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Firm-Level Productivity, Risk, and Return

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This paper provides new evidence about the link between firm-level total factor productivity (TFP) and stock returns. We estimate firm-level TFP and show that it is strongly related to several firm characteristics such as size, the book-to-market ratio, investment, and hiring rate. Low productivity firms earn a significant premium over high productivity firms in the following year, and this premium is countercyclical. We show that a production-based asset pricing model calibrated to match the cross section of measured firm-level TFPs can replicate the empirical relationship between TFP, many firm characteristics, and stock returns. Our results offer an explanation as to how these firm characteristics rationally predict returns.

Keywords: firm-level productivity; cross section of returns

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1. Introduction

Empirical research in finance has documented that many firm characteristics, such as size, book-to-market ratio, investment, and hiring behavior of firms, forecast future stock returns.¹ Recently, a growing strand of literature has introduced neoclassical investment models to explain such differences in firm characteristics and returns. In these models, such as Gomes et al. (2003), Zhang (2005), Li et al. (2009), Tüzel (2010), Lin (2012), Belo and Lin (2012), Jones and Tüzel (2013a), and Belo et al. (2014), ex ante identical firms are exposed to firm-level total factor productivity (TFP) shocks, which lead to different firm characteristics. Firms with low productivity are more vulnerable to business cycles and end up being riskier than high productivity firms. However, none of these papers has estimated firm-level productivity and investigated the relationships between TFP, firm characteristics, and firm returns directly.

In this paper, we estimate firm-level TFP and provide new evidence about the sources of return predictability. We document that our measured TFP is strongly related to several firm characteristics, such as size, the book-to-market ratio, investment, and hiring rate. We find that TFP is positively and monotonically related to contemporaneous monthly stock returns and negatively related to future excess returns and ex ante discount rates. We show that a production-based asset pricing model calibrated to match the cross section of measured firm-level TFPs can replicate the

empirical relationships between TFP, many firm characteristics, and stock returns fairly well. Overall, our results provide an explanation as to why these firm characteristics rationally predict returns.

We estimate firm-level productivity using the semi-parametric method initiated by Olley and Pakes (1996) and construct a panel of TFP levels for publicly traded firms in the United States. We establish a set of stylized facts by examining the summary statistics of firms sorted by TFP into 10 portfolios between 1963 and 2009. We find that differences in measured firm-level TFPs are strongly related to differences in a number of firm characteristics. High TFP firms are typically growth firms with an average book-to-market ratio of about 0.5, and low TFP firms are value firms with an average book-to-market ratio of about 1.4. We find the relationship between firm size and TFP to be similarly monotonic across deciles. The average size of the firms in the lowest TFP decile is 22% of the average firm size, whereas the size of firms in the highest TFP decile is 386% of the average size. In addition, the hiring rate, fixed investment to capital ratio, asset growth, profitability, and inventory growth are all monotonically increasing in firm-level TFP.

We find that low productivity firms have, on average, higher excess returns than high productivity firms. For equal-weighted portfolios, this difference is 7.4% annually. The spread is smaller for value-weighted portfolios, indicating that the effects are stronger across small firms. We also find that there is significant variation in the return spread over business cycles. It is about five times as high during economic contractions as it is during expansions. We

¹ See, for example, Fama and French (1992), Titman et al. (2003), Cooper et al. (2008), Lyandres et al. (2008), Wu et al. (2010), Tüzel (2010), Belo and Lin (2012), and Belo et al. (2014).

interpret the spread in the average returns across these portfolios as the risk premia associated with the higher risk of low productivity firms. A Fama–MacBeth regression of monthly stock returns on lagged firm-level TFP produces a negative and statistically significant average slope for TFP. Quantitatively, our regression results indicate about 8% higher expected returns for the firms in the lowest TFP decile compared to a firm in the highest TFP decile.

In addition to realized returns, we also look at ex ante measures of discount rates. Specifically, we examine implied cost of capital measures calculated using three different methods, namely, those of Gebhardt et al. (2001), Hou et al. (2012), and Tang et al. (2014). The advantage of using an implied cost of capital is that it does not rely on realized returns that are often noisy and may be a bad proxy for expected returns. We confirm the negative relationship between firm productivity and expected returns, finding that the average implied cost of capital for the low TFP portfolio exceeds that of the high TFP portfolio and is statistically significant. Similar to average future returns, the spread in implied cost of capital is also strongly countercyclical.

In an attempt to understand the mechanism behind the negative relationship between the firms' TFP and expected returns, we investigate whether there are systematic differences in the sensitivity of low and high TFP firms' operating performance to aggregate shocks in the economy. We find that the profits of low TFP firms are more sensitive to aggregate shocks than are those of high TFP firms. Furthermore, the sensitivity of low TFP firms increases in recessions, whereas the opposite happens for the high TFP firms. These results provide direct evidence on the higher risk of low TFP firms, especially in recessions, rather than indirect evidence based on realized or ex ante returns.

The parameters of the TFP process are an important input in production-based asset pricing models focused on firm characteristics. We estimate the persistence of firm-level TFP to be 0.7 and the standard deviation of the TFP shock to be 0.27, both at the annual frequency. Our estimates are roughly in line with the parameters used in this literature, in which firm-level TFP processes are typically calibrated to match the moments of some key variables.² Our findings can serve as a direct measurement of the firm-level TFP process to guide future work.

To interpret our empirical findings, we use a production-based asset pricing model similar to those in Zhang (2005), Jones and Tüzel (2013a), and Belo

et al. (2014). We calibrate the model to the TFP moments we estimate and find that it can replicate the empirical relationship between TFP, firm characteristics, and stock returns.

In the model economy, firms are ex ante identical but diverge over time because of idiosyncratic shocks. Firms that receive repeated bad shocks end up being low TFP firms. These firms are characterized by low investment and hiring rates, high book-to-market ratios, and smaller size. Firms that receive multiple good shocks become high TFP firms with high investment and hiring rates, low book-to-market ratios, and large market capitalizations.

In this framework, a negative relationship between a firm's productivity and its level of risk arises endogenously. All firms face aggregate shocks and incur adjustment costs upon changes in the capital stock. In recessions (low aggregate productivity), most firms try to scale back their production and lower their investments and hiring. Even though all firms suffer during a recession, the firms that suffer the most are those with low firm-level TFP. If the recession deepens, these firms have the most pressure to scale back their investments and hence suffer the most from convex adjustment costs, resulting in low firm values and low returns. This is especially important in the presence of a countercyclical price of risk, which is introduced through an exogenous pricing kernel. During recessions, the returns of low productivity firms fluctuate more closely with aggregate productivity, and those firms become particularly risky. The opposite happens in expansions.

Our simulation results indicate that differences in firm-level TFPs can indeed generate realistic differences in firm characteristics and stock returns. In particular, the model can replicate reasonably well the investment to capital ratio, hiring rate, book-to-market ratio, size, and returns of low versus high TFP firms and their variation over the business cycle observed in the data.

Section 2 summarizes the data and our empirical results. Section 3 presents the model and the numerical results for the calibrated economy. Section 4 concludes. The online appendix (available at http://www-bcf.usc.edu/~tuzel/TFP_InternetAppendix_July8.pdf) provides detailed information on the data, the estimation of firm-level productivities, the sensitivity results, and the numerical model solution.

2. Empirical Results

We start this section by summarizing the data and the estimation of TFP. Next, we examine the empirical links between TFP, returns, and other firm characteristics.

² See, for example, Gomes (2001), Hennessy and Whited (2005), and Zhang (2005). In addition, Gourio (2008) estimates the persistence of the idiosyncratic shock to be 0.7 annually using Compustat data on investment and profitability, which is in line with our estimates.

2.1. Data

The key variables for estimating the firm-level productivity are the firm-level value added, employment, and capital. We use firm-level data from Compustat and supplement it with output and investment deflators from the Bureau of Economic Analysis and wage data from the Social Security Administration. The sample is an unbalanced panel with approximately 12,750 distinct firms spanning the years between 1962 and 2009. Following Fama and French (1992), we start our sample in 1962 since Compustat data for earlier years have a serious selection bias. Estimation of TFPs requires at least two years of data, so our TFP estimates start in 1963. Some of the key variables are firm-level capital stock (k_{it}) given by gross plant, property, and equipment (PPEGT), deflated following Hall (1990), and the stock of labor (l_{it}) given by the number of employees (EMP), both from Compustat. We compute firm-level value added using Compustat data on sales, operating income, and employees; we then deflate it using the output deflator.

Monthly stock returns are from the Center for Research in Security Prices (CRSP). We measure the contemporaneous returns over the same horizon as TFPs, matching year t TFPs to returns from January of year t to December of year t . In predictability regressions (calculating the future returns), to ensure that accounting information is already impounded into stock prices, we match CRSP stock return data from July of year t to June of year $t + 1$ with accounting information for fiscal year ending in year $t - 1$, as in Fama and French (1992, 1993), allowing for a six-month gap between fiscal year-end and return tests. To ensure that the accounting data is not outdated by the time of the sorting procedure, our sample includes firms with fiscal year ending in December.³ In other words, we match the productivities calculated using accounting data for the fiscal year ending in December of year $t - 1$ (spanning from 1963 to 2009) to stock returns from July of year t to June of year $t + 1$ (from July 1964 to June 2011). However, our results are very similar if we drop this December fiscal year-end restriction. We provide those results in the online appendix. Similar to Fama and French (1993), our sample includes firms with ordinary common equity as classified by CRSP, excluding ADRs, REITs, and units of beneficial interest, and in order to avoid the survival bias in the data, we include firms in our sample after they have appeared in Compustat for two years. Detailed information about the data is provided in the online appendix.

