Fundamental Risk Sources and Pricing Factors *

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Abstract

Motivated by production-based asset pricing models, we study the pricing power of fundamental risks to understand the prevailing pricing factors. We find that six aggregate productivity components trace 13 of 15 prevailing pricing factors, including all factors proposed in Fama-French six-factor model (Fama and French, 2018), q-factor model (Hou et al., 2020), and the mispricing models (Stambaugh and Yuan, 2017; Daniel et al., 2020), except for the expected investment growth factor (Hou et al., 2020) and the post-earnings-announcement drift (Daniel et al., 2020). However, the first productivity component is not captured by these factor models, which represents the labor risk.

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

Keywords: productivity shocks, production-based asset pricing, pricing factors, empirical asset pricing models

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Motivated from the risk or behavioral perspective, several new factor models have been proposed recently (Fama and French, 2015, 2018; Hou et al., 2015, 2020a; Stambaugh and Yuan, 2017; Daniel et al., 2020), and they successfully account for more anomalies.[1] Given the 15 pricing factors suggested in these models, e.g., a factor zoo (Feng et al., 2019), one might wonder how to differentiate and interpret them. Meanwhile, the neoclassical theory of investment (see, e.g. Cochrane, 1991, 1996; Berk et al., 1999; Zhang, 2005; Liu et al., 2009; Hou et al., 2015) suggests that under some regularities, stock returns are equivalent to the real investment returns, which can be derived from producers' first-order conditions, e.g., firms' optimal investment decisions. This implies that we can construct the pricing kernel from productivity shocks. Indeed, İmrohoroğlu and Tüzel (2014) find that productivity shocks relate to several important firm characteristics. Motivated by these, we explore the common productivity shocks in firm productions to understand the systematic risks which might be captured or missed by the prevailing pricing factors. Empirically, we identify six principal components of productivity shocks, which capture 13 of 15 prevailing factors. That is, these 13 factors represent various aspects of fundamental risks. We show that the size factor, profitability factor, and investment factor used in Fama and French (2015), Fama and French (2018), Hou et al. (2015), and Hou et al. (2020a) represent the same set of fundamental risks, though they are motivated differently from the valuation model and q-theory of investment. We also find that the momentum factor, the mispricing factor in Stambaugh and Yuan (2017) and the long-horizon behavioral factor in Daniel et al. (2020) actually capture fundamental risks, which echoes Hou et al. (2020b). However, the productivity factors fail to capture the expected investment growth factor in Hou et al. (2020a) and the short-horizon behavioral factor in Daniel et al. (2020). Moreover, we find that an important productivity factor, the first principal component, contains information not captured by the existing factors, i.e., a missing factor. We show that this missing factor largely captures the labor risks. Overall, the productivity shocks are priced and the productivity-based model explains various test

[1] See Hou et al. (2020b) for a comprehensive evaluation of 452 anomalies.

assets similarly well to the existing models.

Why should we care about fundamental risk sources? For example, given the large literature on empirical asset pricing models, which typically computes factors from asset prices, one might suggest that we bypass fundamental risks and use those factor returns directly. The reasons build on the promising of the neoclassical theory of investment. Investment-based asset pricing models links real investment returns to the stock returns and suggests that production shocks drive the stock return volatilities. That is, asset price risks arise endogenously from the fundamental risks. That means we can construct the pricing kernel from the productivity shocks. First, this can reveal the fundamental risks behind the prevailing factors, which are mainly constructed in a reduced form. For example, the investment or profitability factors capture corporate responses to the fundamental shocks, so they only indirectly measure the underlying risk sources. Second, the risk sources tell us the difference among return-based factors, which are often hard to differentiate.[2] For example, do different pricing factors represent different or similar fundamental risks? Third, this provides a direct way to understand why stocks with similar characteristics such as investment or profitability comove. Hou et al. (2015) point out that "the factor model requires that returns of stocks with similar investment (and returns of stocks with similar profitability) comove together", but the direct mechanism of comovement is often lack in a factor model. Clearly, if stocks with similar characteristics are exposed to common productivity shocks, then their returns comove. Last, on the other hand, this can serve as tests of investment-based asset pricing models as well. If the fundamental shocks are priced, then they are likely to be found in the prevailing factors.

Empirically, we identify the fundamental risk sources and test their pricing power in four steps. We first estimate firm-level total factor productivity (TFP), closely following Olley and

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

Pakes (1996) and İmrohoroğlu and Tüzel (2014). Second, we apply the asymptotic principal component analysis (e.g. Connor and Korajczyk, 1987; Herskovic et al., 2016; Chen et al., 2018) to estimate the systematic TFP components across all firms. We identify six principal components of productivity shocks and interpret these components as in Kelly et al. (2019). Third, modelling through the pricing kernel, we show the pricing power of these principal components via GMM estimation, using 155 test assets. Fourth, to increase the statistical power, we construct the mimicking productivity factors for these six components and perform asset pricing tests at the monthly frequency, following Adrian et al. (2014) and Chen and Yang (2019). We test whether the productivity factors can capture the prevailing 15 pricing factors and identify fundamental risks behind them. The 15 pricing factors are (1) six factors used in Fama and French (2018), including the market factor (MKT), the size factor (SMB), the value factor (HML), the investment factor (CMA), the profitability factor (RMW), and the momentum factor (MOM); (2) four factors used in Hou et al. (2020a), 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' performance ($PERF$); (4) two behavioral factors used in Daniel et al. (2020), including a factor related to long-horizon behavioral bias (FIN) and a factor related to short-horizon behavioral bias ($PEAD$).

We find that 13 out of 15 pricing factors can be explained by the productivity factors. The exceptions are the expected investment growth factor (EG) and the short-horizon behavioral bias factor ($PEAD$). That is, these 13 pricing factors indeed capture the fundamental risks. The size factor, profitability factor, and investment factor used in Fama and French (2015), Fama and French (2018), Hou et al. (2015), and Hou et al. (2020a) correspond to the second, third, and fourth productivity factor, respectively. We find that the momentum factor is captured by the fifth productivity factor, while the sixth productivity factor captures the mispricing factor in Stambaugh and Yuan (2017) and the long-horizon behavioral factor in

Daniel et al. (2020).

On the other hand, we find that these prevailing 15 pricing factors can explain the second to sixth productivity factors. That is, these productivity shocks are priced and captured by the prevailing factors. However, the prevailing factors can not explain the first productivity component. We dig deeply to understand this missing factor. Empirically, we first show that labor productivity is an important part of total factor productivity and is captured by the first productivity component. Then we construct the labor share portfolios, following Donangelo et al. (2019). We find that these labor share sorted portfolios are not explained by the prevailing pricing factors, as they capture mainly returns to installed capital. However, the first productivity component does fully explain the labor share sorted portfolios. Therefore, returns to installed labor appear to be missing from existing factor models, while the first productivity component tracks such labor risks. Although our main goal is not to propose an alternative factor model, using various test assets, we show that the productivity-based model performs similarly to the existing factor models, as shown by their squared Sharpe ratios or generalized least squares (GLS) R^2s.

This paper follows the tradition of production-based asset pricing literature, e.g., Cochrane (1991), Restoy and Rockinger (1994), Cochrane (1996), Berk et al. (1999), Zhang (2005), and Liu et al. (2009). Neoclassical theory of investment relates real investment returns to the stock returns and suggests that production risks are behind asset price risks. Hou et al. (2015) and Hou et al. (2020a) construct pricing factors based on firm investment and profitability, which are the consequences of production shocks. Closely related to our work, İmrohoroğlu and Tüzel (2014) is the first paper comprehensively showing that firm-level productivity is correlated with lots of firm characteristics and affects stock returns. For example, they show that TFP is related to firm size, book-to-market equity, investment, asset growth, labor hiring, inventory growth, organization capital, capital leases, profitability, net stock issues, and leverage. We build on their results and make progress in three ways. First, İmrohoroğlu and Tüzel (2014) use the total firm-level TFP, while we decompose it into six systematic components and link them with the firm characteristics and pricing factors. Second, beside the pricing factors based on firm characteristics, we also explore the behavioral factors. Last, while İmrohoroğlu and Tüzel (2014) mainly perform correlation analyses, we explicitly estimate the productivity factors and show that the productivity-based factor model performs similarly to the prevailing factor models. In a similar vein, Belo et al. (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 firm production.

Recently, several asset pricing models have been proposed in the empirical literature. Some models use rational risk factors. For example, based on the dividend discount model/surplus clean accounting, Fama and French (2015) construct a five-factor model, including a market factor, a size factor, a value factor, an investment factor, and a profitability factor. Fama and French (2018) further add the momentum factor to the five-factor model to create a six-factor model. Motivated by the neoclassical q-theory of investment, Hou et al. (2015) propose a q-factor model, including a market factor, a size factor, an investment factor, and a profitability factor, where the investment and profitability factors are constructed differently from those in Fama and French (2015). Hou et al. (2020a) add the expected investment growth factor to the q-factor model to create a q^5 model. The other models use mispricing or behavioral factors. For example, Stambaugh and Yuan (2017) suggest a four-factor model, which includes a market factor, a size factor, and two mispricing factors. They construct two mispricing factors by aggregating over six anomalies that are related to firms' management and five anomalies that are related to firms' performance. Daniel et al. (2020) propose a three-factor model, including a market factor, a factor related to managerial responses to long-horizon behavioral bias (which is based on security issuance and repurchase), and a factor related to short-horizon behavioral bias (which captures limited attention and underreaction to earnings information, e.g., post-earnings-announcement drift). Overall, these factor models enjoy some success in explaining more anomalies, but it is often difficult to evaluate these factors.[3] Our paper explores the fundamental risks possibly embedded or missed in these pricing models to understand these pricing factors.

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

The rest of the paper proceeds as follows. Section 1 describes the data and procedures of estimating systematic productivity factors, and presents the estimates. Section 2 tests the pricing power of productivity factors over other prevailing pricing factors and test assets. Section 3 examines the explanatory power of productivity factors over mispricing portfolios in detail. Section 4 identifies a productivity factor missed by the prevailing models and relates it to the labor risk. Finally, Section 5 concludes.

1. Estimating systematic productivity shocks

Production-based asset pricing models relate stock returns with real investment returns (see, e.g. Cochrane, 1991). For example, if production is constant returns to scale, then the producers' first-order conditions suggest that stock returns equal real investment returns state-by-state. Cochrane (1996) and Liu et al. (2009) empirically confirmed this prediction among a cross section of stocks. This suggests that stock return risks are inherited from

[3] Empirically, Hou et al. (2019) show that many seemingly different factor models are closely related. For example, they find that the q-factor and q^5 models subsume the Fama-French five- and six-factor premium and the mispricing factors in Stambaugh and Yuan (2017), but not the PEAD factor in Daniel et al. (2020).

production risks. If stock returns relate to multiple rational pricing factors, firms' production must be subject to multiple systematic productivity shocks, and *vice versa* (see Appendix A for illustrations via a motivating model). Therefore, we can model the pricing kernel from the productivity shocks, suggesting a productivity-based model, which is equivalent to a standard factor model. In this section, we first estimate firm-level productivity. Then we identify systematic productivity shocks across firms.

