7.75). Also, market portfolio is significantly priced on the sixth mimicking productivity portfolio.

Moreover, as we observe in Panel B of Table 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 MISC are highly correlated with the fourth productivity factor (PC4), which suggest that they capture a lot of investment factor as well. This is consistent with findings in Hou et al. (2018), where they argue that MGMT (PERF) is a different investment or profitability measure. Given the fact that our fourth mimicking productivity factor is strongly correlated with the investment factor, the significance of β_{PC4} is consistent with the finding of Hou et al. (2018). The long-horizon behavioral factor (FIN) is fully captured by our productivity-based model.

To avoid the look-ahead bias, we use the extending-window estimation as a robustness check and report results in Panel B of Table 3. One caveat for the extending window approach is that the principal components are not as clear as those from the full-sample estimation because the principal components change with the estimation windows. Nonetheless,

[9]Hou et al. (2018b) show that q-factor model subsumes the Fama-French five-factor premiums.

extending-window estimation shows qualitatively similar results. Overall, our model fully explains 14 of 15 pricing factors, except that PEAD remains marginally significant.

Overall, Table 3 shows that although various pricing factors are constructed in different ways, they really capture the same set of fundamental risks.

3.2. Using productivity factors to explain test portfolios: Time-series regressions

Next, we apply our productivity-based model to many test portfolios. Specifically, since the productivity factors are able to explain many pricing factors, we expect that they explain broad test portfolios as well. We report the alphas from time-series regressions of each test asset in Table 4, using full sample.[10] Our playing fields 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 portfolios (Panel E), and 30 Fama-French industry portfolios (Panel F). The test portfolios are from Kenneth French's website.

Generally, the productivity-based model explains the test portfolios very well. In Panel A, all of 25 size and book-to-market sorted portfolios have insignificant alphas. In Panel B, all of 25 size and operating profitability sorted portfolios have insignificant abnormal returns. The highest alpha is 0.28% per month only, 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%), the drugs (0.55%), and gold (1.07%), have significant alphas. These results suggest that even though TFP and its principal components are estimated from manufacturing industry only, the principal components reflect the aggregate risks across different industries.

[10]We tabulate the complete regression results in Appendix Table C1.

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

Lastly, we examine the ability of productivity factors to explain the cross-sectional return variations by using Fama-MacBeth two-pass regressions. Test assets are 155 portfolios used in Table 4. 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.

We compare the productivity-based model (TFP) with other factor models, including 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 (2017) six-factor model (FF6), Hou et al. (2015) q-factor model (HXZ), Hou et al. (2018) q^5-factor 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 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 5. Table 5 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 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 5^{th} and 95^{th} percentiles of the sampling distribution. The sample period is from January 1972 to December 2015, except for DHS model, which is from July 1972 to December 2014, as limited by data availability.

Table 5 presents the price of risk of each factor across the tested factor models. First, we see that FF3, FF6, and DHS have a significant intercept, γ_0, which are 0.51%, -0.07%, and 0.30%, respectively. Other models, e.g., 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 risks and their magnitudes are close to the average of mimicking productivity factors. 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 marginally significant only (t=1.65). Factors from HXZ, HMXZ, and SY models have about similar size of their average factor returns.

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

3.4. Comparing different models

Previously, we use 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, 2018,b). However, this approach is often sensitive to the choice of LHS portfolios. Alternatively, following Barillas and Shanken (2017) 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 max squared Sharpe ratio of the intercepts for all LHS portfolios, Barillas and Shanken (2017) suggest 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

$$Sh^2(a_i) = a_i' \Sigma_i^{-1} a_i, \tag{8}$$

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:

$$Sh^2(a_i) = Sh^2(\Pi_i, f_i) - Sh^2(f_i). \tag{9}$$

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 max 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 6 presents the maximum squared Sharpe ratios for various factor models. Limited by data availability, we compare FF3, FF4, FF5, FF6, HXZ, HMXZ, DHS, and TFP models.[11] Among all competing models, the productivity-based model delivers a highest maximum squared Sharpe ratio of 0.32. The HMXZ and DHS models have a similar maximum squared Sharpe ratio of 0.26 and 0.27, respectively. But, other models have much lower maximum squared Sharpe ratios, which are below 0.15. One concern about this right-hand-side approach is that there are sampling errors when estimating 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 5^{th} and 95^{th} percentiles of the maximum squared Sharpe ratios from competing models in Panel A of Table 6. We see that even the 5^{th} 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 productivity factors. Panel B reports the intercept (α), its t-statistic, loadings, R^2, residual standard error ($s(e)$), and each productivity factor's marginal contribution to the model $Sh^2(f)$, i.e., $(\frac{\alpha^2}{s(e)^2})$. The t-statistic for the intercept measures if a factor statistically contributes to the model $Sh^2(f)$. We see that except PC2, all other productivity factors have a significant intercept, with a t-statistic 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.

[11]We can't compute $Sh^2(f)$ for SY model as we only have data of spread factors but not the corresponding portfolios.

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

4. Explaining Mispricing portfolios

It is surprising to see that in Table 3, the productivity-based model explains 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 3 seems to suggest that fundamental risks explain most of the mispricing. In this section, we dig this deeply by investigating the 11 mispricing portfolios, the building blocks for 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 data limitation, the sample period is from January 1972 to December 2015, except for the distress risk, 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 7. First, Panel A shows that 9 of 11 anomaly portfolios do not have significant abnormal returns after controlling 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 an intercept of 0.31% per month (t=1.67). It seems that the mimicking productivity factors capture almost all of information from 11 mispricing portfolios. Second, these anomaly portfolios show significant exposure to the fourth productivity factor, 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 models explains 9 of 11 anomalies. The accrual (ACC) and the gross profitability (GP) anomalies have significant abnormal returns. Except the momentum anomaly, all other anomalies have significant exposures to the investment factor (PC4). 9 of 11 anomalies are highly correlated with PC3, the profitability factor.

Overall, Table 7 demonstrates that most anomalies used in Stambaugh and Yuan (2017) can be traced back to the fundamental risks. This echoes Hou et al. (2018), where they show that MGMT (PERF) has strong correlation with the investment (profitability) factor.

5. Identifying a missing factor

So far, we show that productivity factors explain most pricing factors and test portfolios. In this section, we further explore if 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, those 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. Next, we further examine what kind of risk is captured by the first productivity factor. We argue that this missing risk factor is related to the labor risk.

5.1. Identifying a missing factor

If productivity factors and other pricing factors share the common fundamental risks, they should capture similar risk prices. 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, 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. (2018) q^5 model (HMXZ). We run time-series regressions for each productivity factor. Table 8 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 of six mimicking productivity portfolios have sizable and significant raw excess returns, similar to those shown in Table 1. Except PC1, all other 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 SY mispricing factor model or DHS behavioral model, i.e., α^{SY}=0.15%

(t=1.28) and α^{DHS}=-0.08% (t=-0.48), respectively. PC2 has a high correlation with the size factor. The unreported results show that size factor of SY explains most of PC2 return variations. The third mimicking productivity factor (PC3), which captures the profitability, has insignificant abnormal returns for 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 PC2, which brings the excess returns from -0.95% to -0.59% per month. But, Q_{ROE} from the q-factor model seems to have stronger explanatory power than RMW from Fama-French five-factor model. Abnormal returns of the fourth mimicking productivity factor (PC4) disappear when we control for the mispricing factor. Coefficients on both 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., 2018). The fifth mimicking productivity factor (PC5) is fully captured by SY or DHS model. Also, 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 alphas remain significant. Lastly, the sixth mimicking productivity factor (PC6) is explained by 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 controlling for those prevailing pricing factors.[12] 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 is 0.91% per month (t=3.04) from Stambaugh and Yuan (2017) model. This can be inferred from Panel B of Table 1, where PC1 only has a moderate correlation with 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.

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

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 abnormal returns is different from that in Panel A because the first principal component in extending window is negatively correlated with the first principal component from the full-sample estimation. The raw returns of PC1 is about -1.85% per month. The abnormal returns vary from -0.92% to -1.51% per month. PC2 and PC4 have significant raw returns but their intercepts become insignificant once we control for other pricing factors.