³ This is the approach followed by many papers in this literature, including Liu et al. (2009), Eisefeldt and Papanikolaou (2013), and Belo et al. (2014).

2.2. TFP

Total factor productivity is a measure of the overall effectiveness with which capital and labor are used in a production process. It provides a broader gauge of firm-level performance than some of the more conventional measures, such as labor productivity or firm profitability.⁴

We estimate the production function given in

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \omega_{it} + \eta_{it}, \quad (1)$$

where y_{it} is the log of value added for firm i in period t ; l_{it} and k_{it} are log values of labor and capital of the firm, respectively; ω_{it} is the productivity; and η_{it} is an error term not known by the firm or the econometrician. We employ the semiparametric procedure suggested by Olley and Pakes (1996) to estimate the parameters of this production function, which is explained in detail in the online appendix. The major advantage of this approach over more traditional estimation techniques such as the ordinary least squares (OLS) is its ability to control for selection and simultaneity biases and deal with the within firm serial correlation in productivity that plagues many production function estimates.

Once we estimate the production function parameters ($\hat{\beta}_0$, $\hat{\beta}_l$, and $\hat{\beta}_k$), we obtain the firm-level (log) TFPs by

$$\omega_{it} = y_{it} - \hat{\beta}_0 - \hat{\beta}_l l_{it} - \hat{\beta}_k k_{it}. \quad (2)$$

In the estimation, we use industry-specific time dummies. Hence, our firm TFPs are free of the effect of industry or aggregate TFP in any given year.

The production function parameters are estimated every year using all data available up until that year to mitigate a potential look-ahead bias in the TFP estimates. We compute TFPs for each year between 1960 and 2010 using that year's data and the corresponding production function estimates for that year. The estimates for β_l and β_k are quite stable over the years: β_l ranges from 0.68 to 0.76, and β_k ranges from 0.21 to 0.31. The results for the entire sample period and all firms yield a labor share (and standard errors) of 0.75 (0.002) and a capital share of 0.23 (0.003). The estimates for the persistence and conditional volatility of TFP are 0.70 and 0.27, respectively, at the annual frequency.⁵ Production function estimates are fairly

⁴ Profitability captures only the part of the value added that goes to shareholders, and labor productivity can be an inadequate measure of overall efficiency especially in capital intensive industries. See Lieberman and Kang (2008) for a case study of a Korean steelmaker for the differences between TFP and profitability in measuring firm performance.

⁵ The conditional volatility of TFP is computed from the persistence and the cross-sectional standard deviation of firm productivity as 0.27 ($= 0.38 \times \sqrt{1 - 0.7^2}$). The cross-sectional dispersion of firm-level productivity increases from 0.23 in 1963 to 0.53 in 2009. We take the cross-sectional standard deviation to be 0.375, which is the average dispersion over this time period.

similar for the manufacturing (labor share 0.785, capital share 0.196) and nonmanufacturing sectors (labor share 0.723, capital share 0.255). The autocorrelation of TFP is 0.696 for manufacturing and 0.676 for nonmanufacturing firms. Having stable production function estimates over time and for different industries is reassuring since it contributes to the robustness of our asset pricing results to different specifications and data samples. We check the sensitivity of our estimates to a number of alternative specifications, which are summarized in the online appendix.

To gauge the sensibility of our TFP measure, we contrast some of its properties with those obtained from studies that use longitudinal microlevel data sets. For example, we find a significant dispersion in firm-level TFPs. Average TFP of the firms in the lowest TFP portfolio is approximately half of the average TFP of all firms in that year, whereas it is almost twice the average TFP in the highest TFP portfolio. Using data for four-digit textile industries, Dwyer (1998) finds the ratio of the average TFP for firms in the ninth decile of the productivity distribution relative to the average in the second decile to be between 2 and 4 at the plant level. Similar findings are reported in Olley and Pakes (1996) for the telecommunications equipment industry and in Syverson (2004) for four-digit manufacturing industries. For our sample, which consists of TFPs at the firm level rather than plant level, this measure is 1.8. These comparisons provide some confirmation that the dispersion in TFPs obtained in our sample is consistent with plant level evidence presented earlier.

We also examine the evolution of the productivity by constructing a transition probability matrix, which shows the probability of a firm moving from a certain productivity decile in a period to other deciles in the next period. The online appendix presents the transition probability matrix for the firms in our sample sorted into decile TFP portfolios. The probabilities of staying in the lowest or the highest TFP portfolios are about 50%. Probabilities along the diagonal are higher than the rest, indicating that there is some persistence in productivity. These results are similar to the findings reported in Bartelsman and Dhrymes (1998) who examine the transition probabilities of plant-level TFPs in three industries over the 1972–1986 period. They report that about 50%–70% of the plants in the lowest and highest deciles tend to stay in the same bin for all three industries.

2.3. TFP and Firm Characteristics

Table 1 presents the summary statistics and various firm characteristics for firms sorted into 10 portfolios based on the level of their TFP over the 1963–2009 period. Following Fama and French (2008), we set the portfolio breakpoints based on a sample of firms

that excludes microcap firms (firms smaller than the 20th percentile of market cap for NYSE stocks). Including the microcap firms when setting the breakpoints leads to few small or big stocks in extreme portfolios. Note that microcap firms are still included in the portfolios; they are only excluded from the computation of the breakpoints. Although this sorting procedure leads to more stable and balanced portfolios, we get similar results when we compute the breakpoints based on the entire cross section of firms, which are tabulated in the online appendix. The first row provides data on TFP levels of the firms in these portfolios, where average TFP is normalized to be one.

Results in Table 1 indicate a strongly monotonic relationship between TFP and many firm characteristics, including firm size and book-to-market ratios of firms. Market capitalization of firms monotonically increase with TFP. The average size of the firms in the lowest TFP decile is 22% of the average size of all firms in that year, whereas the average size of firms in the highest TFP decile is 386% of the average size.⁶ The book-to-market ratios of the firms monotonically decline with TFP, indicating that high TFP firms are typically growth firms and low TFP firms are value firms. The cross correlation between TFP and SIZE is 0.38 and between TFP and B/M is -0.37 .⁷

The hiring rate, fixed investment to capital ratio, asset growth, investment to capital for organizational capital, and inventory growth are all monotonically increasing in firm-level TFP.⁸ The cross correlations between TFP and investment to capital ratio, the hiring rate, inventories, and asset growth are 0.24, 0.14, 0.11, and 0.23, respectively. The differences in these firm characteristics between the high and low TFP portfolios are significant for all cases. There is significant dispersion in investment to capital ratios of firms; the ratio for fixed investment ranges from 10% for low productivity firms to 32% for high productivity firms, whereas the ratio for organizational capital ranges between 38% to 63%. The results are similar for hiring rate, inventory growth, and asset growth.

⁶ Since the nominal sizes of the firms have a growing trend, we prefer to look at the relative sizes of the firms (firm size/average firm size in that year). The average firm size is approximately \$500 million in 1963 and \$4.5 billion in 2009.

⁷ We calculate the cross correlations across individual stocks each year and then average them across time. Cross correlations between firm characteristics and TFP are presented in the online appendix.

⁸ Fixed investment to capital ratio is given by firm-level gross capital investment (capital expenditures in Compustat deflated by the price deflator for investment) divided by the beginning of the period capital stock. Hiring rate at time t is the percent change in the stock of labor from time $t - 1$ to t . Organizational capital is viewed as a firm-specific capital good that is embodied in the organization itself. We measure organizational capital based on a firm's sales, general, and administrative expenses as in Eisfeldt and Papanikolaou (2013).

Table 1 Descriptive Statistics for TFP-Sorted Portfolios, 1963–2009

	Low	2	3	4	5	6	7	8	9	High	High-Low
TFP	0.61	0.80	0.87	0.93	0.98	1.04	1.12	1.22	1.40	2.06	1.46
SIZE	0.22	0.42	0.59	0.72	0.89	1.25	1.74	2.00	2.88	3.86	3.65
B/M	1.38	1.17	1.00	0.92	0.83	0.76	0.69	0.63	0.54	0.51	−0.87
I/K	0.10	0.10	0.12	0.13	0.14	0.15	0.17	0.20	0.23	0.32	0.22
AG	0.03	0.08	0.12	0.14	0.16	0.20	0.19	0.21	0.26	0.32	0.29
HR	0.00	0.03	0.06	0.08	0.10	0.12	0.11	0.12	0.20	0.18	0.18
INV	0.07	0.11	0.11	0.14	0.19	0.23	0.22	0.44	0.25	0.33	0.26
I_{OC}/OC	0.38	0.36	0.38	0.41	0.41	0.43	0.45	0.50	0.53	0.63	0.25
R&D/PPE	0.08	0.05	0.05	0.05	0.05	0.07	0.07	0.10	0.13	0.20	0.12
RER (*10)	0.02	0.01	0.02	−0.01	0.01	−0.06	−0.01	−0.05	−0.02	−0.20	−0.23
NS	−0.08	−0.07	−0.06	−0.07	−0.06	−0.06	−0.07	−0.10	−0.10	−0.14	−0.06
LEV	0.30	0.29	0.27	0.25	0.23	0.21	0.19	0.17	0.14	0.13	−0.17
ROE	−0.11	0.04	0.07	0.10	0.11	0.12	0.14	0.16	0.17	0.19	0.30
ROA	−0.03	0.03	0.04	0.05	0.06	0.07	0.08	0.08	0.10	0.11	0.14
GPR	0.33	0.38	0.40	0.41	0.42	0.42	0.43	0.44	0.46	0.48	0.14
AGE	16.27	18.09	18.34	17.94	18.23	17.65	17.66	16.70	16.29	14.32	−1.95
N	212	139	110	98	90	85	81	78	73	69	