1.1. Estimating firm-level total factor productivity

We closely follow Olley and Pakes (1996) and İmrohoroğlu and Tüzel (2014) to estimate TFP. Olley and Pakes (1996) address two issues during TFP estimation. First, there is an endogeneity problem in the estimation of TFP because input factors such as labor and capital stock are contemporaneously correlated with TFP. They estimate the production function parameters separately to avoid the simultaneity problem. Second, there is a selection issue. Firms with very low (high) TFP exit (enter) the markets. Olley and Pakes (1996) mitigate this issue by specifying TFP as a function of the survival probability. Olley and Pakes (1996) assume that (1) productivity is a first-order Markov process; (2) capital is predetermined after productivity is observed; (3) investment contains information on productivity. İmrohoroğlu and Tüzel (2014) apply Olley and Pakes (1996) to estimate firm-level TFP. We follow their approach with some modifications.[4]

Assume the simple Cobb-Douglas production function:

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

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

where Y_{it}, Z_{it}, L_{it}, and K_{it} are value-added, productivity, labor, and capital stock of a firm i at time t, respectively. The productivity shocks include both some systematic productivity shocks and an idiosyncratic component. Next, we scale the production function by its capital stock and take the logarithm at both sides. We scale the production function by the capital stock for several reasons. First, since TFP is the residual term, it is often highly correlated with the firm size. Second, this avoids estimating the capital coefficient directly. Third, there is an upward bias in the labor coefficient, without scaling. 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 a regression of TFP in year t against TFP in year $t-1$.

We use annual Compustat data to estimate TFP for common stocks from NYSE/Amex/Nasdaq. We exclude firms with assets or sales below \$1 million, or stock price lower than \$1 at the end of each year. Our main results are based on firms with a four-digit SIC code lower than 4900. These firms are in agriculture, mining, manufacturing, construction, and transportation industries, which fit well the Cobb-Douglas production function. To obtain stable estimates, following Bloom et al. (2018), we assume all firms follow the same production function. Admittedly, this neglects the fact that production function may vary across industries and over time, which might add noise to our estimates. However, we expect this has little impact on our results, because we focus on the systematic components of productivity shocks. Empirically, we show later that such TFP estimates well capture the aggregate risks across different industries. As a robustness check, we also consider an expanded sample to estimate TFP, by further adding firms in wholesale trade and retail trade (SIC codes between 5000 and 5999), and services (SIC does between 7000 and 8999), and find qualitatively similar results, reported in Appendix E. The sample starts from 1966, and 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). Two issues arise as we apply the asymptotic principal component over the TFP matrix. First, the TFP matrix is unbalanced due to missing observations. Connor and Korajczyk (1987) address this issue by replacing the missing observations with zero. They prove that if the missing observations follow the same approximate factor structure, the estimated principal components are close to the true factors. Chen et al. (2018) 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 (denoted as $PC1 - PC6$) based on the model fit and empirical implications.[5] We validate our choice in Section 1.4.

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

1.3. Productivity estimates

We first describe our TFP estimates and their principal components in Table 1.[6] The labor coefficient, β_l, is 0.62, and the capital coefficient, β_K, is 0.34. These numbers are very similar to those reported in Olley and Pakes (1996). Also, these estimates are consistent with the neoclassical models. For example, Zhang (2005) uses 0.30 as the capital coefficient. The production function is slightly decreasing return to scale over the sample period.

Panel A of Table 1 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. Figure 1 plots the time series of six productivity components, together with annual GDP growth. We see that PC1 is counter cyclical while PC2-PC6 are largely procyclical. PC1-PC6 have a correlation coefficient of -0.38, 0.15, 0.25, 0.09, 0.15, 0.10 with GDP growth, respectively. Panel A presents the summary statistics for six principal components (PC1 to PC6). By construction, the standard deviations are normalized as one. R^2 shows to what degree principal components explain TFP growth. For each firm, we run the time-series regression of log TFP growth on principal components. We estimate the fitted value of log TFP growth and its explanatory power. We report the average R^2 in Panel A. For example, the first principal component (PC1) explains 15% of log TFP growth on average. When we add the second principal component (PC2), the average R^2 increases to 24%. The first six principal components explain 52% of log TFP growth, and the marginal increment of R^2 decreases when we add more principal components.

1.4. Validating productivity decomposition

Table 1 shows that the first six components capture about 52% of TFP across firms. We further validate the productivity decomposition in Table 2, i.e., the six principal components reasonably capture the common productivity shocks. We decompose firm-level TFP into the

[6]Table E1 in Appendix E reports similar results using the expanded sample.

systematic and idiosyncratic parts, using the six principal components. Specifically, for each firm, we run the time-series regression of its TFP growth on six principal components. We then use the predicted TFP growth as the systematic TFP growth and the residuals as the idiosyncratic TFP growth. İmrohoroğlu and Tüzel (2014) find that the contemporaneous correlation between stock returns and total firm-level TFP is significantly positive. If TFP and its decomposition are estimated correctly, then both TFP and its systematic part should have positive correlations with contemporaneous stock returns. At the end of each June, we construct the quintile portfolios, sorted on either log TFP growth (ΔTFP) or the systematic TFP growth (ΔTFP_{sys}). The contemporaneous value-weighted portfolio returns are calculated and reported in Panel A of Table 2. We see portfolio returns increase with both the total TFP and its systematic part. Also, the long-short portfolios (high minus low, H-L) generate sizable return spreads, 1.47% for log TFP growth and 0.83% for systematic TFP growth, which is consistent with İmrohoroğlu and Tüzel (2014).

Next, we examine whether the idiosyncratic productivity shocks are priced to further validate our productivity decomposition. That is, can idiosyncratic productivity shocks predict future stock returns? From the asset pricing perspective, we expect that only systematic productivity shocks are priced because firms cannot hedge against systematic uncertainty. We compute the standard deviation of log TFP growth ($\sigma_{\Delta TFP}$), systematic TFP growth ($\sigma_{\Delta TFP_{sys}}$), and idiosyncratic TFP growth ($\sigma_{\Delta TFP_{idio}}$) over the last 5 years. We exclude stocks with a price lower than \$5 and industry-month observations with fewer than 5 firms. In Panel B of Table 2, Models (1)-(3) present the coefficients from Fama-MacBeth regressions of excess stock returns against the total TFP volatilities, systematic TFP volatilities, and idiosyncratic TFP volatilities, together with other control variables. We use the logarithm of the standard deviations. Model (1) shows that the total TFP volatilities are positively correlated with future stock returns. In model (2), we decompose the total TFP volatilities into systematic and idiosyncratic parts. We see that systematic TFP volatility is positively correlated with future stock returns, while idiosyncratic TFP volatility is only marginally significant. We further control for asset growth (AG) and cashflow (CF/K) in model (3). Asset growth is defined as $\frac{AT_t - AT_{t-1}}{AT_{t-1}}$, where AT is total assets. Cashflow is computed as $\frac{IB_t + DP_t}{PPENT_{t-1}}$, where IB is the income before extraordinary items, DP is depreciation and amortization, and PPENT is net property, plant, and equipment. Idiosyncratic TFP volatility becomes insignificant, while systematic TFP volatility remains significantly positive in Model (3). Turning to the return volatilities, in Models (4) and (5), we run panel regressions of return volatilities against the absolute value of log TFP growth, systematic TFP growth, and idiosyncratic TFP growth, with both firm and month fixed effects. Return volatilities are computed by using daily returns over the last year. 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 the six principal components reasonably capture the systematic productivity risks across firms.

1.5. Interpreting principal productivity components

Often, it is difficult to interpret the principal components from principal component analysis. We attempt to understand these principal components in two steps. First, we examine the correlation between the six productivity components and the prevailing factors. Second, we link the productivity factor-loadings with firm characteristics at the firm-level.

Panel B of Table 1 reports the annual correlation coefficients between productivity components and other pricing factors. In the main context, we consider 15 prevailing pricing factors that are either risk based or behavioral based: (1) Six factors used in Fama and French (2018), including the market portfolio (MKT), the size factor (SMB), the value factor (HML), the investment factor (CMA), the profitability factor (RMW), and the momentum factor (UMD). We download these factors and the corresponding portfolios from Kenneth French's website. (2) Five factors used in Hou et al. (2020a), 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. (2020a) to construct these factors. (3) Three mispricing factors used in Stambaugh and Yuan (2017). Stambaugh and Yuan (2017) construct the mispricing factors from 11 mispricing anomalies. They categorize these anomalies into two types of mispricing. One mispricing is related to firm management, MGMT. Another mispricing is related to firm performance, PERF. They also construct a univariate mispricing factor (MIS), including both MGMT and PERF information. We download two mispricing factors (MGMT and PERF) from Robert Stambaugh's website and construct the univariate mispricing factor (MIS) by using their mispricing score.[7] (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).[8] PEAD captures 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.

Panel B of Table 1 shows that none of the pricing factors have a strong correlation with the first productivity component (PC1) except for the momentum factor (UMD) and the short-horizon behavioral factor (PEAD). The correlation between PC1 and UMD is -0.28, while the correlation between PC1 and PEAD is -0.22. However, these two correlations are driven by one extreme observation in 2009.[9] When we exclude the 2009 observation, the correlations become 0.17 and 0.16.[10] Since the first productivity component is the most important factor of the aggregate productivity shocks, it is surprising to see that none of the pricing factors captures this component. We will show that this component captures labor risk in Section 4. Second, we see that PC2 to PC6 have strong correlations with these prevailing pricing factors. The second productivity component (PC2) is negatively correlated with the size factor (SMB and Q_{ME}), with a correlation coefficient of -0.24 and

[7] http://finance.wharton.upenn.edu/~stambaug/

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

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

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

-0.25, respectively. It also has a similar relationship with the expected investment growth factor (EG). The third productivity component (PC3) has a pronounced correlation with the profitability factors (RMW and Q_{ROE}). The correlation coefficient between PC3 and RMW (Q_{ROE}) is -0.48 (-0.42). The fourth productivity 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). İmrohoroğlu and Tüzel (2014) also find similar correlations between total firm-level TFP and firm characteristics like size, book-to-market ratio, investment, and profitability. The fifth productivity principal component (PC5) and the momentum factor (UMD) are positively correlated, with a correlation coefficient of 0.35. The sixth productivity component has significant correlation with the mispricing factor (MIS) and the long-horizon behavioral factor (FIN). The correlations are -0.35 and -0.48, respectively. Overall, Panel B shows that PC2-PC4 are highly correlated with the risk-based factors, while PC5 and PC6 seem to capture the mispricing and behavioral factors. In other words, these pricing factors provide the economic meanings of the principal components.

Kelly et al. (2019) suggest that we can infer each productivity component from its factor loading. If a principal productivity component captures a prevailing pricing factor, then a firm's exposure to this component should relate to the corresponding firm characteristic, which is used to construct the corresponding pricing factor. That is, we can interpret principal components via their factor loadings at a firm-level.

We gradually estimate factor loadings by regressing firm-level TFP against six principal components. That is, we regress TFP against PC1 to estimate a factor loading of PC1 (b_{PC1}) for each firm. Then, we regress TFP residuals, which is unexplained by PC1, against PC2 to estimate a factor loading of PC2 (b_{PC2}). Teasing out the predicted TFP by PC1 allows us to better estimate b_{PC2} because the residual is unrelated to PC1. We estimate other factor loadings in a similar manner. We compute time-varying factor loadings with a 15-year extending window. That is, the first factor loading for each principal component is estimated from 1972 to 1986, and the estimation window extends to 2015. We require at least 13 observations to estimate factor loadings.