5.2. Interpreting the missing factor

We interpret the missing factor, PC1, as a labor factor, for two theoretical reasons. First, total factor productivity in Eq. (2) contains labor factor. For example, total factor productivity can be decomposed into the labor productivity and the capital productivity:

$$\begin{aligned}Log\,TFP_{it} &= Log\,Y_{it} - \beta_L Log\,L_{it} - \beta_K Log\,K_{it} \\ &= \beta_L(Log\,Y_{it} - Log\,L_{it}) + \beta_K(Log\,Y_{it} - Log\,K_{it}) + (1-\beta_L-\beta_K)Log\,Y_{it} \\ &= \beta_L \underbrace{Log\,\frac{Y}{L}_{it}}_{\text{Labor productivity}} + \beta_K \underbrace{Log\,\frac{Y}{K}_{it}}_{\text{Capital productivity}} + (1-\beta_L-\beta_K)Log\,Y_{it}.\end{aligned} \tag{10}$$

Therefore, by construction, TFP measures labor productivity as well as capital productivity when we estimated TFP following Olley and Pakes (1996). However, prevailing pricing factors, like investment or profitability factors in Fama and French (2017), Hou et al. (2015), and Hou et al. (2018), capture mainly the capital productivity, and not specifically designed to capture the labor productivity. This suggests that the missing factor, PC1, likely captures the labor risk.

Second, recent literature suggests that labor risks are important sources to the equity premium. Installed labor affects firm value when there exist some labor market frictions. Current literature considers several sources of labor frictions: costly to hire and fire employees

(Merz and Yashiv, 2007; Belo et al., 2014), wage rigidity (Favilukis and Lin, 2016a,b) , 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 the operating leverage (Danthine and Donaldson, 2002; Donangelo, 2014; Donangelo et al., 2018), or due to the fact that shareholders provide insurance to workers (Marfè, 2016, 2017; Hartman-Glaser et al., 2017; Lettau et al., 2018).

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 the total productivity at firm level. In the first column of Panel A of Table 9, we report Fama-MacBeth regression of log TFP growth on the labor productivity growth, the capital productivity growth, and the output growth. The labor productivity growth is the log growth of labor productivity, $Log\,\frac{Y_{it}}{L_{it}}$, the capital productivity is the log growth of capital productivity, $Log\,\frac{Y_{it}}{K_{it}}$, and the output growth is the log growth of output. The coefficient on the labor productivity growth is 0.39 (t=44.50), which is larger than that on the capital productivity growth is 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 the aggregate labor growth and capital growth. The aggregate labor growth and capital growth data are from Federal Reserve Bank of San Francisco.[13] The second and third columns of Panel A of Table 9 show that both PC1 and R^{PC1} have significant coefficients on the aggregate labor growth, but not aggregate capital growth. Therefore, PC1 mainly captures the labor productivity.

Third, we investigate the asset pricing implications of labor risk. Following Donangelo et al. (2018), we construct the labor share portfolios. Labor share is defined as the ratio of the labor expense over the value-added. Value-added (Y_{it}) is $\frac{Sales_{it}-Materials_{it}}{GDP\_deflator}$. Material cost

[13]https://www.frbsf.org/economic-research/indicators-data/total-factor-productivity-tfp/