Notes. For each variable, averages are first taken over all firms in that portfolio, then over years. Average TFP each year is normalized to be 1. SIZE is the market capitalization of firms in June of year $t + 1$. Average size each year is normalized to 1. B/M is the ratio of book equity for the last fiscal year-end in year t divided by market equity in December of year t . I/K is the fixed investment to capital ratio. AG is the change in the natural log of assets, HR is the change in the natural log of number of employees, and INV is the change in the natural log of total inventories, all measured from year $t - 1$ to year t . I_{OC}/OC is the ratio of investment in organization capital to the stock of organization capital in year t , both computed from the deflated sales, general and administrative expenses. R&D/PPE is the ratio of research and development expenses to gross PPE in year t . RER is the ratio of buildings + capital leases to PPE in year t , adjusted for industries. NS is the change in the natural log of the split-adjusted shares outstanding from the fiscal year-end in $t - 1$ to t . LEV is the ratio of long-term debt holdings in year t to the firm's total assets calculated as the sum of their long-term debt and the market value of their equity in December of year t . ROE is the net income in year t divided by book equity for year t . ROA is the net income in year t divided by total assets for year t . GPR is the gross profits in year t divided by book assets for year t . AGE is the number of years since the firm first shows up in Compustat. N is the average number of firms in each portfolio in year t . Portfolio breakpoints are based on a sample of firms that excludes microcap firms.

The firms in the lowest productivity decile do not increase their workforce and their assets grow on average 3%, whereas firms in the highest productivity decile increase their workforce by 18% and experience 32% asset growth. Inventory growth varies between 7% and 33%. The ratio of research and development expense (R&D) to the property, plant, and equipment (PPE) of the firm also tends to increase with TFP, but the relationship is not perfectly monotonic. Table 1 also shows that the real estate ratio of low productivity firms exceeds the average in their industry, whereas the real estate ratio of high productivity firms is lower than their industry average. The relationship between the average age (computed as the number of years since the firm first shows up in Compustat) and TFP is inverse U-shaped.

We also investigate the relationship between firm TFP and measures of profitability. Productivity and profitability have often been used interchangeably in finance literature (e.g., Gourio 2007, Novy-Marx 2013) where unobserved productivity is frequently proxied by measures of profitability.⁹ We look at three

profitability measures. Our first measure is the return on equity (ROE) used in Fama and French (2008) and calculated as net income available to common stockholders/book equity. The second measure is the return on assets (ROA), defined as net income/total assets. The last profitability measure (GPR) is gross profits/book assets from Novy-Marx (2013). All three measures of profitability are monotonically and positively related to TFP. The cross correlation of TFP with GPR is quite modest (0.19), whereas its correlations with ROE and ROA are higher (0.46 and 0.59, respectively).

We report additional firm characteristics that are found to be related to future stock returns. Net stock issues (net shares) are on average negative for all portfolios but are particularly low for high TFP firms. Also, TFP is negatively related to leverage, with the least productive firms possessing the highest leverage.

2.4. Asset Pricing Implications

2.4.1. Returns of TFP-Sorted Portfolios. In Table 2, we investigate the relationship between our firm-level TFPs and the contemporaneous and future annualized excess returns (excess of the risk free rate). The table presents both equal and value-weighted portfolio returns for firms sorted into 10 portfolios based on the level of TFP in year t . Our results show that TFP

⁹ Even though productivity and profitability are expected to be related, their calculation and interpretation are different. Profits can be interpreted as the rents to capital owners (which are the owners of the firm), whereas productivity is a measure of how efficient the firm is in converting inputs (labor and capital) to outputs (value added).

Table 2 Excess Returns for TFP-Sorted Portfolios (% Annualized)

	Low	2	3	4	5	6	7	8	9	High	High-Low
Contemporaneous returns, January 1963–December 2009											
r_{EW}^e	0.52 (0.14)	8.35 (2.40)	11.19 (3.32)	12.42 (3.76)	13.52 (4.09)	14.84 (4.55)	16.01 (5.07)	16.99 (5.27)	18.63 (5.66)	20.22 (5.87)	19.70 (10.85)
σ_{EW}^e	23.48	21.43	20.80	20.40	20.81	20.46	20.01	20.69	20.97	22.18	12.43
r_{VW}^e	−3.42 (−1.01)	2.05 (0.67)	4.70 (1.72)	4.46 (1.58)	5.55 (2.06)	5.86 (2.19)	7.44 (3.12)	5.46 (2.22)	6.93 (2.92)	8.95 (3.45)	12.37 (5.82)
σ_{VW}^e	22.11	20.09	17.98	18.45	17.97	17.70	16.34	16.59	16.23	17.39	14.10
Future returns, July 1964–June 2011											
All states, 564 months											
r_{EW}^e	14.01 (3.62)	11.88 (3.52)	10.51 (3.16)	10.67 (3.20)	9.98 (3.11)	9.65 (3.03)	7.60 (2.41)	8.96 (2.74)	8.11 (2.45)	6.65 (1.94)	−7.35 (−3.99)
σ_{EW}^e	23.48	21.43	20.80	20.40	20.81	20.46	20.01	20.69	20.97	22.18	12.43
r_{VW}^e	7.40 (2.23)	6.65 (2.24)	7.23 (2.49)	6.82 (2.32)	6.27 (2.40)	6.38 (2.43)	4.71 (1.92)	5.62 (2.23)	5.38 (2.16)	4.85 (1.80)	−2.55 (−1.26)
σ_{VW}^e	22.11	20.09	17.98	18.45	17.97	17.70	16.34	16.59	16.23	17.39	14.10
Expansions, 468 months											
r_{EW}^e	9.22 (2.23)	7.80 (2.17)	6.99 (1.95)	6.69 (1.86)	6.31 (1.83)	6.70 (1.94)	4.60 (1.35)	5.67 (1.61)	5.33 (1.49)	4.79 (1.30)	−4.43 (−2.34)
σ_{EW}^e	23.62	20.41	20.51	20.59	19.82	19.90	19.99	20.38	20.76	21.53	11.72
r_{VW}^e	4.01 (1.12)	4.59 (1.43)	5.29 (1.68)	4.36 (1.35)	4.28 (1.48)	4.74 (1.65)	2.75 (1.03)	4.03 (1.46)	4.34 (1.63)	4.26 (1.47)	0.25 (0.12)
σ_{VW}^e	21.22	19.08	18.98	19.42	17.28	17.35	16.28	16.66	16.14	17.37	13.04
Contractions, 96 months											
r_{EW}^e	37.33 (3.83)	31.79 (3.66)	27.68 (3.29)	30.04 (3.62)	27.85 (3.46)	24.04 (2.99)	22.26 (2.83)	25.00 (3.02)	21.69 (2.59)	15.71 (1.74)	−21.61 (−4.22)
σ_{EW}^e	24.49	22.03	21.39	21.06	20.42	20.80	19.88	21.80	21.55	23.51	13.78
r_{VW}^e	23.93 (2.75)	16.71 (2.19)	16.69 (2.22)	18.83 (2.69)	16.00 (2.56)	14.42 (2.18)	14.30 (2.32)	13.39 (2.17)	10.45 (1.53)	7.70 (1.06)	−16.22 (−3.28)
σ_{VW}^e	23.15	21.34	20.17	18.83	17.39	18.30	17.07	17.53	19.34	19.62	13.91

Notes. In this table, r_{EW}^e is equal-weighted monthly excess returns (excess of risk free rate); r_{VW}^e is value-weighted monthly excess returns, annualized (averages are taken over time (%)); and σ_{EW}^e and σ_{VW}^e are the corresponding standard deviations. Contemporaneous returns are measured in the year of the portfolio formation, from January of year t to December of year t . Future returns are measured in the year following the portfolio formation, from July of year $t + 1$ to June of year $t + 2$ and annualized (%). The t -statistics, computed using the Newey–West estimator allowing for one lag of serial correlation in returns, are in parentheses. We annualize numbers by multiplying by 12. Expansion and contraction periods are designated in June of year $t + 1$ based on the level of (one-sided HP-filtered) industrial production in May of that year. Returns over the expansions and contractions are measured from July of year $t + 1$ to June of year $t + 2$. Their t -statistics are computed from a regression of returns on expansion and contraction indicator variables (without an intercept), using the Newey–West correction.

is positively and monotonically related to contemporaneous stock returns. The difference between the contemporaneous returns of high and low TFP firms is 19.7% for equal-weighted portfolios and 12.4% for value-weighted portfolios, and both spreads are statistically significant.¹⁰ The relationship between the level of TFP and future excess returns is equally striking for equal-weighted portfolios: low productivity firms on average earn a 7.4% annual premium over high productivity firms in the following year, and the

return spread is statistically significant. The unconditional return spread is lower (2.6%) and not significant for the value-weighted portfolios.¹¹

To understand the relationship between TFP and future returns over the business cycles, we separate our sample into expansionary and contractionary periods around the portfolio formation time. We use industrial production as our business cycle variable. Industrial production is a widely used measure of economic activity that is available at monthly

¹⁰ In untabulated results, we find even a stronger relationship between the innovations in TFP and contemporaneous stock returns. When we sort firms based on innovations in TFP, the spread in returns is 42% for the equal-weighted and 22% for the value-weighted portfolios.