We include firm characteristics that represent prevailing pricing factors. Those variables are labor share (LS), size, cash flow (CFK), investment rate (IK), cumulative stock return over the previous 11 months lagged by one month ($R_{2,12}$), and mispricing score (MIS). We also consider other characteristics which might relate to stock returns, e.g., book-to-market ratio (BM), idiosyncratic volatility (Ivol), last month return (R_1), and leverage (Lev). Labor share is defined as the ratio of labor expense over value-added. Size is defined as the logarithmic value of market capitalization. Cash-flow (CF) is income before extraordinary items (IB) divided by lagged net property, plant, and equipment (PPENT). Investment rate (IK) is the ratio of capital expenditure (CAPX) plus inventory change (INVT) minus sales of property, plant, and equipment (SPPE) over lagged gross property, plant, and equipment (PPEGT).[11] Mispricing score (MIS) is the average rank score estimated from 11 mispricing portfolios (Stambaugh and Yuan, 2017). Book-to-market equity ratio (BM) is the ratio of book equity to the market equity (Fama and French, 1993). Idiosyncratic volatility (Ivol) is the standard deviation of residuals from the Fama-French three-factor model, using within month daily returns. Leverage (Lev) is the ratio of long-term debt (DLCC) plus current liabilities (DLC) over long-term debt, current liabilities, and shareholder's equity (SEQ). Factor-loadings and firm characteristics are winsorized at 1% and 99%. We exclude firms with missing employment growth or a stock price less than \$5. All variables are standardized. We use both firm and year fixed effects.

Table 3 reports the regression results. Columns (1)-(6) report the regression results using the first six firm characteristics. We see that all factor loadings strongly reflect the corresponding firm characteristics. Except for b_{PC4}, the corresponding variable has the largest t-statistic.[12] This suggests that principal components capture the prevailing pricing factors. For example, in column (1), the factor loading of PC1 (b_{PC1}) significantly positively relates

[11] We set missing observations of SPPE as zeros.

[12] Because MGMT (part of mispricing score) relates to the investment factor (Hou et al., 2019), the mispricing score has the largest t-statistics in Column (4).

to labor share (LS), with a coefficient of 0.021 (t=2.73). This suggests that PC1 can be interpreted as labor share risk. In column (2), b_{PC2} is positively related to firm size. Its magnitude is 0.069 (t=3.834), which is the largest among the six variables, suggesting PC2 captures firm size. b_{PC3} is negatively related to cash flow (CFK) with a coefficient of -0.04 (t=-3.067). This is consistent with the negative correlation between PC3 and profitability factors (RMW and Q_{ROE}). Therefore, PC3 traces the profitability risk. Similarly, in Columns (4)-(6), we see that b_{PC4} has a negative coefficient on investment ratio (IK); b_{PC5} is positively related to cumulative returns over previous 11 months; b_{PC6} is also positively related to the mispricing score. This suggests that PC4-PC6 capture the investment, momentum, and mispricing factor, respectively. Results are qualitatively similar, after controlling for book-to-market equity ratio, idiosyncratic volatility, return reversal, and leverage, as shown in Columns (7)-(12).

Overall, Panel B of Table 1 and Table 3 demonstrate that the six productivity components can be interpreted as the corresponding firm characteristics.

2. Asset pricing tests

In this section, we examine the pricing power of productivity factors in two ways. First, We directly use the six non-tradable TFP components. We perform GMM estimation over these annual productivity components. We also run cross-sectional regressions and compare the performances of various factor models, following Kan et al. (2013). However, since we only have 44 annual TFP estimates, this might limit the statistical power. Second, to increase the statistical power, we further use the projection method to construct the mimicking portfolios for productivity components and perform the asset pricing tests at monthly frequency. We also compare the performances of different factor models at monthly frequency. These two approaches complement each other. We verify that the prevailing pricing factors capture the fundamental risks.[13]

[13]Tables E2, E3, and E4 in Appendix E report similar results using the expanded sample.

2.1. *Asset pricing tests: Using non-tradable TFP components*

2.1.1. *GMM estimation*

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

$$m_{t+1} - \mathbb{E}_t[m_{t+1}] = -b'(f_{t+1} - \mu_f). \tag{4}$$

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

$$\frac{M_{t,t+1}}{\mathbb{E}[M_{t,t+1}]} \approx 1 + m_{t+1} - \mathbb{E}[m_{t+1}] = 1 - b'(f_{t+1} - \mu_f). \tag{5}$$

From the basic asset pricing equation, we have

$$\mathbb{E}[R^e_{i,t+1} M_{t,t+1}] = 0 = \mathbb{E}\left[\frac{M_{t,t+1}}{\mathbb{E}[M_{t,t+1}]} R^e_{i,t+1}\right], \tag{6}$$

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

$$\mathbb{E}[R^e_{i,t+1}(1 - b'(f_{t+1} - \mu_f))] = 0. \tag{7}$$

Therefore, we have the following moment conditions:

$$\mathbb{E} = \begin{bmatrix} R^e_{i,t+1}[1 - b'(f_{t+1} - \mu_f)] \\ f_{t+1} - \mu_f \end{bmatrix}. \tag{8}$$

We use a two-step GMM estimation with a Newey-West one-lag adjustment.[14]

We use 155 test assets, including 25 size and book-to-market sorted portfolios, 25 size and operating profitability sorted portfolios, 25 size and investment sorted portfolios, 25 size and idiosyncratic volatility sorted portfolios, 25 size and momentum sorted portfolios, and 30 Fama-French industry portfolios. For comparison, we estimate the Fama and French (1993) three-factor model (FF3), Fama and French (2015) 5-factor model (FF5), Fama and French (2018) six-factor model (FF6), Hou et al. (2015) q-factor model (HMZ), Hou et al. (2020a) q^5-factor model (HMXZ), and Daniel et al. (2018) (DHS).[15] The sample period of those pricing factors is from 1973 to 2016. We obtain annual test assets and Fama-French factors from Kenneth French's website.

Table 4 presents the GMM estimation results. Panel A of Table 4 reports the coefficient estimates for b. Then, in Panel B, we compute the implied price of risk for each factor (λ), i.e., $\lambda = \Sigma_f b$, where Σ_f is the variance-covariance matrix of factors. Panel C shows the goodness of fit. We estimate the adjusted R^2, root-mean-square errors ($RMSE$), and Hansen's J test of overidentification. The adjusted R^2 is defined as one minus the ratio of the cross-sectional variance of the pricing errors to the cross-sectional variance of realized average test portfolio returns, following Campbell and Vuolteenaho (2004).

First, we see that the productivity factors have significant coefficients. That is, the six principal components are significantly priced over test portfolios. For example, PC1 has a coefficient of 3.82 with a t-statistic of 16.16. This implies a price of risk of 8.90% per year. The coefficient for PC5 is 4.91 (t-statistic = 21.54) and its price of risk is 11.42% per year.

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

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

Other principal components have a sizable price of risk as well. For other factor models, the prices of risk vary. For example, five of six factors in FF6 have significant coefficients. For HMXZ, Q_{IA} and EG are the most important factors, which have a sizable price of risk, 3.65% and 6.67%, respectively. But the size factor and the profitability factor are insignificant in HMXZ.

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

2.1.2. Cross-sectional regressions

Next, following Kan et al. (2013), we further run the cross-sectional generalized least squares (GLS) regressions and compare the performances of various asset pricing models based on their R^2s.[16] That is, we examine whether two models have equal R^2s. Kan et al. (2013) derive the asymptotic distribution of cross-sectional R^2 estimator and suggest that we can test the equality of R^2s from competing models by constructing the distribution of R^2s. They allow a misspecified factor model to have a true R^2 less than 1.

Closely following Kan et al. (2013), we choose 25 size and book-to-market sorted portfolios.[17] Similar to Lewellen et al. (2010) and Kan et al. (2013), we run the cross-sectional GLS

[16]We thanks Kan et al. (2013) for sharing their codes at http://www-2.rotman.utoronto.ca/ kan/research.htm

[17]They use 25 size and book-to-market sorted portfolios and 5 Fama-French industry portfolios. We cannot add industry portfolios because of the limited number of observations. Untabulated results show that TFP has comparable R^2 as FF5, FF6, HXZ, and HMXZ using different test assets, including 25 size and operating profitability portfolios, 25 size and investment sorted portfolios, 25 size and momentum sorted portfolios, and 25 size and idiosyncratic volatility sorted portfolios.

regressions of various factor models. In the first stage, we run the time-series regressions of each model to estimate the factor loadings for each test asset over the full sample. Then, we run the cross-sectional regression of the time-series average of test asset returns against the estimated factor loadings. The sample period is from 1972 to 2015.

Table 5 reports the difference of R^2s in row i and column j, $R_i^2 - R_j^2$ and their corresponding p-values in parenthesis. Difference in R^2 between FF3 and TFP is about -0.26 with a p-value of 0.07. Also, difference between DHS and TFP is about -0.34 with a p-value of 0.01. These suggest that TFP has a larger R^2 than FF3 and DHS, e.g., better explaining the test assets. There are no significant differences between TFP and other factor models. For example, the difference between FF6 and TFP is about -0.11 but it fails to reject the null. For other pairs, FF6 is better than FF3 and FF5 in explaining test assets at the 10% significance level. Also, HMXZ has a higher R^2 than DHS at 10% significance level. Overall, the equality tests confirm that the productivity-based model has comparable asset pricing power as other prevailing factor models.

2.2. Asset pricing tests: Using mimicking portfolios

The above GMM estimation uses six TFP components directly, but one might concern about the statistical power of the above GMM estimation, since we only have 44 annual productivity estimates. Next, to increase the statistical power, we use the projection method to construct the mimicking factors for the six TFP components and perform the asset pricing tests at the monthly frequency. Also, it is easy to interpret the pricing of productivity factors, which are non-traded, via the mimicking portfolios.

2.2.1. Constructing mimicking productivity factors

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

$$PC_n = \kappa_{0,n} + \kappa'_{x,n} X^a_{t,n} + u_t, n = 1, 2, ..., 6, \tag{9}$$

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

- $X_{t,1}$ = [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]

[18] Although the projection method may suffer from the fact that the mimicking portfolios might be sensitive to the choices of base assets, at least we can view this as complements and cross-checks for the GMM estimation results reported in Subsection 2.1.1.

- $X_{t,4}$ = [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 the 7 portfolios other than the excess market return (MKT) and the mispricing factor (MIS), the first letter describes the size group, i.e., small (S) or big (B). The second letter describes the investment group, i.e., small (S), medium (M), or large (L). The third letter describes the profitability group, i.e., low (L), medium (M), and high (H). For example, SSL denotes the portfolio of stocks with small size, small investment, and low profitability. Overall, 5 base assets are common across all productivity factors, and the rest of them are different. Each annual mimicking productivity portfolio tracks its productivity principal component very well. On average, the annual correlation coefficient between each productivity principal component and its mimicking portfolio is about 0.53.