($Materials_{it}$) is total expenses minus labor expense. Total expense is sales minus operating income before depreciation and amortization (oibdp). Labor expense is the staff expense (xlr). Only a small number of firms report the staff expense in Compustat. We replace those missing observations with the interaction of industry average labor expense ratio and total expense. Specifically, we first calculate the labor expense ratio, $\frac{xlr_{it}}{sales_{it}-oibdp_{it}}$, for each firm. Next, in each year we estimate the industry average of the labor expense ratio at 4-digit SIC, with at least three firms available in the industry. Otherwise, we estimate the average of the labor expense ratio at 3-digit SIC. In the same manner, we estimate the industry average of labor expense ratio at 2-digit and 1-digit SIC code. Then, we back out the staff expense by multiplying the industry average labor expense ratio and total expense. If the labor expense is still missing, we interpolate those missing observations with the interaction of annual wage from the Bureau of Labor Statistics and the number of employees. We exclude financial and utility firms. Also, we exclude firms with a stock price below \$5, total assets below 12.5 million dollars, the number of employees below 100, or the sales growth or the asset growth above 100%. Finally, we trim the labor share at 0.5^{th} and 99.5^{th} 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 9. Consistent with Donangelo et al. (2018), the portfolio returns monotonically increase with labor share. As the labor share increases, the labor risk increases because the wage is sticky (Belo et al., 2014; Donangelo et al., 2018). The long-short portfolio of the labor share, R^{EX}, is 0.47% per month (t=2.98). The long-short portfolio generates significant alphas across different models except for the productivity-based model. This suggests that the prevailing factors cannot explain the labor risk. But 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 9, we presents 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 that the productivity-based model explains other pricing factors when we replace the first productivity factor with the labor share factor. We run the time-series regressions of each pricing factors on the labor share factor and the second to sixth mimicking productivity factors and present the intercepts and the coefficients of each factor in Panel A of Table 10. 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 pricing factors. However, it cannot fully explain the profitability factors (RMW and Q_{ROE}), the investment factors (CMA and Q_{IA}), expected investment growth factor (EG), and $PEAD$. 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 PC1 may better capture labor risk than LS measure.

Lastly, we run Fama-MacBeth regression using the prevailing factor models augmented with the first mimicking productivity portfolio (PC1) or the labor share factor (LS). If the labor risk is missed by the prevailing factor models, adding the missing factor should improve their empirical performances. In Panel B of Table 10, we report the Fama-MacBeth regression results, using the 155 portfolios from Table 5 as test assets. First, we see that PC1 is significantly priced in all models while LS is priced in FF6, HMXZ, and DHS models. Adding the labor factor (PC1 or LS) improves the model performances, especially for FF6 and DHS models. For example, after adding PC1, FF6 model has an insignificant intercept (t=-1.41). Also, the adjusted R^2 increases by 0.04. When the DHS model adds 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.

6. Conclusions

Inspired by the neoclassical theory, we start with productivity shocks in firms' production to identify multiple systematic productivity risks and explore their asset pricing implications. We find that the first six productivity factors well explain lots of test assets and the prevailing pricing factors, including Fama and French (2018) six factors, 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 the common risk sources behind these seemingly different factors. In particular, we find an important productivity factor missed in these empirical asset pricing models, which we interpret as the labor risk. This suggests the importance of recognizing labor risk in asset pricing models. Overall, we show the productivity-based model performs at least as well as the prevailing factor models.

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Table 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 factor (Q_{ME}), investment factor (Q_{IA}), and profitability factor (Q_{ROE}), Hou et al. (2018) expected investment growth factor (EG), and 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, but Daniel et al. (2018) factors are from 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 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 returns 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 last 5 year TFP growth. Systematic TFP volatility is the standard deviation of last 5 year systematic TFP growth. Idiosyncratic TFP volatility is the standard deviation of last 5 year idiosyncratic TFP growth, which 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	0.74	0.95	1.20	1.63	1.47
	(0.66)	(3.27)	(4.95)	(6.23)	(7.36)	(9.49)
ΔTFP_{sys}	0.65	0.79	0.84	1.14	1.48	0.83
	(2.58)	(3.86)	(4.35)	(5.78)	(6.27)	(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	0.14		
		(2.44)	(2.35)		
$\sigma_{\Delta TFP,idio}$		0.09	0.08		
		(1.78)	(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 3. **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 factor (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. (2018) 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 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 4. **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-statistic				
Panel A: 25 size and book-to-market (BM) 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 (Op) 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 (Inv) 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 (Ivol) sorted portfolios										
	Low Ivol	2	3	4	High Ivol	Low Ivol	2	3	4	High Ivol
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-statistic				
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 5. **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, including 25 size and book-to-market sorted portfolios, 25 size and operating profitability sorted portfolios, 25 size and investment 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 (2018) six-factor model (FF6), Hou et al. (2015) q-factor model (HMZ), 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 the productivity-based model (TFP). 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 Shanken (1992). The adjusted R^2 follows Jagannathan and Wang (1996). The 5^{th} and 95^{th} percentiles of the adjusted R^2 distribution from a bootstrap simulation of 10,000 times are reported in brackets. The sample period is from January 1972 to December 2015, but Daniel et al. (2018) factors are from July 1972 to December 2014.