¹¹ We get similar results when we relax the December fiscal year-end requirement and compute the breakpoints based on the entire cross section of firms: -7.65% ($t = 4.10$) return spread for the equal-weighted portfolios and -1.29% ($t = 0.59$) for the value-weighted portfolios. We reproduce Table 2 with these procedures and present it in the online appendix.

frequency (as opposed to the gross domestic product (GDP), which is available at quarterly frequency). We define recessions as periods when industrial production is more than one standard deviation below its mean.¹² We designate recession/expansion in June of each year and look at the returns of TFP-sorted portfolios over the following 12 months.

We find that the negative relationship between TFP and expected returns persists both in expansions and in contractions for equal-weighted portfolios. However, there are significant differences in returns over the business cycles. The average level of expected returns is much higher in recessions, approximately 25%, than expansions, 6.5%. The spread between the returns of high and low TFP portfolios is also much higher during contractions, 21.6%, than expansions, 4.4%, in equal-weighted portfolios. For value-weighted portfolios, the spread is 16% and is significant over contractions. During expansions, however, the spread is not significant.

Even though all portfolios have higher expected returns in recessions, the increase in expected returns of low TFP portfolios is particularly large, from 9% in expansions to 37% in contractions. For high TFP firms, expected returns increase from 5% in expansions to 16% in contractions. We interpret the spread in the average returns across these portfolios, especially in recessions, as the risk premia associated with the higher risk of low productivity firms.

In Table 3, we investigate whether widely used asset pricing models such as the capital asset pricing model (CAPM) and Fama–French (FF) three-factor model capture the variation in excess returns of TFP-sorted portfolios. As we demonstrate in Table 1, TFP is significantly related to size and B/M at the firm level. Hence, we explore whether the returns of TFP-sorted portfolios are systematically related to SMB and HML.¹³

¹² We apply a one-sided HP-filter to the monthly industrial production series (smoothing parameter is 129,600, based on Ravn and Uhlig 2002). A standard HP-filter uses observations at $t + i$, $i > 0$, to construct the time t point estimates, and hence would introduce lookahead bias in the estimates, whereas a one-sided filter does not. The industrial production for the past month is typically announced two–three weeks after the end of the month. We designate recession/expansion years at the end of June of each year based on the industrial production levels in May to make sure that the data is available to investors in real time. The National Bureau of Economic Research (NBER) business cycle dates are typically announced several months after the start of recessions/expansions and so are not available to investors in real time. Nevertheless, our recession designations based on industrial production and NBER dates match almost perfectly, so the results are nearly identical if we use NBER dates instead.

¹³ MKT is excess market returns; SMB is returns of portfolio that is long in small, short in big firms; HML is returns of portfolio that is long in high B/M, short in low B/M firms. (Fama and French 1992, 1993; among others).

Table 3 presents the alphas and betas of TFP-sorted portfolios for the CAPM and FF models. Betas are estimated by regressing the portfolio excess returns on the factors. Alphas are estimated as intercepts from the regressions of excess portfolio returns. Monthly alphas are annualized by multiplying by 12. The top panel reports the results for the equally weighted portfolios, and the lower panel reports the value-weighted portfolio results.

We find that low TFP portfolios load heavily on SMB, whereas the loadings of the high TFP portfolios are low, even negative in some cases. The loadings on HML are nonmonotonic, but higher TFP portfolios have lower loadings than lower TFP portfolios. The equal-weighted portfolios have a nonmonotonic loading on MKT, whereas the value-weighted low TFP portfolios have significantly higher loading on MKT compared to the high TFP portfolios. Neither the CAPM, nor the FF three-factor model completely explain the return spread in the equally weighted portfolios: the high-low TFP portfolio has a CAPM alpha around -8% and FF alpha of -4% , which are both statistically significant. The spreads in alphas of value-weighted portfolios are not statistically significant.

Our takeaway from these results is not necessarily that TFP is a separate risk factor that is not captured by these factors but rather that TFP is systematically related to SMB, and to some extent to HML, which we further investigate empirically and through a model economy.

2.4.2. Fama–MacBeth Regressions. In this section, we run Fama–MacBeth cross-sectional regressions (Fama and MacBeth 1973) of monthly stock returns on lagged firm-level TFP as well as other control variables. The estimates of the slope coefficients in Fama–MacBeth regressions allow us to determine the magnitude of the effect of the firm characteristics on excess stock returns. In all specifications, the dependent variable is the excess monthly stock returns, annualized to make the magnitudes comparable to the results in Table 2.

The cross-sectional regression, where log TFP is the only explanatory variable, produces an average slope of -5.4 . The magnitude of the effect is significant both statistically (t -statistics -3.3) and economically. The -5.4 average regression coefficient translates into approximately 8% higher expected returns for the firms in the lowest TFP decile compared to a firm in the highest TFP decile.

Next, we examine the marginal predictive power of TFP after controlling for several firm characteristics that are known to predict stock returns. We find that the cross-sectional regressions that include investment to capital ratio; hiring rate; inventory growth; asset growth; different measures of profitability (ROE,

Table 3 Alphas and Betas of Portfolios Sorted on TFP (% Annualized)—Dependent Variable: Excess Returns, July 1964–June 2011

	Low	2	3	4	5	6	7	8	9	High	High-Low
Equal-weighted portfolios											
CAPM											
Alpha	7.80 (3.50)	6.10 (3.51)	4.65 (2.89)	4.72 (3.01)	4.09 (2.92)	3.65 (2.78)	1.64 (1.26)	2.78 (2.09)	1.83 (1.40)	0.13 (0.10)	−7.67 (−4.13)
MKT	1.19 (22.94)	1.11 (25.22)	1.12 (26.77)	1.14 (27.97)	1.13 (34.51)	1.15 (36.78)	1.14 (37.09)	1.19 (40.26)	1.21 (41.14)	1.25 (42.16)	0.06 (1.47)
FF											
Alpha	3.07 (2.26)	1.37 (1.37)	0.34 (0.36)	0.63 (0.64)	0.83 (0.84)	1.02 (1.15)	−1.06 (−1.14)	0.89 (0.94)	0.47 (0.47)	−0.68 (−0.61)	−3.75 (−2.52)
MKT	1.03 (29.31)	1.03 (34.83)	1.05 (36.53)	1.07 (34.41)	1.07 (35.14)	1.06 (41.14)	1.07 (38.83)	1.08 (42.24)	1.09 (39.63)	1.11 (44.22)	0.08 (2.62)
HML	0.39 (5.36)	0.50 (9.73)	0.46 (8.44)	0.43 (7.89)	0.34 (6.20)	0.22 (4.58)	0.24 (4.67)	0.09 (1.98)	0.01 (0.22)	−0.09 (−2.18)	−0.48 (−6.75)
SMB	1.10 (16.91)	0.83 (13.23)	0.75 (11.22)	0.73 (11.66)	0.58 (8.71)	0.61 (9.62)	0.58 (8.41)	0.58 (10.92)	0.55 (11.83)	0.55 (11.34)	−0.55 (−11.18)
Value-weighted portfolios											
CAPM											
Alpha	1.00 (0.69)	0.83 (0.65)	1.59 (1.29)	1.10 (0.88)	1.06 (1.00)	1.12 (1.02)	−0.22 (−0.22)	0.59 (0.54)	0.59 (0.47)	−0.36 (−0.29)	−1.36 (−0.70)
MKT	1.23 (41.48)	1.12 (37.39)	1.08 (30.04)	1.10 (31.02)	1.00 (44.18)	1.01 (42.92)	0.95 (45.23)	0.97 (36.83)	0.92 (29.51)	1.00 (36.44)	−0.23 (−5.51)
FF											
Alpha	−0.55 (−0.40)	−1.11 (−0.92)	−0.65 (−0.56)	−0.36 (−0.32)	0.21 (0.20)	0.43 (0.39)	0.01 (0.01)	1.29 (1.24)	1.48 (1.24)	1.33 (1.19)	1.88 (1.11)
MKT	1.19 (35.76)	1.15 (33.96)	1.12 (35.19)	1.15 (29.86)	1.05 (44.45)	1.05 (43.64)	0.98 (41.59)	1.01 (37.53)	0.98 (34.27)	1.00 (37.92)	−0.19 (−4.39)
HML	0.15 (2.39)	0.30 (5.76)	0.34 (5.98)	0.26 (4.03)	0.18 (3.78)	0.15 (3.67)	0.01 (0.33)	−0.03 (−0.61)	−0.03 (−0.63)	−0.22 (−5.26)	−0.37 (−4.78)
SMB	0.31 (5.43)	0.12 (1.84)	0.16 (3.66)	0.01 (0.09)	−0.07 (−1.33)	−0.05 (−1.16)	−0.13 (−2.70)	−0.24 (−7.89)	−0.30 (−8.73)	−0.20 (−5.54)	−0.51 (−8.22)

Notes. This table presents the regressions of equal-weighted and value-weighted excess portfolio returns on various factor returns. MKT, SMB, and HML factors are taken from Ken French's website (<http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/>). The portfolios are sorted on TFP. Alphas are annualized (%). Returns are measured from July 1964 to June 2011. The *t*-statistics, computed using the Newey–West estimator allowing for one lag of serial correlation in returns, are in parentheses.