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

$$PC_{n,t} = \tilde{\kappa}'_{x,n} X_t^m \tag{10}$$

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

When we construct the mimicking productivity portfolios, the full-sample estimation has more statistical power, but two look-ahead biases emerge. First, look-ahead bias occurs when we apply the principal component analysis over the TFP matrix using the full sample. Second, it also occurs when we construct the mimicking portfolios since the portfolio weights ($\kappa_{x,n}$) are estimated in the full sample. To avoid the look-ahead biases, we also construct the mimicking productivity portfolios with an extending window as a robustness check. That is, both principal component analysis and the mimicking portfolio weights are computed with data up to year t. The extending window starts from 2001 to allow for a sufficient number of observations. In other words, the principal components and their portfolio weights are estimated from 1972 to 2001 first, and then extended to 2015. Also, to estimate the weights with a sufficient degree of freedom for the extending-window case, we use only 6 base assets, as follows:

- $X_{t,1}$ = [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].

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

Panel C of Table 1 reports the mean, standard deviation (S.D.), Sharpe ratio (SR), and pairwise correlations among mimicking portfolios. The first mimicking productivity portfolio (PC1) has an average return of 1.31% per month and a standard deviation of 7.38% per month. Its monthly Sharpe ratio is 0.18. Other mimicking portfolios also have sizable mean returns and Sharpe ratios. Since the pairwise correlation coefficients across the mimicking factors are not very sizable, this alleviates the multicollinearity concern.

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

Panel B of Table 1 shows that PC2-PC6 are highly correlated with the prevailing pricing factors. In this subsection, we formally test whether productivity factors can capture these pricing factors. We use the six mimicking productivity factors, and the empirical asset pricing model is as follows:

$$R_{i,t} = \alpha_i + \beta_{PC1,i}PC1_t + \beta_{PC2,i}PC2_t + \beta_{PC3,i}PC3_t + \beta_{PC4,i}PC4_t + \beta_{PC5,i}PC5_t + \beta_{PC6,i}PC6_t + \epsilon_{i,t}, \tag{11}$$

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

Panel A reports the results using full-sample estimation. First, 13 of 15 pricing factors have insignificant pricing errors after we control for six mimicking productivity portfolios. This suggests that these 13 pricing factors share common fundamental risk sources. Only 2 pricing factors have significant alphas. The expected investment growth factor (EG) in Hou et al. (2020a) has an alpha of 0.32% per month. The alpha is significantly positive (t=2.79), but its magnitude is about 43% of the factor return after we control for the six productivity factors. The post-earnings-announcement drift (PEAD) also has a significantly positive alpha of 0.46% per month, and our productivity-based model captures about 30% of its factor return.[19]

Turning to the factor loadings, we see 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

[19]Hou et al. (2019) also find that the q-factor and q^5 models fail to capture the PEAD factor in Daniel et al. (2018).

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.[20] They represent the same set of productivity shocks, i.e., the second, third, and fourth principal component of productivity shocks.

The fifth mimicking productivity factor is significantly priced for the momentum factor (UMD), with a factor loading of 1.07 (t=7.75). As we observe in Panel B of Table 1, the sixth productivity component has a significant correlation with the univariate mispricing factor (MIS), with a factor loading of -0.30 (t=-9.44). The two components, MGMT and PERF, have significantly negative coefficients on the sixth mimicking productivity factor, -0.13 (t=-3.67) and -0.42 (t=-5.55), respectively. We also can see that MGMT and MIS are highly correlated with the fourth productivity factor (PC4), which suggests that they capture a lot of the investment factor as well. This is consistent with findings of Hou et al. (2020a), who argue that MGMT (PERF) is a different investment or profitability measure. Since 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. (2020a). The long-horizon behavioral factor (FIN) is fully captured by our productivity-based model. In short, these mispricing and behavioral factors appear to capture the systematic productivity shocks.

To avoid the look-ahead bias, we use the extending-window estimation as a robustness check and report results in Panel B of Table 6. Because the principal components vary with the estimation windows during the extending-window estimation, this makes the estimation results not comparable with those from the full-sample estimation. Still, we see qualitatively similar results from the extending-window estimation. That is, our model fully explains 14 of 15 pricing factors, and only PEAD remains marginally significant.

[20] Hou et al. (2019) show that the q-factor model subsumes the Fama-French five-factor premiums.

Overall, Table 6 shows that although various pricing factors are motivated and constructed in different ways, they really capture the same set of fundamental risks.

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

Next, we apply our productivity-based model to many test portfolios. Since the productivity factors are able to explain many pricing factors, we expect them to explain broad test portfolios as well. We report the alphas from time-series regressions of each test asset in Table 7, using the full sample.[21] Our playing fields include 155 portfolios used in Table 4.

Generally, the productivity-based model explains the test portfolios very well. In Panel A, all 25 size and book-to-market sorted portfolios have insignificant alphas. In Panel B, all 25 size and operating profitability sorted portfolios have insignificant abnormal returns. The highest alpha is only 0.28% per month, which is fairly low. We see similar results in Panel C for 25 size and investment sorted portfolios. In Panels D and E, the abnormal returns are generally small, and only 2 of 50 portfolios are marginally significant. In Panel F, we see that 27 of 30 Fama-French industry portfolios have insignificant abnormal returns. Only industries like smoke (0.72%), drugs (0.55%), and gold (1.07%) have significant alphas. These results suggest that even though TFP and its principal components are estimated mainly from the manufacturing industry, the productivity factors reflect the aggregate risks across different industries.[22]

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

We further examine the ability of productivity factors to explain the cross-sectional return variations by using Fama-MacBeth two-pass regressions. The test assets are the 155 portfolios used in Table 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.

[21] We tabulate the complete regression results in Appendix C.

[22] Table E3 shows similar results from the expanded sample.

We compare the productivity-based model (TFP) with other factor models, including the Fama and French (1993) three-factor model (FF3), Carhart (1997) four-factor model (FF4), Fama and French (2015) five-factor model (FF5), Fama and French (2017) six-factor model (FF6), Hou et al. (2015) q-factor model (HXZ), Hou et al. (2020a) 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 the full sample. Second, we run the cross-sectional regression of all test assets against the estimated factor loadings in each month and report the time-series average of the price of risk in Table 8. Table 8 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 the DHS model sample period, which is from July 1972 to December 2014 due to limited data availability.

Table 8 presents the price of risk of each factor across the tested factor models. First, we see that FF3, FF6, and DHS have significant intercepts, γ_0, which are 0.51%, -0.07%, and 0.30%, respectively. Other models, i.e., FF5, HXZ, HMXZ, SY, and TFP, have insignificant intercepts. That is, these models explain almost all return variations among test portfolios.

Next, we check the price of risk for each pricing factor. The price of risk should be equal to the mean excess return of the corresponding factor. Mimicking productivity factors have significant prices of risk and their magnitudes are close to the average of mimicking productivity factors. The results are qualitatively consistent with those from GMM estimation in Table 4.[23] For FF5, even though the intercept is insignificant, the price of risk for HML, γ_{HML}, is insignificant, and its magnitude (0.07%) is quite different from the average return of HML (0.36%). Also, the price of risk for SMB, $\gamma_{SMB} = 0.22$, is only marginally significant (t=1.65). Factors from the HXZ, HMXZ, and SY models have prices of risk close to the average factor returns.

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

2.2.5. Comparing different models: Maximum squared Sharpe ratio

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

[23] Note that the price of the sixth component appears to have different signs in Tables 4 and 8. The reason is that the signs of coefficient used in Eq. (10) change after we normalize the coefficients.

Hou et al., 2015, 2020a, 2019). 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 that we rank competing models on the maximum squared Sharpe ratio for model factors.

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

$$Sh^2(a_i) = a_i' \Sigma_i^{-1} a_i, \tag{12}$$

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:

$$Sh^2(a_i) = Sh^2(\Pi_i, f_i) - Sh^2(f_i). \tag{13}$$

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 9 presents the maximum squared Sharpe ratios for various factor models. Limited by data availability, we compare the FF3, FF4, FF5, FF6, HXZ, HMXZ, DHS, and TFP models.[24] Of all competing models, the productivity-based model delivers the

[24]We can't compute $Sh^2(f)$ for the SY model as we have only the data for spread factors, not the

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. In contrast, other models have much lower maximum squared Sharpe ratios of below 0.15. One concern about this right-hand-side approach is that there are sampling errors when we estimate tangent portfolios, which are larger for models with more factors. This becomes an issue when we compare non-nested models. Following Fama and French (2018), we use bootstrap simulations to provide the distribution of the maximum squared Sharpe ratios. Specifically, we bootstrap the time-series data of factors by sampling with replacement. Then we estimate the maximum squared Sharpe ratio. We repeat these procedures 10,000 times and report the 5^{th} and 95^{th} percentiles of the maximum squared Sharpe ratios from the competing models in Panel A of Table 9. 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 of the 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 indicates whether a factor statistically contributes to the model $Sh^2(f)$. We see that except for PC2, all productivity factors have a significant intercept, with a t-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.

We close this section by concluding that the productivity-based model explains most of the pricing factors and test assets in both time-series and cross-section tests. The productivity-based model performs similarly well as other factor models. These findings support that the idea that fundamental risks are embodied in most pricing factors.

corresponding portfolios.

3. Explaining Mispricing portfolios

It is surprising to see that in Table 6, the productivity-based model explains the Stambaugh and Yuan (2017) mispricing factors (MGMT, PERF, and MIS). Stambaugh and Yuan (2017) construct the mispricing factors by using 11 mispricing anomalies, which they attribute to behavioral bias and market frictions. But Table 6 seems to suggest that fundamental risks explain most of the mispricing. In this section, we dig deeply by investigating the 11 mispricing portfolios, the building blocks for the mispricing factors, to see if the productivity-based model is able to explain these 11 anomalies. The 11 mispricing anomalies are the net equity issuance (ISS, Ritter, 1991), the composite equity issuance (CI, Daniel and Titman, 2006), the accruals (ACC, Sloan, 1996), the net operating assets (NOA, Hirshleifer et al., 2004), the asset growth (AG, Cooper et al., 2008), the investment-to-assets ratio (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 assets (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 limitations, the sample period is from January 1972 to December 2015, except for the distress risk sample period, which is from October 1973 to December 2015.

We present the time-series regression coefficients of these 11 anomaly portfolios on mimicking productivity factors in Panel A of Table 10. First, Panel A shows that 9 of 11 anomaly portfolios do not have significant abnormal returns after we control for the productivity factors. The accrual portfolio (ACC), and the O-score portfolio (OSCO) have only marginally significant abnormal returns. The accrual portfolio has an intercept of 0.23% per month (t=1.78), and the O-score portfolio has an intercept of 0.31% per month (t=1.67). It seems that the mimicking productivity factors capture most information from the 11 mispricing portfolios. Second, these anomaly portfolios show significant exposure to the fourth productivity 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 model explains 9 of 11 anomalies. The accrual (ACC) and the gross profitability (GP) anomalies have significant abnormal returns. Except for the momentum anomaly, all anomalies have significant exposure to the investment factor (PC4). 9 of 11 anomalies are highly correlated with PC3, the profitability factor.

Overall, Table 10 demonstrates that most anomalies used in Stambaugh and Yuan (2017) can be traced back to the fundamental risks. This echoes Hou et al. (2020a), who show that MGMT (PERF) has a strong correlation with the investment (profitability) factor.