	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										
$\gamma_{Q_{ME}}$							0.33	2.31	0.31	2.22						
$\gamma_{Q_{IA}}$							0.35	2.91	0.38	3.24						
$\gamma_{Q_{ROE}}$							0.56	3.98	0.52	3.63						
γ_{EG}									0.64	4.29						
$\gamma_{MIS_{ME}}$											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 6. **Examining 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 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. (2018) q^5 model (HMXZ), Daniel et al. (2018) behavioral factor model (DHS), and the productivity-based model (TFP). The 5^{th} and 95^{th} percentiles of the $Sh^2(f)$ distribution from a bootstrap simulation of 10,000 times are reported in brackets. Panel B reports the intercept (α, % per month), its t-statistic (t-stat), loadings, R^2, residual standard error ($s(e)$, % per month), and each productivity factor'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 Daniel et al. (2018) factors are 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 7. **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 the 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 Fama and 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 8. **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 (2018) 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. (2018) 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 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						
	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^{HXZ}	-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 9. **Interpreting the missing factor as labor risk factor**

In Panel A, the first column presents Fama-MacBeth regression of total TFP growth (ΔTFP) on labor productivity growth (ΔLabor productivity), capital productivity growth (ΔCapital productivity), and output growth (ΔOutput). The second and third columns report the time-series regressions of first productivity component (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 labor share factor and productivity components. The sample period is from January 1972 to December 2015.

Panel A: Productivity and labor risk							
	ΔTFP	PC1	R^{PC1}				
ΔLabor productivity	0.39						
	(44.50)						
ΔCapital productivity	0.22						
	(23.19)						
ΔOutput	0.04						
	(4.50)						
$\Delta Labor^{Agg}$		-0.20	-3.70				
		(-2.67)	(-3.39)				
$\Delta Capital^{Agg}$		0.18	2.34				
		(1.04)	(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 labor share factor and the first productivity factor							
	PC1	PC2	PC3	PC4	PC5	PC6	
LS factor	0.43	-0.11	0.14	0.15	-0.11	0.09	

Table 10. **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. (2018) q^5 model (HMXZ), Stambaugh and Yuan (2017) mispricing factor model (SY), and Daniel et al. (2018) behavioral 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 5^{th} and 95^{th} percentiles of the adjusted R^2 distribution from a bootstrap simulation of 10,000 times are reported in brackets. The sample period is from January 1972 to December 2015, but Daniel et al. (2018) factors are 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	PEAD	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	0.51	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	5.67	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	-0.03	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	-0.94	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	-0.04	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	-1.12	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	0.02	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	0.52	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	0.02	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	0.96	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	0.19	-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	3.21	-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	-0.02	-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	-0.83	-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	0.07	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				
$\gamma_{Q_{ME}}$													0.28	2.01	0.33	2.30
$\gamma_{Q_{IA}}$													0.37	3.08	0.34	2.93
$\gamma_{Q_{ROE}}$													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
$\gamma_{Q_{ME}}$	0.28	1.96	0.30	2.15								
$\gamma_{Q_{IA}}$	0.40	3.35	0.37	3.15								
$\gamma_{Q_{ROE}}$	0.51	3.59	0.49	3.46								
γ_{EG}	0.62	4.16	0.71	5.19								
$\gamma_{MIS_{ME}}$					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)	