ROA, gross profitability); net shares; real estate ratio; leverage; R&D; and firm age all produce negative and statistically significant average slopes for TFP. Only the specifications that include book to market and size erode the significance of TFP.¹⁴

The results of these predictability regressions should be interpreted with caution, however. In production-based asset pricing models, shocks to firm-level productivity create ex post differences across firms in terms of the level of TFP, which affect the riskiness of a stock and its future expected returns. The same shock is the fundamental variable that drives

the differences in size, B/M, and many other firm characteristics across firms. To the extent that such models correctly describe firm behavior, characteristics such as size, B/M, and investment/capital ratio should be strongly correlated with productivity. Furthermore, even if firm productivity is the fundamental variable that drives firm behavior, it is arguably measured with more noise than characteristics such as size or B/M, which are observable rather than estimated. As a result, in return predictability regressions, which include both firm productivity and other firm characteristics as forecasting variables, the better measured variables are expected to drive out productivity. Our overall goal is to shed some light on why firm characteristics can rationally predict returns and not necessarily to come up with a variable that outperforms other firm characteristics in return predictability regressions.

TFP, Expected Profitability, and Expected Investment. The results of the Fama–MacBeth regressions, similar to our earlier results based on portfolio sorts,

¹⁴ Average slopes (and the *t*-statistics) of TFP while controlling for the following firm characteristics are −4.4 (−2.5) for investment to capital ratio; −4.7 (−2.7) for hiring rate; −4.7 (−2.6) for inventory growth; −3.5 (−2.0) for asset growth; −3.9 (−2.9) for ROE; −3.2 (−2.3) for ROA; −6.4 (−3.8) for gross profitability; −5.4 (−3.2) for net shares; −7.0 (−3.3) for real estate ratio; −4.2 (−2.8) for leverage; −5.7 (−3.4) for R&D; and −5.5 (−3.3) for firm age. The average slope declines to −1.5 (−1.1) controlling for book to market and to −1.7 (−1.5) controlling for size.

demonstrate that high TFP firms have lower future returns. In §2.3 we also show that TFP is positively related to both firm investments and profitability. These results may be somewhat surprising, given that the literature has documented a negative relationship between investments and future returns, but generally positive relationship between profitability and future returns.

To understand the relationship between the market/book value of the equity, expected future profitability, expected future investments, and expected returns in more detail, we use the valuation equation given in Fama and French (2006):

$$\frac{M_t}{B_t} = \sum_{\tau=1}^{\infty} \frac{E((Y_{t+\tau}/B_t) - (\Delta B_{t+\tau}/B_t))}{(1+r)^\tau}, \quad (3)$$

where M_t and B_t are the market and book value of equity, respectively, and Y_t is the equity earnings per share. The predictions that come out of the valuation equation about the link between expected returns, r ; expected investments, $E_t(\Delta B_{t+\tau}/B_t)$; and expected profitability, $E_t(Y_{t+\tau}/B_t)$, are the following: (1) Controlling for the M/B , and expected profitability, firms with high expected investment (and asset growth) have low expected stock returns. (2) Controlling for the M/B , and expected asset growth, firms with high expected profitability have high expected stock returns. Therefore, expected profitability and expected investment are related to expected returns with the opposite sign after controlling for the remaining two variables. Proxying for expected future profitability and investments with current profitability and investments, Fama and French (2006) have confirmed these relationships in the data.¹⁵

Table 4 investigates how TFP is related to future profitability and asset growth in Equation (3).¹⁶ We find that TFP strongly predicts both future profitability and future asset growth for several years. The slope coefficient estimates imply that profitability and asset growth of firms in the highest TFP decile will be roughly 14 and 17 percentage points higher, respectively, than the firms in the lowest TFP decile in the next year. Slightly higher slope coefficient estimates for the asset growth, at least in the first year, imply that TFP produces wider spreads in future asset growth than in future profitability.¹⁷ Furthermore, TFP is strongly positively related to M/B

Table 4 Forecasting Profitability and Asset Growth with TFP

j (years)	TFP slope coefficients predicting:	
	Profit _{$t+j$} /Asset _{t}	(Asset _{$t+j$} – Asset _{$t+j-1$})/Asset _{t}
1	0.095 (31.7)	0.113 (11.3)
2	0.091 (11.4)	0.067 (3.9)
3	0.080 (16.0)	0.055 (4.2)

Notes. This table presents the results of panel regressions of future profitability (Profit _{$t+j$} /Asset _{t}) and asset growth ((Asset _{$t+j$} – Asset _{$t+j-1$})/Asset _{t}) on TFP. Profit is net income, as defined in Fama and French (2008). Asset is total assets. Year fixed effects are included. The sample period is from 1964 to 2009, and the total number of observations varies between 34,707 and 43,106. Standard errors are clustered by firm, and t -statistics are in parentheses.

(Table 1), which, according to Equation (3), implies low expected returns. Thus our results appear consistent with basic valuation theory and the recent empirical work in this area.

2.4.3. Ex Ante Discount Rates of TFP-Sorted Portfolios. In both the portfolio approach and the Fama–MacBeth regressions reported in the previous section, we proxy expected returns with ex post realized returns. A common concern about approximating expected returns with realized returns is that the realized returns are very volatile and can be a bad proxy for expected returns, especially with relatively short time-series data. To address this concern, we use an ex ante measure of the discount rates, the implied cost of capital, and examine its cross-sectional relationship with TFP.

The implied cost of capital (ICC) of a given firm is the internal rate of return that equates the firm's stock price to the present value of expected future cash flows (earnings forecasts). Most ICC estimates in the literature, such as Gebhardt et al. (2001; hereafter, GLS), rely on analyst forecasts of future earnings. However, analyst forecasts are not available in the first few years of our sample period. Furthermore, analysts tend to follow larger and more visible stocks, so earnings forecasts of many firms in our sample are not available. As an alternative, Hou et al. (2012; hereafter, HVDZ) and Tang et al. (2014; hereafter, TWZ) use statistical models to forecast earnings and ROE, respectively. We use ICC measures calculated as described in GLS, HVDZ, and TWZ.

they predict each other. Also, sorting firms on TFP produces wider spreads in asset growth compared to the spreads generated by sorting on profitability; and also wider spreads in profitability, compared to the spreads generated by sorting firms on asset growth. Hence, TFP is more related to asset growth and profitability than they are to each other.

¹⁵ Novy-Marx (2013) and Hou et al. (2012) report similar findings.

¹⁶ We scale firm profits by total assets, rather than book equity, to be able to compare the slope coefficients from two regressions.

¹⁷ Fama and French (2006) also document that profitability and asset growth are related. They find that, in univariate regressions, current profitability predicts future asset growth and current asset growth predicts future profitability with positive sign. In untabulated results, we find that TFP predicts both variables better than

Table 5 Implied Cost of Capital for TFP-Sorted Portfolios (% Annualized)

	Low	2	3	4	5	6	7	8	9	High	High-Low
All states											
GLS_{EW}	10.73	10.60	10.67	10.13	9.86	9.63	9.27	9.27	8.86	9.02	−1.71 (−6.65)
GLS_{VW}	9.68	9.49	9.60	9.14	9.02	9.05	8.48	8.28	8.16	8.50	−1.18 (−3.56)
$HVDZ_{EW}$	13.57	12.67	11.49	10.95	10.26	9.73	9.36	8.84	8.28	8.18	−5.39 (−18.88)
$HVDZ_{VW}$	8.91	8.93	8.72	8.57	8.27	8.18	7.72	7.52	7.14	7.20	−1.71 (−5.09)
TWZ_{EW}	9.77	10.15	9.76	9.46	9.02	8.68	8.48	8.03	7.41	7.25	−2.53 (−6.98)
TWZ_{VW}	8.77	9.00	8.74	8.63	8.37	8.16	7.89	7.67	7.07	6.91	−1.86 (−5.39)
Expansions											
GLS_{EW}	10.47	10.44	10.17	9.96	9.69	9.48	9.15	9.15	8.76	8.90	−1.58 (−5.80)
GLS_{VW}	9.42	9.28	9.39	9.01	8.79	8.88	8.33	8.23	7.96	8.34	−1.08 (−2.81)
$HVDZ_{EW}$	12.88	12.08	11.11	10.49	9.90	9.41	9.00	8.52	8.06	7.93	−4.95 (−15.67)
$HVDZ_{VW}$	8.53	8.45	8.44	8.28	7.98	7.89	7.46	7.39	6.87	6.90	−1.63 (−4.35)
TWZ_{EW}	9.37	9.74	9.43	9.17	8.73	8.45	8.13	7.79	7.23	7.07	−2.30 (−6.37)
TWZ_{VW}	8.45	8.64	8.51	8.36	8.08	7.96	7.68	7.63	6.87	6.71	−1.75 (−4.62)
Contractions											
GLS_{EW}	11.97	11.37	13.04	10.95	10.70	10.39	9.84	9.87	9.33	9.59	−2.37 (−3.61)
GLS_{VW}	10.89	10.51	10.61	9.79	10.15	9.85	9.21	8.52	9.15	9.26	−1.63 (−3.34)
$HVDZ_{EW}$	16.40	15.10	13.08	12.85	11.72	11.08	10.84	10.15	9.19	9.22	−7.19 (−20.95)
$HVDZ_{VW}$	10.47	10.91	9.85	9.78	9.47	9.37	8.78	8.05	8.23	8.41	−2.06 (−3.40)
TWZ_{EW}	11.44	11.84	11.11	10.65	10.18	9.65	9.92	9.05	8.14	7.96	−3.49 (−5.72)
TWZ_{VW}	10.08	10.47	9.70	9.71	9.59	9.02	8.77	7.86	7.86	7.74	−2.34 (−4.48)