4. Identifying a missing factor

So far, we have shown that productivity factors explain most pricing factors and test portfolios. In this section, we further explore whether the mimicking productivity portfolios can be explained by other pricing factors. If the mimicking productivity portfolios have the same risk sources as other pricing factors, the mimicking productivity portfolios should also be explained by other pricing factors. We show that the first productivity factor is not captured by other prevailing factors.[25] Next, we explore the risk behind the first productivity factor. We suggest that this missing risk factor is related to the labor risk.

4.1. Identifying a missing factor

If productivity factors and other pricing factors share common fundamental risks, they should represent similar risks. We test whether productivity factors can be explained by prevailing pricing factors. The benchmark models include the CAPM, Fama and French (1993) three-factor model (FF3), Carhart (1997) four-factor model (FF4), Fama and French (2015) five-factor model (FF5), Fama and French (2018) six-factor model, Stambaugh and Yuan (2017) mispricing factor model (SY), Daniel et al. (2020) behavioral model (DHS), Hou et al. (2015) q-factor model (HXZ), and Hou et al. (2020a) q^5 model (HMXZ). We run time-series regressions for each productivity factor. Table 11 reports the intercept (α^{model}) and R^2 from each model. Panel A uses the full sample, while Panel B uses the extending window.

Examining Panel A, we see that all six mimicking productivity portfolios have sizable and significant raw excess returns, similar to those shown in Table 1. Except for PC1, all productivity factors (PC2-PC6) can be explained by some benchmark models. That is, PC2-PC6 share common fundamental risks with other pricing factors. For example, the abnormal return of the second mimicking productivity factor (PC2) loses its significance when we apply the SY mispricing factor model or the DHS behavioral model, i.e., 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 the size factor of SY explains most of the PC2 return variations. The third mimicking productivity factor (PC3), which captures profitability, has insignificant abnormal returns for the HXZ model. α^{HXZ} is -0.11% per month (t=-0.37). The coefficient on the profitability factor (Q_{ROE}) is -0.69 (t=-6.19). FF5 can partially explain PC3, which brings the excess returns from -0.95% to -0.59% per month. But the Q_{ROE} from the q-

[25]Table E5 in Appendix E reports similar results using the expanded sample.

factor model seems to have stronger explanatory power than RMW from the Fama-French five-factor model. The abnormal returns of the fourth mimicking productivity factor (PC4) disappear when we control for the mispricing factor. Coefficients on both the size factor and MGMT are very significant, 2.28 (t=7.54) and 1.33 (t=5.93), respectively. This suggests that MGMT contains information about the investment factor (Hou et al., 2020a). The fifth mimicking productivity factor (PC5) is fully captured by the SY or DHS model. Also, the HMXZ model generates a marginally significant alpha for PC5. These insignificant alphas are mainly driven by PERF, PEAD, and EG, which are highly correlated with the momentum factor (UMD). FF4 and FF6 explain more than half of the abnormal returns, but the alphas remain significant. Lastly, the sixth mimicking productivity factor (PC6) is explained by the FF6, DHS, HXZ, and HMXZ models.

Importantly, Panel A shows that the first mimicking productivity factor (PC1) is missed by prevailing factors. PC1 has significant alphas after we control for these prevailing pricing factors.[26] Its raw return is 1.30% per month (t=4.71). Across 9 factor models, the magnitudes of their alphas are similar. The lowest alpha of 0.91% per month (t=3.04) is from the Stambaugh and Yuan (2017) model. This can be inferred from Panel B of Table 1, where PC1 has a moderate correlation with the momentum factor but very low correlations with all other pricing factors. Overall, the explanatory power (R^2) is fairly low, ranging from 0 to 0.12. The low R^2 further suggests that the first mimicking productivity factor is a missing factor from the prevailing factor models.

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

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

insignificant once we control for other pricing factors.

4.2. 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 the labor factor. For example, total factor productivity can be decomposed into labor productivity and capital productivity:

$$\begin{aligned}
Log\,TFP_{it} &= Log\,Y_{it} - \beta_L Log\,L_{it} - \beta_K Log\,K_{it} \\
&= \beta_L(Log\,Y_{it} - Log\,L_{it}) + \beta_K(Log\,Y_{it} - Log\,K_{it}) + (1-\beta_L-\beta_K)Log\,Y_{it} \\
&= \beta_L \underbrace{Log\,\frac{Y}{L}_{it}}_{\text{Labor productivity}} + \beta_K \underbrace{Log\,\frac{Y}{K}_{it}}_{\text{Capital productivity}} + (1-\beta_L-\beta_K)Log\,Y_{it}.
\end{aligned} \tag{14}$$

Therefore, by construction, TFP measures labor productivity as well as capital productivity when we estimate TFP following Olley and Pakes (1996). Indeed, İmrohoroğlu and Tüzel (2014) show that firm-level TFP is correlated with labor hiring. However, prevailing pricing factors, like the investment or profitability factors in Fama and French (2017), Hou et al. (2015), and Hou et al. (2020a), capture mainly capital productivity and are not specifically designed to capture labor productivity. This suggests that the missing factor (PC1) likely captures the labor risk.

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

Moreover, we empirically establish the connection between PC1 and labor risk in four steps. First, we explore how labor productivity and capital productivity contribute to total productivity at the firm level. In the first column of Panel A of Table 12, we report the Fama-MacBeth regression of log TFP growth on labor productivity growth, capital productivity growth, and output growth. Labor productivity growth is the log growth of labor productivity, $Log\,\frac{Y_{it}}{L_{it}}$; capital productivity is the log growth of capital productivity, $Log\,\frac{Y_{it}}{K_{it}}$; and output growth is the log growth of output. The coefficient on labor productivity growth is 0.39 (t=44.50), which is larger than that on capital productivity growth, 0.22 (t=23.19). Hence, labor productivity is an important part of total factor productivity.

Second, we link the first productivity principal component (PC1) with aggregate labor productivity, by running time-series regressions of either PC1 or its mimicking productivity portfolio, labeled as R^{PC1}, on aggregate labor growth and capital growth. The aggregate labor growth and capital growth data are from the Federal Reserve Bank of San Francisco.[27] The second and third columns of Panel A of Table 12 show that both PC1 and R^{PC1} have significant coefficients on aggregate labor growth, but not on aggregate capital growth. Therefore, PC1 captures mainly labor productivity.

Third, we investigate the asset pricing implications of labor risk. Following Donangelo et al. (2019), 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 $\frac{SALE_{it}-Materials_{it}}{GDP\ deflator_t}$. Material cost ($Materials_{it}$) is total expenses minus labor expense. Total expense is sales (SALE) minus operating income before depreciation and amortization (OIBDP). Labor expense is the staff expense (XLR). Only a small number of firms report their staff expense in Compustat. We replace the missing observations with the interaction of the industry average labor expense ratio and total expense. Specifically, we first calculate the labor expense ratio, $\frac{XLR_{it}}{SALE_{it}-OIBDP_{it}}$, for each firm. Next, in each year we estimate the industry average of the

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

labor expense ratio at the 4-digit SIC code level, with at least three firms available in the industry. Otherwise, we estimate the average of the labor expense ratio at the 3-digit SIC code level. In the same manner, we estimate the industry average of the labor expense ratio at the 2-digit and 1-digit SIC code level. Then, we back out the staff expense by multiplying the industry average labor expense ratio and total expense. If the labor expense is still missing, we interpolate those missing observations with the interaction of annual wage from the Bureau of Labor Statistics and the number of employees. We exclude financial and utility firms. We also exclude firms with a stock price below \$5, total assets below \$12.5 million, the number of employees below 100, or sales growth or asset growth above 100%. Finally, we trim the labor share at the 0.5^{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 12. Consistent with Donangelo et al. (2019), 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., 2019). The long-short portfolio has an average return of 0.47% per month (t=2.98) and significant alphas across all models except for the productivity-based model. This suggests that the prevailing factors cannot explain the labor risk. However, the six productivity factors track the labor risk well.

Fourth, we check whether the first productivity component is related to the labor risk. In Panel C of Table 12, we present the annual correlation coefficients between the annual long-short labor share portfolio return (LS factor) and the six productivity components (PC1 to PC6). LS factor is highly correlated with the first productivity principal component (PC1), with a correlation coefficient of 0.43, while its correlations with other productivity components are very minor. This further confirms that PC1 captures the labor risk.

If the labor share factor and the first productivity factor capture similar labor risks, we expect the productivity-based model to explain other pricing factors when we replace the first productivity factor with the labor share factor. We run the time-series regressions of each pricing factor on the labor share factor and the second to sixth mimicking productivity factors. The intercepts and the coefficients of each factor appear in Panel A of Table 13. The labor factor, LS, is significantly priced among most pricing factors, except for HML and $PEAD$. Similar to the productivity-based model, this labor-share-augmented productivity model explains most of the pricing factors. However, it cannot fully explain the profitability factors (RMW and Q_{ROE}), the investment factors (CMA and Q_{IA}), the expected investment growth factor (EG), or $PEAD$. Overall, it performs worse than the productivity-based model. This is not surprising, as the labor-augmented productivity model can't fully explain PC1 as well, which suggests that PC1 may better capture labor risk than the LS measure.

Lastly, we run a Fama-MacBeth regression using the prevailing factor models augmented with the first mimicking productivity portfolio (PC1) or the labor share factor (LS). If the prevailing factor models miss the labor risk, adding the missing factor should improve their empirical performances. In Panel B of Table 13, we report the Fama-MacBeth regression results, using the 155 portfolios from Table 8 as test assets. First, we see that PC1 is significantly priced in all models, while LS is priced in the FF6, HMXZ, and DHS models. Adding the labor factor (PC1 or LS) improves the model performances, especially for the FF6 and DHS models. For example, after we add PC1, the FF6 model has an insignificant intercept (t=-1.41). Also, the adjusted R^2 increases by 0.04. When the DHS model includes the LS factor, the intercept becomes insignificant (t=-0.03) and the adjusted R^2 increases from 0.18 to 0.51. Overall, the missing factor (PC1 or LS) helps to reduce the intercepts of various models. Also, even though some factor models, such as FF5 or HXZ, already have insignificant intercepts, the missing factor increases their explanatory power. Therefore, the labor risk helps other factor models to explain the stock returns.

5. Conclusions

Inspired by production-based asset pricing models, we start with productivity shocks in firms' production to identify multiple systematic productivity risks and explore their asset pricing implications. Fundamental shocks drive firms' optimal investment decisions and the pricing kernel, suggesting a productivity-based model. We find that the first six productivity factors well explain many test assets and 13 of 15 prevailing pricing factors, including the Fama and French (2018) six factors, the Hou et al. (2015) q factors, the mispricing factors in Stambaugh and Yuan (2017), and the long-horizon behavioral factor in Daniel et al. (2020). This indicates productivity shocks are priced and these prevailing factors indeed represent the fundamental risks in the economy. In fact, these factors share common risk sources, even though they are motivated and constructed differently. In particular, we find that these empirical asset pricing models miss an important productivity factor, which we interpret as the labor risk. This suggests the importance of recognizing labor risk in asset pricing models.