Online Appendices

A. *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:

$$Y_{it} = L_{it}^{\beta_L} K_{it}^{\beta_K} Z_{it} \tag{1}$$

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

$$K_{it+1} = I_{it} + (1-\delta)K_{it} \tag{2}$$

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

$$L_{it+1} = H_{it} + (1-\psi)L_{it} \tag{3}$$

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:

$$\begin{aligned}
\max_{I_{it},H_{it}} \quad & Y_{it} - I_{it} - G(I_{it}, K_{it}) - W_t L_{it} - \phi(H_{it}, L_{it}) && (4)\\
& +\mathbb{E}_t\{M_{t,t+1}[Y_{it+1} + (1-\delta)K_{it+1} - W_{t+1}L_{it+1}]\} \\
s.t. \quad & K_{it+1} = I_{it} + (1-\delta)K_{it} && (5)\\
& L_{it+1} = H_{it} + (1-\psi)L_{it}, && (6)
\end{aligned}$$

where W_t is exogenously given wage.[14]

The Lagragian function is

$$\begin{aligned}\mathcal{L} =& Y_{it} - I_{it} - G(I_{it}, K_{it}) - W_t L_{it} - \phi(H_{it}, L_{it}) \\ &+ \mathbb{E}_t\{M_{t,t+1}[Y_{it+1} + (1-\delta)K_{it+1} - W_{t+1}L_{it+1}]\} \\ &- q_{it}^K[K_{it+1} - I_{it} - (1-\delta)K_{it}] \\ &- q_{it}^L[L_{it+1} - H_{it} - (1-\psi)L_{it}].\end{aligned} \tag{7}$$

where q_{it}^K and q_{it}^L are the Lagragian multipliers associated with capital installation and labor hiring constraints in Eqs. (5) and (6), respectively. $G_{I_{it}}$, $Y_{K_{it+1}}$, $\phi_{H_{it}}$, 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:

$$q_{it}^K - 1 - G_{I_{it}} = 0 \tag{8}$$

$$\mathbb{E}_t\{M_{t,t+1}[Y_{K_{it+1}} + (1-\delta)]\} - q_{it}^K = 0 \tag{9}$$

$$q_{it}^L - \phi_{H_{it}} = 0 \tag{10}$$

$$\mathbb{E}_t\{M_{t,t+1}[Y_{L_{it+1}} - W_{t+1}]\} - q_{it}^L = 0. \tag{11}$$

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

$$q_{it}^K = 1 + G_{I_{it}} = \mathbb{E}_t\{M_{t,t+1}[Y_{K_{it+1}} + (1-\delta)]\}. \tag{12}$$

The marginal costs and benefits of labor hiring is given by

$$q_{it}^L = \phi_{H_{it}} = \mathbb{E}_t\{M_{t,t+1}[Y_{L_{it+1}} - W_{t+1}]\}. \tag{13}$$

[14] For simplicity, we don't consider wage bargaining process here.

The ex-dividend stock price is

$$P_{it} = \mathbb{E}_t\{M_{t,t+1}[Y_{it+1} + (1-\delta)K_{it+1} - W_{t+1}L_{it+1}]\}. \tag{14}$$

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

$$P_{it} = q_{it}^K K_{it+1} + q_{it}^L L_{it+1}. \tag{15}$$

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

$$R_{it,t+1} = \frac{Y(Z_{it+1}, K_{it+1}, L_{it+1}) + (1-\delta)K_{it+1} - W_{t+1}L_{it+1}}{\mathbb{E}_t\{M_{t,t+1}[Y(Z_{it+1}, K_{it+1}, L_{it+1}) + (1-\delta)K_{it+1} - W_{t+1}L_{it+1}]\}}. \tag{16}$$

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

$$log\, Z_{it} = b_i X_t + \varepsilon_{it}, \tag{17}$$

where X_t is a vector consisting 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. (16) says that the expected stock returns are affected by these systematic risks. In other words, if the expected stock 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.

B. 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. Sample period starts from 1965 to 2015. Compustat items used include total assets (at), net PPE (ppent), sale (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. We include common stocks listed at NYSE/Amex/Nasdaq with 4-digit SIC codes less than 4900. This corresponds to agriculture, mining, construction, manufacturing, and transportation industries. Also, firms with sales or total assets less than \$1 millions, or with negative employees, capital expenditure, and depreciation are excluded. Firms with value-added and material costs less than 0.01 are excluded as well. 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 more than 2 years to avoid the survivorship bias.