Notes. GLS_{EW} , $HVDZ_{EW}$, and TWZ_{EW} are equal-weighted implied cost of capital; GLS_{VW} , $HVDZ_{VW}$, and TWZ_{VW} are value-weighted implied cost of capital, annual (averages are taken over time (%)). $HVDZ$ and TWZ expected returns are estimated for the period from July 1970 to June 2011, and GLS expected returns start in July 1976. The t -statistics, computed using the Newey–West estimator allowing for one lag of serial correlation in returns, are in parentheses. Expansion and contraction periods are designated in June of each year (when ICCs are computed) based on the level of (one-sided HP-filtered) industrial production in May of that year. Returns over the expansions and contractions are measured from July of that year to June of the following year. Their t -statistics are computed from a regression of returns on expansion and contraction indicator variables (without an intercept), using the Newey–West correction.

ICC for each firm is estimated at the end of June of each calendar year t using the end-of-June firm market value and the earnings and ROE forecasts made at the previous fiscal year-end. We match the ICC estimates of individual firms with these firms' most recent TFP estimates. $HVDZ$ - and TWZ -based ICCs span the period from July 1970 to June 2011, with roughly 4,200+ unique firms and 37,000 firm \times year observations. GLS based ICCs start in July 1976, and have roughly 3,870 unique firms and 28,000 observations.

Table 5 presents the average implied cost of capital estimates for portfolios sorted on productivity. The relationship between TFP and the cost of capital measured from all three ICC measures is negative and quite monotonic. The firms with low productivity have higher discount rates (ICC) than firms with high productivity using all ICC measures and both for equal- and value-weighted portfolios. The spreads between the high and low TFP firms' expected returns are all negative and highly

statistically significant, implying that firms with low productivity have higher ex ante discount rates, and so are riskier than high productivity firms.

In addition to the unconditional discount rates, Table 5 also presents the ICCs conditional on whether the economy is expanding or contracting around the portfolio formation time. Similar to the results based on average realized returns in Table 2, both the levels of implied cost of capital and the spread between the low and high TFP portfolios are countercyclical. The spreads between the discount rates of low and high TFP portfolios increase roughly 50%–100% for all ICC measures and for both equal and value-weighted portfolios as the economy moves from expansions to contractions. However, most of the increases in expected returns happen in the low TFP portfolio returns. Even though all firms are riskier in recessions, firms with low productivity are hit particularly hard and thus bear more risk than firms with high TFPs.

2.4.4. Inspecting the Mechanism with Operating Performance. Our results indicate that firm-level TFPs are systematically related to many firm characteristics and firms with low TFP have higher future realized returns and implied cost of capital. Furthermore, we document that the return spreads between the low and high TFP firms increase during recessions, and this increase is mostly due to a surge in expected returns of low TFP firms. Our interpretation of this return evidence is that low TFP firms are riskier than high TFP firms, and they are particularly risky in recessions. In this section, we provide additional evidence on the higher risk of low TFP firms that is not based on realized or ex ante returns. We investigate whether there are systematic differences in the sensitivity of low and high TFP firms' operating performance to aggregate shocks in the economy. The existence of such differences would shed some light on the mechanism behind the risk and return differentials between low and high TFP firms.

We conjecture that operating performance of low TFP firms would be more sensitive to aggregate shocks than the high TFP firms, especially during bad economic times. We measure the operating performance of firms with their profitability. To test this hypothesis, we examine pooled time series/cross-sectional regressions of the following form:

$$\Delta \text{Profit}_{it} = b_1 \Delta \text{Profit}_{\text{agg},t} + b_2 \Delta \text{Profit}_{\text{agg},t} \times IP_{t-1} + \varepsilon_{it}, \quad (4)$$

where $\Delta \text{Profit}_{it}$ is the change in the profits (net income) of firm i between year $t - 1$ and t , scaled by firm's assets in year $t - 1$.¹⁸ We proxy aggregate

shocks with the cross-sectional average of $\Delta \text{Profit}_{i,t}$ over all firms in our sample. Replacing $\Delta \text{Profit}_{\text{agg},t}$ with change in aggregate labor productivity reported by the Bureau of Labor Statistics yields similar results. Note that we cannot calculate aggregate productivity by averaging our firm-level TFPs as our TFP estimates are free of industry and year effects. Using ΔProfit on each side of the regression, at the firm level on the left-hand side and aggregate on the right-hand side, brings a beta-like interpretation to the regression coefficients. Our business cycle variable is the one-sided HP-filtered industrial production standardized to have a standard deviation of 1. We separate firms into 10 TFP groups based on their TFPs in year $t - 1$, similar to the decile portfolios used earlier. We run panel regressions in each TFP group and present the results in Table 6.

Examination of panel A reveals that, unconditionally, low TFP firms have higher sensitivity to aggregate shocks in the economy. The regression coefficient is 2 for the firms in the lowest TFP group, goes down to around 0.6 for higher TFP groups, and increases to 0.75 for the firms in the highest TFP group. More importantly, panel B shows that low TFP firms' sensitivity to aggregate shocks increases in bad economic times (when industrial production is low). One standard deviation decrease in industrial production increases the sensitivity of lowest TFP firms by approximately 0.25. The pattern reverses for high TFP firms: Their profits' sensitivity to aggregate shocks increases in good times by approximately 0.5. These results are consistent with our earlier findings based on returns/discount rates and imply a higher risk for low TFP firms, especially when the economy is doing poorly.

3. Model

In this section we investigate whether a standard production-based asset pricing model where firms are subject to both aggregate and idiosyncratic productivity shocks is capable of accounting for the cross-sectional relationship between TFP, firm-level characteristics, and stock returns documented empirically. We calibrate the model using the firm-level TFP estimates summarized in §2.2 and examine the resulting firm-level characteristics and firm returns generated by the model economy.

3.1. Firms

There are many firms that produce a homogeneous good using capital and labor. These firms are subject to different productivity shocks.

The production function for firm i is given by

$$Y_{it} = F(A_t, Z_{it}, K_{it}, L_{it}) = A_t Z_{it} K_{it}^{\alpha_K} L_{it}^{\alpha_L},$$

¹⁸ This regression is obtained from writing our empirical model in levels with year and firm fixed effects and then taking the first differences, which leads to the elimination of year and firm fixed effects.

Table 6 Profitability Regressions for TFP-Sorted Panels—Dependent Variable: $\Delta\text{Profit}_{i,t}$

	Low TFP	2	3	4	5	6	7	8	9	High TFP
Panel A										
$\Delta\text{Profit}_{\text{agg},t}$	2.03 (14.9)	0.85 (8.2)	0.96 (6.8)	0.66 (6.3)	0.62 (6.8)	0.63 (6.2)	0.65 (5.2)	0.69 (6.0)	0.66 (4.6)	0.75 (4.7)
Panel B										
$\Delta\text{Profit}_{\text{agg},t}$	1.81 (15.8)	0.76 (7.9)	0.87 (8.3)	0.74 (8.0)	0.70 (7.3)	0.66 (6.0)	0.85 (6.8)	0.74 (6.3)	0.72 (5.0)	1.19 (7.4)
$\Delta\text{Profit}_{\text{agg},t} \times$ IP_{t-1}	-0.25 (-2.5)	-0.10 (-1.1)	-0.11 (-0.8)	0.10 (1.0)	0.10 (1.5)	0.04 (0.5)	0.26 (3.4)	0.06 (0.6)	0.07 (0.7)	0.54 (4.6)

Notes. This table presents the results of panel regressions of change in firm-level profitability on change in aggregate profitability and change in aggregate profitability conditional on past industrial production. Change in profitability is measured as the level difference between current and past profits, scaled by lagged assets. Change in aggregate profitability is measured as the cross-sectional average of firm-level changes. Firms are sorted into 10 TFP groups based on past year's TFPs. The sample period is from 1964 to 2009, and the total number of observations is 43,106. Standard errors are clustered by firm, and *t*-statistics are in parentheses.

where K_{it} denotes the beginning of period t capital stock of firm i , and L_{it} denotes the labor used in production by firm i during period t . Labor and capital shares are given by α_l and α_k , where $\alpha_l + \alpha_k \in (0, 1)$. Aggregate productivity is denoted by $a_t = \log(A_t)$. a_t has a stationary and monotone Markov transition function, given by $p_a(a_{t+1} | a_t)$, as follows:

$$a_{t+1} = \rho_a a_t + \varepsilon_{t+1}^a, \quad (5)$$

where $\varepsilon_{t+1}^a \sim \text{i.i.d. } N(0, \sigma_a^2)$. The firm productivity, $z_{it} = \log(Z_{it})$, has a stationary and monotone Markov transition function, denoted by $p_{z_i}(z_{i,t+1} | z_{it})$, as follows:

$$z_{i,t+1} = \rho_z z_{it} + \varepsilon_{i,t+1}^z, \quad (6)$$

where $\varepsilon_{i,t+1}^z \sim \text{i.i.d. } N(0, \sigma_z^2)$, and $\varepsilon_{i,t+1}^z$ and $\varepsilon_{j,t+1}^z$ are uncorrelated for any pair of firms (i, j) with $i \neq j$.