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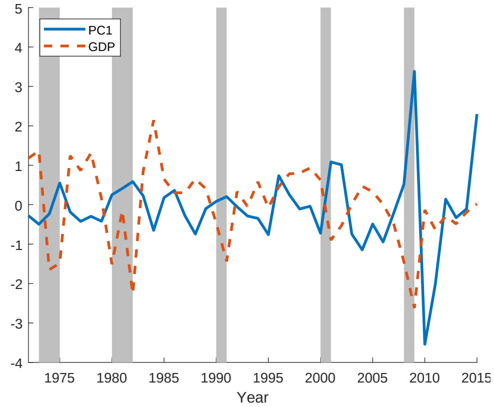
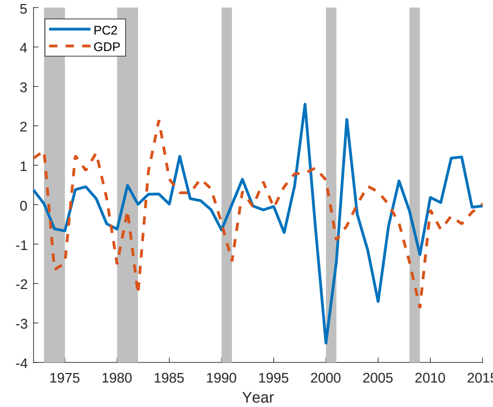


(a) PC1



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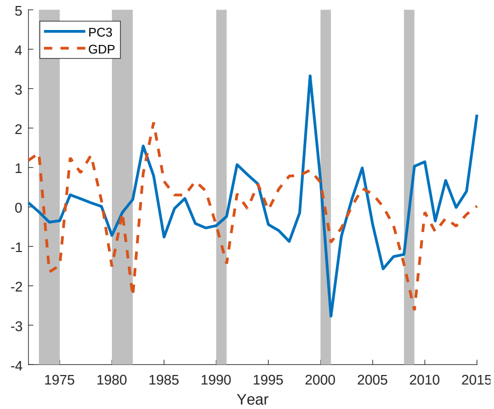

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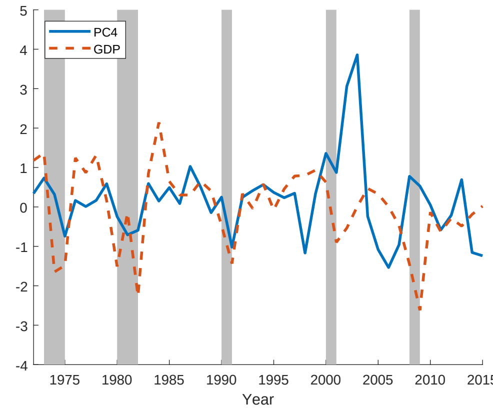

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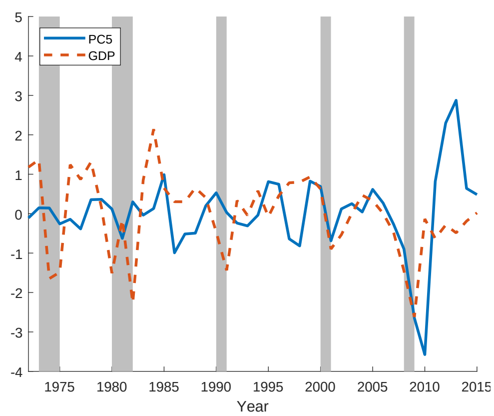

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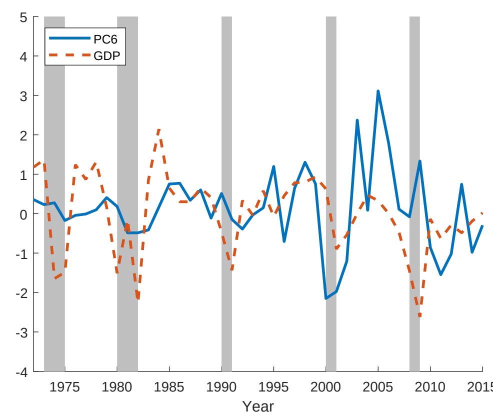

(f) PC6

Fig. 1. Productivity components and GDP growth

These figures plot the time-series of productivity components (PC1 to PC6) against annual GDP growth. All series are standardized. The shaded areas are NBER recession periods. The sample period is from 1972 to 2015.

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 the 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); Stambaugh and Yuan (2017) mispricing factor (MIS); and Daniel et al. (2018) long-horizon behavioral factor (FIN) and short-horizon behavioral factor (PEAD). Panel C presents the monthly mean (% per month), standard deviation (% per month, S.D.), Sharpe ratio (SR), and correlations for the mimicking portfolios of six principal components. The sample period is from January 1972 to December 2015, except for the Daniel et al. (2018) factors, which have a sample period of July 1972 to December 2014.

Panel A: TFP and its 6 principal components

	Mean	S.D.	Min	Max	10%	25%	50%	75%	90%	AR(1)	R^2
ΔTFP	0.01	0.19	-1.35	1.26	-0.20	-0.08	0.01	0.10	0.22	0.07	
PC1	-0.08	1.01	-3.54	3.38	-0.76	-0.46	-0.15	0.25	0.74	-0.03	0.15
PC2	-0.06	1.01	-3.51	2.55	-1.15	-0.57	0.01	0.38	1.18	0.20	0.24
PC3	0.05	1.01	-2.77	3.32	-0.88	-0.46	-0.03	0.63	1.07	0.24	0.32
PC4	0.17	1.00	-1.54	3.86	-1.08	-0.41	0.24	0.55	0.87	0.45	0.39
PC5	0.03	1.01	-3.57	2.87	-0.82	-0.35	0.12	0.51	0.82	0.45	0.46
PC6	0.12	1.00	-2.15	3.11	-1.02	-0.40	0.11	0.62	1.30	0.25	0.52

Panel B: Correlations between 6 TFP components and pricing factors

	MKT	SMB	HML	CMA	RMW	UMD	Q_{ME}	Q_{IA}	Q_{ROE}	EG	MIS	FIN	PEAD
MKT	1.00												
SMB	0.15	1.00											
HML	-0.27	0.17	1.00										
CMA	-0.36	0.17	0.71	1.00									
RMW	-0.30	-0.13	0.21	0.04	1.00								
UMD	-0.21	-0.26	-0.16	-0.11	0.02	1.00							
Q_{ME}	0.10	0.99	0.20	0.17	-0.08	-0.20	1.00						
Q_{IA}	-0.38	0.05	0.68	0.93	0.09	-0.05	0.07	1.00					
Q_{ROE}	-0.27	-0.38	-0.08	-0.13	0.72	0.52	-0.30	0.00	1.00				
EG	-0.26	-0.10	0.10	0.23	0.29	0.36	-0.06	0.21	0.37	1.00			
MIS	-0.52	-0.39	0.11	0.31	0.31	0.61	-0.33	0.33	0.52	0.66	1.00		
FIN	-0.56	-0.22	0.67	0.57	0.55	0.16	-0.19	0.59	0.35	0.36	0.57	1.00	
PEAD	0.00	-0.07	-0.06	-0.02	-0.27	0.55	-0.03	0.01	0.18	0.29	0.43	-0.04	1.00
PC1	-0.01	0.01	-0.07	-0.14	0.11	-0.28	0.01	-0.14	-0.08	0.14	-0.01	-0.05	-0.22
PC2	0.12	-0.24	-0.14	-0.12	-0.16	0.17	-0.25	0.00	0.05	-0.24	0.09	0.05	0.20
PC3	0.19	0.06	-0.15	-0.07	-0.48	-0.06	0.01	-0.23	-0.42	-0.02	-0.18	-0.27	0.11
PC4	-0.14	0.28	0.21	0.50	0.00	-0.13	0.26	0.43	-0.22	0.12	0.03	0.17	-0.12
PC5	0.09	-0.10	0.01	-0.04	-0.09	0.35	-0.09	-0.07	0.13	0.09	0.17	-0.04	0.19
PC6	0.34	-0.14	-0.23	-0.29	-0.44	-0.17	-0.18	-0.26	-0.29	-0.27	-0.35	-0.48	-0.07

Panel C: Statistics of monthly mimicking productivity portfolios

	Mean	SD	SR	PC2	PC3	PC4	PC5	PC6
PC1	1.31	7.38	0.18	0.36	0.05	0.22	-0.03	-0.27
PC2	0.39	3.55	0.11		-0.21	-0.38	0.26	-0.07
PC3	-0.95	5.67	-0.17			0.15	0.21	0.20
PC4	1.59	10.25	0.16				-0.30	-0.24
PC5	0.70	2.12	0.33					-0.39
PC6	-0.99	4.85	-0.20					

Table 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 TFP growth over the last 5 year. Systematic TFP volatility is the standard deviation of systematic TFP growth over the last 5 year. Idiosyncratic TFP volatility is the standard deviation of idiosyncratic TFP growth over the last 5 year. Idiosyncratic TFP growth is total TFP growth - systematic TFP growth. Asset growth is $\frac{AT_t - AT_{t-1}}{AT_{t-1}}$ where AT is total assets. Cash flow is $\frac{IB_t + DP_t}{PPENT_{t-1}}$. IB is income before extraordinary items. DP is depreciation and amortization. PPENT is 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)			
$\lvert\Delta TFP\rvert$					0.20	
					(7.49)	
$\lvert\Delta TFP_{sys}\rvert$						0.11
						(2.76)
$\lvert\Delta TFP_{idio}\rvert$						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. **Interpreting six productivity components**