To calculate real values, we use GDP deflator (NIPA Table 1.1.9 qtr line1) and price index for nonresidential private fixed investment(NIPA Table 5.3.4 qtr line2). We obtain employees' earnings data from Bureau of Labor Statistics (CES0500000030). 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 minus operating income before depreciation and amortization (oibdp). Labor expense is the staff expense (xlr). However, only a small number of firms report the staff expense. We replace those missing observations with the interaction of industry average labor expense ratio and total expense. To be specific, we calculate the labor expense ratio, $\frac{xlr_{it}}{sales_{it}-oibdp_{it}}$, for each firm. Next, in each year we estimate the industry average of the labor expense ratio at 4-digit SIC. In each 4-digit SIC code, the number of firms should be greater than 3. Otherwise, we estimate the industry average of the labor expense ratio at 3-digit SIC. In the same manner, we estimate the industry average of labor expense ratio at 2-digit and 1-digit SIC code. Then, we back out the staff expense by multiplying the industry average labor expense ratio and total expense. If the labor expense is still missing, we interpolate those missing observations with the interaction of annual wage from the Bureau of Labor Statistics and the number of employees.

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

Investment (I_{it}) is capital expenditure deflated by 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. İmrohoroğlu and Tüzel (2014) show how to estimate Olley and Pakes (1996) TFP using annual COMPUSTAT and share their codes.[15] Our TFP estimation process is based on İmrohoroğlu and Tüzel (2014)

[15] http://www-bcf.usc.edu/ tuzel/TFPUpload/Programs/

with some modifications.

We start from the simple Cobb-Douglas production technology.

$$Y_{it} = L_{it}^{\beta_L} K_{it}^{\beta_K} Z_{it}, \tag{18}$$

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 labor coefficient, without scaling. After being scaled by the capital stock and transformed into logarithmic values, Eq. (18) can be rewritten as

$$Log\frac{Y_{it}}{K_{it}} = \beta_L Log\frac{L_{it}}{K_{it}} + (\beta_K + \beta_L - 1)LogK_{it} + LogZ_{it}. \tag{19}$$

We define $Log\frac{Y_{it}}{K_{it}}$, $Log\frac{L_{it}}{K_{it}}$, $LogK_{it}$, and $LogZ_{it}$ as yk_{it}, lk_{it}, k_{it}, and z_{it}. Also, denote β_L and $(\beta_K + \beta_L - 1)$ as β_l and β_k. Rewrite Eq. (19) as

$$yk_{it} = \beta_l lk_{it} + \beta_k k_{it} + z_{it}. \tag{20}$$

When facing the productivity shock (z_{it}) at t, a firm decides the optimal labor and 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}.

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

$$y_{it} = \beta_l lk_{it} + \beta_k k_{it} + \beta_0 + \beta_{ik} ik_{it} + \beta_{ik^2} ik_{it}^2 + \beta_{ik^3} ik_{it}^3 + \eta_j + \epsilon_{it}, \tag{21}$$

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

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

$$\begin{aligned} E_t(yk_{i,t+1} - \widehat{\beta_l} lk_{i,t+1} - \eta_j) &= \beta_k k_{i,t+1} + E_t(z_{i,t+1} | z_{i,t}, survival) \\ &= \beta_k k_{i,t+1} + g(z_{it}, \widehat{P}_{survival,t}), \end{aligned} \tag{22}$$

where $\widehat{P}_{survival,t}$ is the probability of a firm survival from t to $t+1$. The probability is estimated with the probit regression of a survival indicator variable on the 3^{rd}-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 $\beta_0 + \beta_{ik} ik_{it} + \beta_{ik^2} ik_{it}^2 + \beta_{ik^3} ik_{it}^3$. The function g is the polynomials of the survival probability ($\widehat{P}_{survival,t}$) and lagged TFP (z_{it}). At this step, we estimate the coefficient of capital, $\widehat{\beta_k}$, which gives $\widehat{\beta_K}$.

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

$$TFP_{it} = exp(yk_{it} - \widehat{\beta_l} lk_{i,t} - (\beta_K \widehat{+ \beta_l} - 1)k_{it} - \eta_j). \tag{23}$$

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.