The capital accumulation rule is $K_{i,t+1} = (1 - \delta)K_{it} + I_{it}$, where I_{it} denotes investment and δ denotes the depreciation rate of installed capital.

Investment is subject to quadratic adjustment costs given by g_{it} :

$$g(I_{it}, K_{it}) = \frac{1}{2} \eta \left(\frac{I_{it}}{K_{it}} - \delta \right)^2 K_{it}, \quad (7)$$

with $\eta > 0$. In this specification, investors incur no adjustment cost when net investment is zero, i.e., when the firm replaces its depleted capital stock and maintains its capital level.

Firms are equity financed and face a perfectly elastic supply of labor at a given stochastic equilibrium real wage rate W_t , as in Jones and Tüzel (2013a) and Belo et al. (2014). The equilibrium wage rate, given by

$$W_t = \exp(\omega a_t), \quad (8)$$

is assumed to be increasing with aggregate productivity, with $0 \leq \omega \leq 1$ determining the sensitivity of

the relation.¹⁹ Hiring decisions are made after firms observe the productivity shocks and labor is adjusted freely; hence, for each firm, marginal product of labor equals the wage rate

$$F_{L_{it}} = F_L(A_t, Z_{it}, K_{it}, L_{it}) = W_t.$$

Dividends to shareholders are equal to

$$D_{it} = Y_{it} - [I_{it} + g_{it}] - W_t L_{it}. \quad (9)$$

At each date t , firms choose $\{I_{i,t}, L_{i,t}\}$ to maximize the net present value of their expected dividend stream, V_{it} , which is the firm value

$$V_{it} = \max_{\{I_{i,t+k}, L_{i,t+k}\}} E_t \left[\sum_{k=0}^{\infty} M_{t,t+k} D_{i,t+k} \right], \quad (10)$$

subject to Equations (5)–(8), where $M_{t,t+k}$ is the stochastic discount factor between time t and $t+k$.

The first-order conditions for the firm's optimization problem leads to the pricing equation

$$1 = \int \int M_{t,t+1} R_{i,t+1}^I p_{z_i}(z_{i,t+1} | z_{it}) p_a(a_{t+1} | a_t) d_{z_i} d_a, \quad (11)$$

where the returns to investment are given by

$$R_{i,t+1}^I = \frac{F_{K_{i,t+1}} + (1 - \delta)q_{i,t+1} + \frac{1}{2} \eta \left((I_{i,t+1}/K_{i,t+1})^2 - \delta^2 \right)}{q_{it}}, \quad (12)$$

and where

$$F_{K_{it}} = F_K(A_t, Z_{it}, K_{it}, L_{it}).$$

¹⁹ With competitive labor markets, wage equals the value of the marginal product of labor. In general equilibrium with a representative firm, the marginal product of labor is $mpl = \exp(at) \alpha_l L^{\alpha_l - 1} K^{\alpha_k}$. Hence, wage is a function of aggregate productivity, total labor force, and the capital stock used in production. Here we abstract from aggregate labor and capital and model wage as a function of aggregate productivity.

Tobin's (marginal) q , the consumption good value of a newly installed unit of capital, is

$$q_{it} = 1 + \eta \left(\frac{I_{it}}{K_{it}} - \delta \right). \quad (13)$$

The pricing equation (Equation (11)) establishes a link between the marginal cost and benefit of investing. The term in the denominator of the right-hand side of the equation, q_{it} , measures the marginal cost of investing. The terms in the numerator represent the discounted marginal benefit of investing. The firm optimally chooses I_{it} such that the marginal cost of investing equals the discounted marginal benefit.

The returns to the firm are defined as²⁰

$$R_{i,t+1}^S = \frac{V_{i,t+1}}{V_{it} - D_{it}}. \quad (14)$$

3.2. The Stochastic Discount Factor

Since the purpose of our model is to examine the cross-sectional variation across firms, we use a framework where time-series properties of returns are matched by using an exogenous pricing kernel. Following Berk et al. (1999) and Zhang (2005), we directly parameterize the pricing kernel without explicitly modeling the consumer's problem. As in Jones and Tüzel (2013a), the pricing kernel is given by

$$\begin{aligned} \log M_{t+1} &= \log \beta - \gamma_t \epsilon_{t+1}^a - \frac{1}{2} \gamma_t^2 \sigma_a^2, \\ \log \gamma_t &= \gamma_0 + \gamma_1 a_t, \end{aligned} \quad (15)$$

where β , $\gamma_0 > 0$, and $\gamma_1 < 0$ are constant parameters.

This pricing kernel shares a number of similarities with Zhang (2005); M_{t+1} , the stochastic discount factor from time t to $t+1$, is driven by ϵ_{t+1}^a , the shock to the aggregate productivity process in period $t+1$. The volatility of M_{t+1} is time varying, driven by the γ_t process. This volatility takes higher values following business cycle contractions and lower values following expansions, implying a countercyclical price of risk as the result. In the absence of countercyclical price of risk, the risk premia generated in the economy does not change with economic conditions. Empirically, existence of time varying risk premia is well documented (Fama and Schwert 1977, Fama and Bliss 1987, Fama and French 1989, Campbell and Shiller 1991, Cochrane and Piazzesi 2005, Jones and Tüzel 2013b, among many others). Our empirical results in Tables 2 and 5, that average (future) realized returns and implied cost of capital are much higher in contractions, compared to expansions, provide additional motivation for modeling countercyclical price of risk.

²⁰ We do not assume constant returns to scale in the production function. In the presence of constant returns to scale, firm return would be equivalent to the returns to fixed investment, R_{t+1}^I . With slightly decreasing returns to scale, firm returns slightly diverge from the investment returns.

3.3. Calibration

Solving our model generates firms' investment and hiring decisions as functions of the state variables, which are the aggregate and firm-level productivity and the capital of the firm. Since the stochastic discount factor and the wages are specified exogenously, the solution does not require aggregation. Hence, the distribution of the capital stock, a high dimensional object is not a part of the state space. This feature of the model simplifies the solution of the model significantly. The details of the numerical solution are explained in the Internet appendix.

To be consistent with our annual empirical results, we calibrate the model at annual frequency.²¹ We derive the parameters of the firm-level productivity process from the production function estimations in §2.2. The persistence of the firm productivity process, ρ_z , is 0.7. The conditional volatility of firm productivity, σ_z , is computed from ρ_z and the cross-sectional standard deviation of firm productivity as 0.27. Even though our production function estimates discussed in §2.2 imply almost constant returns to scale, we model technology as slightly decreasing returns to scale, with $\alpha_k + \alpha_l = 0.95$, which makes studying the relationship between firm size and productivity possible.

We take the parameters of the aggregate productivity from King and Rebelo (1999) and annualize them. Their point estimates for ρ_a and σ_a are 0.979 and 0.0072, respectively, using quarterly data, implying annual parameters of 0.922 and 0.014. The depreciation rate for fixed capital is set to 8%. We set the wage function parameter ω to 0.2 to match the aggregate wage cyclicality in the data.²²

We choose the pricing kernel parameters β , γ_0 , and γ_1 to match the average riskless rate and the first two moments of aggregate value-weighted excess stock returns measured from the data used in our empirical exercise. The discount factor β is 0.988, which implies an annual risk free rate of 1.2%; γ_0 and γ_1 are 3.27 and -13.32 , respectively, and generate annual excess mean returns and standard deviation of 6.16% and 17%, respectively. Finally, the adjustment cost parameter, η , is set to 4.45 to replicate the value-weighted average (annual) volatility of investment to capital ratio of 15.7% in our data.

To compute the model statistics, we perform 500 simulations of the model economy with 4,000 firms

²¹ Calibration of the model economy based on alternative TFP estimations (summarized in the online appendix) yields very similar asset pricing results.

²² We measure cyclicality in the data as the correlation between real GDP growth and real wage growth. Real wages are constructed by dividing the nominal wages by the domestic hours worked, and deflating by the GDP deflator (all using National Income and Product Accounts data). This correlation is 0.3 in the data.

over 50 periods (years), which is roughly comparable to the length and average breadth of our empirical sample.

3.4. Model Mechanism and Results

The key mechanism relating firm-level productivity to expected returns involves the interaction of convex adjustment costs and the countercyclical Sharpe ratios assumed in our pricing kernel. Firm risk derives from its inability to freely adjust its capital following shocks to aggregate and firm-level productivity. In this economy, aggregate productivity shocks drive the business cycles. In bad times (low aggregate productivity level), net present value of investments go down because of lower expected cash flows and higher discount rates. Hence, all firms would like to invest less and hire less. Even though firms can freely adjust their labor, they incur adjustment costs when they change their capital stock.²³ In states of low aggregate productivity, a bad aggregate shock tends to have a larger negative effect on the low TFP firms. These firms would have a lower investment rate (i.e., reduce their capital stock relatively more) than the high TFP firms. Because of the convexity in adjustment costs, low TFP firms, who are at a steeper part of the adjustment costs, sustain a higher cost (relative to their output) while reducing their capital stock in a recession than high TFP firms. A positive aggregate shock, on the other hand, results in a bigger relative decrease in adjustment costs for these firms compared to more productive firms, hence benefiting the low TFP firms more than the others. Therefore, the returns of the low TFP firms covary more with changes in the economic conditions during recessions. The opposite happens in expansions.