This table presents panel regression results of factor loadings of the six productivity components on firm characteristics, following Kelly et al. (2019). For each firm, we gradually estimate factor loadings by regressing its TFP against the six principal productivity components, using a 15 year-extending window. That is, we regress firm-level TFP against PC1 to estimate a factor loading of PC1 (b_{PC1}). Then we regress TFP residuals, which is unexplained by PC1, against PC2 to estimate a factor loading of PC2 (b_{PC2}). Other factor loadings are estimated in a similar manner. Firm characteristics are as follows. Labor share (LS) is the ratio of labor expense over value-added. Size is the logarithmic of market capitalization. Cash flow (CF) is income before extraordinary items (IB) divided by lagged net property, plant, and equipment (PPENT). Investment (IK) is the ratio of capital expenditure (CAPX) plus inventory change (INVT) minus sales of property, plant, and equipment (SPPE) over lagged gross property, plant, and equipment (PPEGT). Cumulative return ($R_{2,12}$) is the cumulative stock return from the previous 11 months lagged by one month. Mispricing score (MIS) is the average rank score estimated from 11 mispricing portfolios in Stambaugh and Yuan (2017). Book-to-market equity ratio (BM) is the ratio of book equity to market equity. Idiosyncratic volatility (Ivol) is the standard deviation of residuals from the Fama-French three-factor model, using within month daily returns. Leverage (Lev) is the ratio of long-term debt (DLCC) plus current liabilities (DLC) over long-term debt, current liabilities, and shareholder's equity (SEQ). t-statistics are in the parentheses. The sample period is from 1972 to 2015.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	b_{PC1}	b_{PC2}	b_{PC3}	b_{PC4}	b_{PC5}	b_{PC6}	b_{PC1}	b_{PC2}	b_{PC3}	b_{PC4}	b_{PC5}	b_{PC6}
LS	0.021	-0.006	0.014	-0.023	0.017	-0.001	0.025	-0.026	0.015	0.001	0.036	-0.003
	(2.730)	(-0.752)	(1.906)	(-2.779)	(1.846)	(-0.103)	(2.011)	(-1.860)	(1.240)	(0.052)	(2.321)	(-0.211)
Size	-0.031	0.069	-0.016	0.041	-0.022	-0.070	-0.028	0.062	-0.015	0.031	-0.020	-0.066
	(-1.888)	(3.834)	(-0.984)	(2.276)	(-1.110)	(-3.412)	(-1.835)	(3.620)	(-0.962)	(1.826)	(-1.074)	(-3.376)
CFK	0.004	-0.007	-0.040	0.007	-0.047	0.022	0.005	-0.007	-0.041	0.010	-0.046	0.022
	(0.315)	(-0.501)	(-3.067)	(0.480)	(-2.923)	(1.300)	(0.377)	(-0.473)	(-3.170)	(0.708)	(-2.846)	(1.322)
IK	-0.006	-0.027	0.009	-0.037	0.008	-0.026	-0.007	-0.026	0.009	-0.038	0.007	-0.027
	(-0.527)	(-1.983)	(0.745)	(-2.801)	(0.549)	(-1.689)	(-0.608)	(-1.949)	(0.770)	(-2.887)	(0.478)	(-1.767)
$R_{2,12}$	0.010	0.015	0.011	-0.008	0.029	0.005	0.010	0.016	0.011	-0.007	0.030	0.005
	(1.781)	(2.477)	(2.062)	(-1.310)	(4.279)	(0.679)	(1.761)	(2.568)	(2.024)	(-1.153)	(4.419)	(0.732)
MIS	0.007	-0.012	0.008	-0.024	0.022	0.029	0.006	-0.009	0.008	-0.018	0.022	0.026
	(1.037)	(-1.722)	(1.300)	(-3.356)	(2.799)	(3.583)	(0.935)	(-1.324)	(1.244)	(-2.632)	(2.946)	(3.305)
BM							-0.009	0.026	0.000	-0.029	-0.022	-0.001
							(-0.741)	(1.992)	(0.013)	(-2.282)	(-1.575)	(-0.086)
Ivol							0.012	-0.009	-0.009	0.002	0.009	0.023
							(1.535)	(-1.020)	(-1.134)	(0.229)	(0.988)	(2.352)
R_1							0.004	0.013	-0.003	0.011	0.009	0.005
							(0.787)	(2.395)	(-0.614)	(1.961)	(1.412)	(0.828)
Lev							-0.006	-0.000	0.003	-0.014	-0.003	-0.004
							(-1.201)	(-0.005)	(0.729)	(-2.594)	(-0.521)	(-0.654)
Cons	0.003	-0.010	0.003	-0.006	0.002	0.011	0.003	-0.007	0.001	-0.003	0.003	0.012
	(0.663)	(-1.871)	(0.627)	(-1.239)	(0.407)	(1.924)	(0.733)	(-1.354)	(0.236)	(-0.547)	(0.542)	(2.002)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	12840	12840	12840	12840	12840	12840	12817	12817	12817	12817	12817	12817
R^2	0.809	0.762	0.816	0.766	0.715	0.691	0.809	0.762	0.816	0.766	0.715	0.691

Table 4. **Asset pricing tests: Two-step GMM**

This table presents the two-step GMM estimation with one-lag Newey-West adjustment of various factor models. Factor models include the Fama and French (1993) three-factor model (FF3), Fama and French (2015) five-factor model (FF5), Fama and French (2018) six-factor model (FF6), Hou et al. (2015) q-factor model (HMZ), Hou et al. (2018) q^5-factor model (HMXZ), Daniel et al. (2020) (DHS), and the productivity-based model (TFP). The productivity-based model use six principal components estimated from firm-level TFP. Test assets are 155 portfolios, 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. Panel A shows the coefficients (coeff, b) from GMM estimation and their t-statistics (t-stat). Panel B reports the implied price of risk (λ) for each factor, based on the coefficients in Panel A. Panel C presents the statistics of goodness of fit, including R^2, root-mean-square errors ($RMSE$), and p-value of Hansen's J test of overidentification. R^2 is defined as one minus the ratio of the cross-sectional variance of the pricing errors to the cross-sectional variance of realized average portfolio returns, following Campbell and Vuolteenaho (2004). The annual data are from 1973 to 2014 for DHS model and from 1973 to 2016 for other models.

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

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

Table 5. **Comparing factor models: Examining R^2s**

We run cross-sectional GLS regressions of various factor models and compare their performances via R^2. Factor models include the Fama and French (1993) three-factor model (FF3), Fama and French (2015) five-factor model (FF5), Fama and French (2018) six-factor model (FF6), Hou et al. (2015) q-factor model (HMZ), Hou et al. (2020a) q^5 model (HMXZ), Daniel et al. (2020) (DHS), and the productivity-based model (TFP). Test assets are 25 size and book-to-market sorted portfolios. This table reports the pairwise comparison of the cross-sectional GLS R^2s of two factor models. We report the difference between the cross-sectional R^2s of two models in row i and column j, $R_i^2 - R_j^2$, and the corresponding p-value in parentheses for testing the null hypothesis that $R_i^2 = R_j^2$. The p-values are adjusted under the assumption that the models are potentially misspecified, following Kan et al. (2013). The sample period is from 1972 to 2015 except for the DHS model, which is from 1973 to 2014.

	FF5	FF6	HXZ	HMXZ	DHS	TFP
FF3	-0.07	-0.17	-0.17	-0.21	0.01	-0.26
p-value	(0.11)	(0.09)	(0.13)	(0.11)	(0.90)	(0.07)
FF5		-0.08	-0.08	-0.14	0.14	-0.19
p-value		(0.08)	(0.25)	(0.25)	(0.22)	(0.20)
FF6			-0.00	-0.06	0.23	-0.11
p-value			(0.95)	(0.52)	(0.12)	(0.47)
HXZ				-0.06	0.24	-0.11
p-value				(0.25)	(0.10)	(0.46)
HMXZ					0.27	-0.05
p-value					(0.09)	(0.78)
DHS						-0.34
p-value						(0.01)

Table 6. **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 management (MGMT) and firm performance (PERF); Hou et al. (2018) expected investment growth factor (EG); and Daniel et al. (2020) short horizon earning surprise factor (PEAD) and long horizon financing factor (FIN). The intercepts and factor loadings are estimated either over the full sample (Panel A) or in extending windows (Panel B). The Newey-West adjusted t-statistics (t-stat) with 6-month (4-month) lags are provided. The sample period is from January 1972 to December 2015, but the Daniel et al. (2020) factors are from July 1972 to December 2014. The testing period for Panel B is from January 2001 to December 2015, but it is from January 2001 to December 2014 for the Daniel et al. (2020) 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 7. **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 8. **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, 25 size and momentum sorted portfolios, 25 size and idiosyncratic risk sorted portfolios, 30 Fama-French industry portfolios, and the tested pricing factors. Tested factor models are the Fama and French (1993) three-factor model (FF3), Fama and French (2015) five-factor model (FF5), Fama and French (2018) six-factor model (FF6), Hou et al. (2015) q-factor model (HMZ), Hou et al. (2018) q^5 model (HMXZ), Stambaugh and Yuan (2017) mispricing factor model (SY), Daniel et al. (2018) behavioral factor model (DHS), and productivity-based model (TFP). The factor betas are computed over the full sample. 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 the 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 9. **Comparing factor models: Maximum squared Sharpe ratio**

Panel A presents the maximum squared Sharpe ratio ($Sh^2(f)$) of the tangency portfolios constructed with pricing factors from different factor models. Factor models include the Fama and French (1993) three-factor model (FF3), Carhart (1997) four-factor model (FF4), Fama and French (2015) five-factor model (FF5), Fama and French (2018) six-factor model (FF6), Hou et al. (2015) q-factor model (HXZ), Hou et al. (2018) q^5 model (HMXZ), Daniel et al. (2020) behavioral factor model (DHS), and 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 the productivity factors. The sample period is from January 1972 to December 2015, but the sample period for the Daniel et al. (2020) factors is from July 1972 to December 2014.

Panel A: Maximum squared Sharpe ratio

	FF3	FF4	FF5	FF6	HXZ	HMXZ	DHS	TFP
$Sh^2(f)$	0.04	0.09	0.10	0.14	0.15	0.26	0.27	0.32
(5^{th}, 95^{th})	(0.02, 0.08)	(0.06, 0.16)	(0.07, 0.17)	(0.10, 0.22)	(0.10, 0.22)	(0.19, 0.36)	(0.20, 0.37)	(0.26, 0.44)

Panel B: Spanning regressions and marginal contributions to $Sh^2(f)$ for the TFP model

	α	PC1	PC2	PC3	PC4	PC5	PC6	t-stat	R^2	$s(e)$	$\frac{\alpha^2}{s(e)^2}$
PC1	1.13		1.15	0.35	0.16	-1.03	-0.53	3.59	0.36	5.89	0.037
PC2	-0.15	0.24		-0.18	-0.11	0.50	0.12	-1.22	0.43	2.68	0.003
PC3	-1.76	0.20	-0.51		0.16	1.62	0.65	-7.22	0.36	4.52	0.152
PC4	2.63	0.27	-0.90	0.46		-2.14	-0.92	5.05	0.44	7.69	0.117
PC5	0.75	-0.06	0.15	0.17	-0.08		-0.27	8.48	0.52	1.46	0.261
PC6	0.85	-0.18	0.20	0.38	-0.18	-1.48		3.86	0.50	3.44	0.062

Table 10. **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 management (MGMT) or mispricing related to performance (PERF). Panel B tabulates similar results, but the mimicking portfolios of productivity factors are constructed with base assets excluding the mispricing factor. Acc denotes accruals, following Sloan (1996). AG denotes asset growth, following Cooper et al. (2008). CI denotes composite equity issuance, following Daniel and Titman (2006). InvA denotes investment-to-assets ratio, following Titman et al. (2004). NOA denotes net operating assets, following Hirshleifer et al. (2004). ISS denotes net equity issuance, following Ritter (1991). DIST denotes financial distress, following Campbell et al. (2008). GP denotes gross profitability, following Novy-Marx (2013). Mom denotes momentum following Jegadeesh and Titman (1993). OSCO denotes O-score, following Ohlson (1980). ROA denotes return on assets, 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 in 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 from 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 11. **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. (2020) 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 by 100. Newey-West adjusted t-statistics with 6-month (4-month for Panel B) lags are provided in parentheses. The sample period is from January 1972 to December 2015, but the Daniel et al. (2020) factors are from July 1972 to December 2014. The testing period for Panel B is from January 2001 to December 2015, but it is from January 2001 to December 2014 for the Daniel et al. (2020) 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 12. **Interpreting the missing factor as labor risk**

In Panel A, the first column presents the Fama-MacBeth regressions 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 the 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 the 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 the labor share factor and productivity factors							
	PC1	PC2	PC3	PC4	PC5	PC6	
LS factor	0.43	-0.11	0.14	0.15	-0.11	0.09	

Table 13. **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 the sample period for the Daniel et al. (2018) factors is from July 1972 to December 2014.