C. Explaining the first mimicking productivity factor

D. Alternative test assets

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Table B1. **Explaining the first productivity factor 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 (2016) five-factor model (FF5), Fama and French (2018) 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. (2018) q^5 model (HMXZ). All returns are multiplied with 100. Newey-West adjusted t-statistics (t-stat) 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. The testing period for panel B is from January 2001 to December 2015.

Panel A. Full-sample estimation								
CAPM	α	MKT						R^2
Coeff	1.29	0.04						0.00
t-stat	4.41	0.45						
FF3	α	MKT	SMB	HML				R^2
Coeff	1.37	-0.10	0.54	-0.30				0.06
t-stat	4.82	-1.05	3.38	-1.98				
FF4	α	MKT	SMB	HML	UMD			R^2
Coeff	1.17	-0.06	0.54	-0.23	0.21			0.08
t-stat	3.79	-0.59	3.14	-1.39	2.14			
FF5	α	MKT	SMB	HML	CMA	RMW		R^2
Coeff	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		
FF6	α	MKT	SMB	HML	CMA	RMW	UMD	R^2
Coeff	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	
SY	α	MKT	MIS_ME	MGMT	PERF			R^2
Coeff	0.91	-0.02	0.64	-0.20	0.43			0.12
t-stat	3.04	-0.18	4.54	-1.17	3.77			
DHS	α	MKT	FIN	PEAD				R^2
Coeff	1.27	-0.03	-0.19	0.34				0.02
t-stat	3.60	-0.30	-1.57	1.25				
HXZ	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}			R^2
Coeff	1.35	-0.09	0.42	-0.45	0.19			0.04
t-stat	4.20	-0.93	3.15	-1.80	1.34			
HXMZ	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}	EG		R^2
Coeff	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								
CAPM	α	MKT						R^2
Coeff	-1.85	0.32						0.04
t-stat	-3.84	2.10						
FF3	α	MKT	SMB	HML				R^2
Coeff	-1.51	0.49	-0.86	-0.60				0.23
t-stat	-3.50	4.82	-4.64	-3.29				
FF4	α	MKT	SMB	HML	UMD			R^2
Coeff	-1.39	0.33	-0.86	-0.59	-0.28			0.27
t-stat	-3.24	2.92	-4.98	-4.18	-2.36			
FF5	α	MKT	SMB	HML	CMA	RMW		R^2
Coeff	-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		
FF6	α	MKT	SMB	HML	CMA	RMW	UMD	R^2
Coeff	-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	
SY	α	MKT	MIS_{ME}	MGMT	PERF			R^2
Coeff	-0.92	0.26	-1.25	-0.51	-0.21			0.30
t-stat.	-2.19	1.82	-6.60	-3.54	-1.85			
DHS	α	MKT	FIN	PEAD				R^2
Coeff	-1.19	-0.05	-0.56	-0.57				0.13
t-stat	-2.68	-0.42	-3.03	-1.81				
HXZ	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}			R^2
Coeff	-1.04	0.21	-1.13	-0.72	-0.65			0.33
t-stat	-2.86	1.60	-6.31	-3.95	-3.10			
HXMZ	α	MKT	Q_{ME}	Q_{IA}	Q_{ROE}	EG		R^2
Coeff	-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 C1. **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-statistic				
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-statistic				
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-statistic				
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-statistic				
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-statistic				
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-statistic				
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-statistic				
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 C2. **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-statistic				
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-statistic				
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-statistic				
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-statistic				
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-statistic				
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-statistic				
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-statistic				
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 C3. **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-statistic				
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-statistic				
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-statistic				
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-statistic				
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-statistic				
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-statistic				
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-statistic				
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 C4. **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-statistic		
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-statistic		
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-statistic		
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-statistic		
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-statistic		
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-statistic				
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-statistic				
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 C5. **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 volatility 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 Ivol	2	3	4	High Ivol	Low Ivol	2	3	4	High Ivol
	α(% per month)					t-statistic				
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-statistic				
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-statistic				
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-statistic				
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-statistic				
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-statistic				
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-statistic				
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 C6. **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 Fama-French 30 industry portfolios. Factors include six productivity factors. The Newey-West t-statistics (t-stat) 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