Panel A: Regression of risk factors on TFP factor-mimicking portfolio augmented with the 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 with 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:

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

where Y_{it}, Z_{it}, L_{it}, and K_{it} are value-added, productivity, labor, and capital stock of a firm i at time t, respectively. 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.[28]

The Lagragian function is

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

where q^K_{it} and q^L_{it} 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:

$$q^K_{it} - 1 - G_{I_{it}} = 0 \tag{8}$$

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

$$q^L_{it} - \phi_{H_{it}} = 0 \tag{10}$$

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

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

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

The marginal costs and benefits of labor hiring is given by

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

[28] 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 property, plant, and equipment (PPENT), sales (SALE), operating income before depreciation (OIBDP), depreciation (DP), capital expenditure (CAPX), depletion and amortization (DPACT), employees (EMP), and staff expense (XLR).

We apply several filters to estimate coefficients of labor and capital. Our main results use common stocks listed at NYSE/Amex/Nasdaq with 4-digit SIC codes less than 4900. This corresponds to agriculture, mining, construction, manufacturing, and transportation industries. We also consider an expanded sample, by further including firms in wholesale trade and retail trade (SIC codes between 5000 and 5999), and services (SIC does between 7000 and 8999), as a robustness check. 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). This table reports weekly earnings, which are annualized to be used in calculations.

(2) Input variables

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

Capital stock (K_{it}) is net property, plant, and equipment divided by the capital price deflator. We calculate the capital price deflator by following İmrohoroğlu and Tüzel (2014). First, we compute the age of capital in each year. Age of capital stock is $\frac{DPACT_{it}}{DP_{it}}$. We further take a 3-year moving average to smooth the capital age. Then, we match 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.[29] Our TFP estimation process is based on İmrohoroğlu and Tüzel (2014) with some modifications.

We start from the simple Cobb-Douglas production technology.

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

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}.

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

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. Alternative test assets

Tables C1-C6 show the complete time-series regression results of various test portfolios on the productivity factors.

D. Explaining the first mimicking productivity factor

Table D1 report the time-series regression results of PC1 on various factor models.

E. Robustness checks: Using an expanded sample

In this section, we replicate all main results, using an expanded sample. That is, we estimate TFP for firms with a four-digit SIC code lower than 4900 (agriculture, mining, manufacturing, construction, and transportation industry), or between 5000 and 5999 (wholesale trade and retail trade), or between 7000 and 8999 (services industry). We present the descriptive statistics in Table E1. Table E2 presents the time-series regression results, using productivity factors to explain other pricing factors. Table E3 reports the time-series regression results, using productivity factors to explain various test portfolios. Table E4 reports the cross-sectional regression results, using various factor models, including the productivity-based model. Table E5 reports the time-series regression results, using other pricing factors to explain productivity factors. Overall, the results are qualitatively similar to those reported in Tables 1, 3, 4, 5, and 8.

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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

Table D1. **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, except for the Daniel et al. (2018) factors, which have a sample period of July 1972 to December 2014. The testing period for panel B starts from January 2001.

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 E1. **TFP growth factors: Descriptive statistics and relations with other factors, using an expanded sample**

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

Panel A: TFP and its 6 principal components

	Mean	S.D.	Min	Max	10%	25%	50%	75%	90%	AR(1)	R^2
ΔTFP	0.01	0.20	-1.15	1.13	-0.20	-0.08	0.01	0.10	0.23	0.07	
PC1	-0.11	1.01	-3.18	3.34	-1.06	-0.53	-0.16	0.24	0.90	0.03	0.14
PC2	-0.12	1.00	-4.19	3.13	-0.83	-0.38	-0.13	0.21	0.59	-0.11	0.22
PC3	-0.24	0.98	-4.13	1.53	-1.11	-0.47	-0.10	0.25	0.62	0.20	0.29
PC4	-0.14	1.00	-3.51	1.73	-0.93	-0.55	-0.10	0.35	1.30	0.32	0.37
PC5	0.01	1.01	-3.21	2.63	-0.91	-0.42	0.01	0.46	1.10	0.27	0.43
PC6	0.01	1.01	-2.28	3.71	-0.94	-0.54	-0.09	0.55	1.19	0.35	0.50

Panel B: Correlations between 6 TFP components and pricing factors

	MKT	SMB	HML	CMA	RMW	UMD	Q_{ME}	Q_{IA}	Q_{ROE}	EG	MIS	FIN	PEAD
MKT	1.00												
SMB	0.15	1.00											
HML	-0.27	0.17	1.00										
CMA	-0.36	0.17	0.71	1.00									
RMW	-0.30	-0.13	0.21	0.04	1.00								
UMD	-0.21	-0.26	-0.16	-0.11	0.02	1.00							
Q_{ME}	0.10	0.99	0.20	0.17	-0.08	-0.20	1.00						
Q_{IA}	-0.38	0.05	0.68	0.93	0.09	-0.05	0.07	1.00					
Q_{ROE}	-0.27	-0.38	-0.08	-0.13	0.72	0.52	-0.30	0.00	1.00				
EG	-0.26	-0.10	0.10	0.23	0.29	0.36	-0.06	0.21	0.37	1.00			
MIS	-0.52	-0.39	0.11	0.31	0.31	0.61	-0.33	0.33	0.52	0.66	1.00		
FIN	-0.56	-0.22	0.67	0.57	0.55	0.16	-0.19	0.59	0.35	0.36	0.57	1.00	
PEAD	0.00	-0.07	-0.06	-0.02	-0.27	0.55	-0.03	0.01	0.18	0.29	0.43	-0.04	1.00
PC1	-0.03	0.00	-0.09	-0.13	0.15	-0.27	0.01	-0.08	-0.09	0.16	0.02	-0.01	-0.22
PC2	-0.07	0.02	0.32	0.12	0.30	-0.19	0.04	0.08	0.12	0.16	0.03	0.10	-0.08
PC3	0.00	-0.29	0.02	-0.21	0.30	-0.02	-0.31	-0.08	0.30	-0.29	-0.01	0.20	-0.11
PC4	0.21	-0.06	-0.20	-0.31	-0.33	-0.11	-0.05	-0.35	-0.27	-0.13	-0.28	-0.28	-0.11
PC5	-0.24	0.19	0.20	0.42	0.25	-0.21	0.18	0.39	-0.06	0.13	0.07	0.32	-0.14
PC6	0.22	-0.07	-0.13	-0.07	-0.31	0.06	-0.11	-0.15	-0.12	-0.07	0.07	-0.16	0.40

Panel C: Statistics of monthly mimicking productivity portfolios

	Mean	S.D.	SR	PC2	PC3	PC4	PC5	PC6
PC1	0.69	4.12	0.17	0.11	-0.13	-0.18	0.25	0.33
PC2	1.49	15.78	0.09		-0.03	-0.46	0.38	-0.03
PC3	-0.44	4.40	-0.10			-0.14	-0.50	-0.23
PC4	-1.78	6.81	-0.26				-0.64	-0.15
PC5	0.76	13.19	0.06					0.04
PC6	0.10	2.37	0.04					

Table E2. **Using productivity factors to explain other pricing factors: An expanded sample**

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

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

Table E3. **Explaining various test portfolios with productivity factors: An expanded sample**

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

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

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

Table E4. **Cross-sectional regressions of various factor models: An expanded sample**

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

	FF3		FF5		FF6		HXZ		HMXZ		SY		DHS		TFP	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.51	5.35	0.01	0.29	-0.07	-2.24	0.00	-0.03	-0.06	-1.10	-0.03	-0.44	0.30	2.43	0.22	1.58
γ_{MKT}	0.06	0.29	0.47	2.30	0.59	2.91	0.49	2.32	0.57	2.73	0.57	2.70	0.42	1.81		
γ_{SMB}	0.09	0.70	0.22	1.65	0.21	1.55										
γ_{HML}	0.24	1.65	0.07	0.53	0.28	2.10										
γ_{CMA}			0.29	2.52	0.26	2.29										
γ_{RMW}			0.43	4.01	0.27	2.75										
γ_{UMD}					0.73	3.72										
$\gamma_{Q_{ME}}$							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}															0.62	2.42
γ_{PC2}															1.35	1.93
γ_{PC3}															-0.47	-1.64
γ_{PC4}															-1.78	-5.09
γ_{PC5}															0.63	1.069
γ_{PC6}															0.15	0.85
R^2	0.06		0.44		0.60		0.52		0.58		0.61		0.18		0.78	
(5^{th}, 95^{th})	(0.03, 0.49)		(0.27, 0.59)		(0.44, 0.70)		(0.32, 0.63)		(0.40, 0.66)		(0.40, 0.68)		(0.03, 0.49)		(0.55, 0.80)	

Table E5. **Explaining productivity factors with other pricing factors: An expanded sample**

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

	PC1	PC2	PC3	PC4	PC5	PC6
R^{EX}	0.69 (4.42)	1.49 (1.82)	-0.44 (-2.24)	-1.78 (-5.19)	0.76 (1.19)	0.10 (0.96)
α^{CAPM}	0.71 (4.60)	1.73 (2.04)	-0.45 (-2.34)	-1.95 (-5.30)	1.39 (2.32)	-0.01 (-0.06)
R^2	0.00	0.02	0.00	0.04	0.17	0.16
α^{FF3}	0.52 (3.31)	1.07 (1.37)	-0.37 (-2.04)	-1.65 (-5.10)	0.74 (1.62)	0.04 (0.42)
R^2	0.08	0.09	0.47	0.11	0.52	0.19
α^{FF4}	0.57 (3.43)	0.69 (0.95)	-0.14 (-0.92)	-1.13 (-3.87)	0.16 (0.34)	-0.12 (-1.10)
R^2	0.08	0.10	0.53	0.23	0.56	0.28
α^{FF5}	0.50 (3.28)	-0.02 (-0.03)	-0.44 (-2.14)	-0.60 (-2.25)	-0.28 (-0.67)	-0.10 (-0.82)
R^2	0.10	0.22	0.50	0.51	0.63	0.26
α^{FF6}	0.55 (3.50)	-0.21 (-0.31)	-0.24 (-1.45)	-0.31 (-1.22)	-0.61 (-1.46)	-0.21 (-1.99)
R^2	0.10	0.23	0.56	0.56	0.65	0.33
α^{SY}	0.36 (2.07)	-0.90 (-1.18)	0.225 (1.57)	-0.03 (-0.09)	-1.52 (-3.43)	-0.41 (-4.32)
R^2	0.09	0.15	0.47	0.42	0.64	0.41
α^{DHS}	0.66 (3.55)	0.11 (0.16)	-0.48 (-1.79)	-0.68 (-2.43)	0.72 (1.22)	-0.35 (-2.98)
R^2	0.03	0.16	0.07	0.27	0.18	0.24
α^{HXZ}	0.81 (5.17)	-0.27 (-0.34)	-0.67 (-3.08)	0.07 (0.32)	-0.46 (-1.03)	0.00 (0.00)
R^2	0.19	0.14	0.52	0.70	0.61	0.20
α^{HMXZ}	0.74 (4.56)	-0.47 (-0.61)	-0.28 (-1.89)	0.20 (0.99)	-0.95 (-2.05)	-0.18 (-1.48)
R^2	0.19	0.15	0.59	0.70	0.62	0.25