The countercyclical Sharpe ratio breaks the symmetry between recessions and expansions.²⁴ We assume that the volatility of the pricing kernel is a decreasing function of aggregate productivity; implying higher Sharpe ratios (and discount rates) in bad times. Risk is defined as the covariation of the returns with the pricing kernel. Higher volatility of the pricing kernel implies higher covariation with the kernel, hence higher risk in bad times. Lower rates of investment of low productivity firms tend to occur during recessions when Sharpe ratios are high, making them especially risky. Therefore, low productivity firms, during economic downturns, have the highest expected returns. These firms are the primary drivers

of negative cross-sectional relations between expected returns and firm productivity. Higher rates of investment of high productivity firms, on the other hand, tend to occur during expansionary periods when Sharpe ratios are low, and therefore result in lower expected returns for these firms.

Unlike Zhang (2005) and many other papers in this literature, our model does not have operating leverage (fixed costs of production). Operating leverage magnifies the differences between low and high productivity firms since it disproportionately affects the low productivity firms. Our model, instead, features labor as a factor of production as in Tüzel (2010), Jones and Tüzel (2013a), and Belo et al. (2014). The marginal product of labor is equalized across firms as labor is free to move between them. This leads to vastly different optimal hiring and investment decisions between firms and generates significant heterogeneity without incorporating operating leverage.

To clarify the effect of labor in the model, we derive the profit of the firm (abstracting from the capital adjustment costs):

$$\Pi_{it} = A_t Z_{it} K_{it}^{\alpha_k} L_{it}^{\alpha_l} - W_t L_{it},$$

where firms choose labor intratemporally:

$$L_{it} = \arg \max_L \Pi_{it} = \left(\frac{\alpha_l A_t Z_{it} K_{it}^{\alpha_k}}{W_t} \right)^{1/(1-\alpha_l)},$$

wages are given by $W_t = \exp(\omega a_t)$, and $0 \leq \omega \leq 1$. So, firm profits are

$$\Pi_{it}^* = \kappa A_t^{(1-\omega\alpha_l)/(1-\alpha_l)} (Z_{it} K_{it}^{\alpha_k})^{1/(1-\alpha_l)}, \quad (16)$$

where $\kappa = (1 - \alpha_l) \alpha_l^{\alpha_l/(1-\alpha_l)}$. In comparison, the profit function in Zhang (2005) is

$$\Pi_{it}^{\text{Zhang}} = A_t Z_{it} K_{it}^{\alpha_k} - f,$$

where f denotes fixed cost of production. Since α_l , the share of labor, is 0.72 in our calibration, firm profits in our model are 3.6 times ($1/(1 - \alpha_l) = 3.6$) as sensitive to firm TFP and capital as the firms in Zhang (2005). Therefore, our model already generates significant amount of dispersion in firm profits without fixed costs of production. Besides this effect in the cross section, for $\omega < 1$ (i.e., lower sensitivity of wages to aggregate TFP), the effect of aggregate shocks on the firms is amplified, hence all the firms in the economy get riskier compared to the benchmark case in Zhang (2005).

Table 7 presents the results on the cross section of firms. Similar to our empirical analysis, we form decile portfolios by sorting firms on the basis of past TFP level. The table shows average firm characteristics and expected returns of these portfolios as well as

²³ Note that adjustment costs are defined over net investment, rather than gross investment. Hence, adjustment costs are high when investment is higher, as well as lower than depreciated capital.

²⁴ For simplicity, we assume symmetric adjustment costs, but asymmetric adjustment costs as in Zhang (2005) or Tüzel (2010) would also break this symmetry and strengthen our results.

Table 7 Model Implied Characteristics and Excess Returns for TFP-Sorted Portfolios

	Low	2	3	4	5	6	7	8	9	High	High-Low	
											Model	Data
TFP	0.52	0.68	0.78	0.87	0.95	1.05	1.16	1.29	1.48	1.93	1.41	1.46
I/K	0.01	0.02	0.03	0.04	0.06	0.07	0.10	0.12	0.17	0.30	0.30	0.22
HR	−0.25	0.00	0.18	0.33	0.49	0.67	0.88	1.14	1.53	2.60	2.85	0.18
Size	0.50	0.61	0.68	0.76	0.83	0.92	1.03	1.17	1.40	2.10	1.60	3.65
B/M	1.37	1.18	1.10	1.03	0.98	0.94	0.89	0.85	0.80	0.74	−0.63	−0.87
Future returns												
Mean excess returns												
All states												
r^e	11.40	9.93	9.10	8.43	7.81	7.21	6.59	5.90	5.02	3.41	−8.00 (−13.87, −5.50)	−7.35
Expansions												
r^e	6.82	5.54	4.83	4.25	3.73	3.22	2.69	2.11	1.39	0.08	−6.74 (−9.81, −5.40)	−4.43
Contractions												
r^e	25.44	23.71	22.66	21.78	20.97	20.17	19.32	18.36	17.13	14.37	−11.08 (−23.29, −5.06)	−21.61

Notes. This table reports the model-implied average characteristics and future mean excess returns of the TFP-sorted portfolios. All values are based on 500 simulations of 4,000 firms for 50 periods (years). Point estimates are simulation averages, and confidence intervals (in parentheses) are constructed from the 2.5th and 97.5th percentiles of the simulated distributions of those spreads. Expansion and contraction periods are designated in year t based on the level of aggregate TFP in that year. Mean excess returns are measured in the following year. The equivalent empirical observations of high-low portfolios are given in the last column. All values are annual and in percentage terms.

the spreads between the low and high portfolios. We also present confidence intervals around the model-implied values of the spreads in returns. The results indicate that the model is able to match the data presented in Tables 1 and 2 reasonably well. The parameters of the firm-level TFP process are taken from the empirical estimates, so it is not surprising that the average TFP of the simulated portfolios are matched almost exactly to the data. However, the model is not calibrated to match the cross section of the remaining characteristics, namely, the investment to capital ratio, the hiring rate, firm size, book-to-market ratio, and the expected returns. We find that the investment to capital ratio and hiring rate both increase monotonically with TFP. Productive firms rationally invest and hire more than the unproductive firms since both capital and labor will be more efficient (their net present value would be higher) for those firms. The dispersion in investment to capital ratios generated by the model economy is reasonably close to what we observe in the data (0.3 versus 0.22), the dispersion in hiring rates of low versus high productivity firms is an order of magnitude bigger in the model.²⁵

TFP is also monotonically and positively related to size and negatively related to B/M. In the model, firm size is the ex-dividend value of the firm, $V_{it} - D_{it}$,

which is approximately equal to $q_t K_{t+1}$ (the amount of capital, K_{t+1} , times Tobin's q , q_{it}).²⁶ Tobin's marginal q is linear in investment to capital ratio (Equation (13)), which is monotonically increasing in TFP. Likewise, the amount of capital, K_{t+1} , is increasing in TFP because of the positive relationship between investment and TFP and the persistence in productivity. Therefore, we expect to see a positive relationship between TFP and firm size. B/M, the ratio of book value to the market value of the firm, is measured as the amount of capital, K_{t+1} , divided by the ex-dividend value of the firm, $V_{it} - D_{it}$. Hence, B/M is approximately equal to the inverse of the Tobin's marginal q (q_{it}) in the model.²⁷ This leads to a negative relationship between B/M and TFP. The model is quite successful in matching the magnitude of the dispersion in B/M (−0.63 versus −0.87). Also, the model is able to capture about half of the size dispersion found in the data (1.60 versus 3.65). These results indicate that TFP shock alone can account for a significant fraction of the cross-sectional dispersion in firm characteristics found in the data.

Table 7 also reports that the expected returns of TFP-sorted portfolios decline monotonically with TFP. The spread in expected returns, −8.00%, is close to the empirical spread of −7.35% reported in Table 2.

²⁵ This problem could be alleviated by introducing adjustment costs in hiring/firing, which is currently assumed to be costless. Adjustment costs in hiring would reduce the volatility in hiring rate, and hence reduce the dispersion in the hiring rate of the most productive and least productive firms.

²⁶ In the presence of constant returns to scale, $V_{it} - D_{it} = q_t K_{t+1}$. With decreasing returns to scale, $V_{it} - D_{it}$ slightly exceeds $q_t K_{t+1}$.

²⁷ M/B would be exactly equal to Tobin's marginal q when the production technology is constant returns to scale.

These returns are calculated by weighting the firms in the portfolios equally, but, value weighting the portfolios leads to quantitatively very similar results. Furthermore, consistent with our empirical findings, both the average expected returns and the spread between the low and high TFP portfolio returns are much higher in contractions, compared to expansions. For this exercise, each year, we define periods where aggregate productivity is more than one standard deviation lower than the mean (based on short sample statistics) as contractions, and the remaining periods as expansions. This definition leads to designating roughly 15% of the sample period as contractions, which is in line with the frequency of contractionary periods in the data (96 out of 564 months in our sample period). The excess returns are measured in the following year. The model generates -6.74% and -11.08% spread in returns of TFP-sorted portfolios in expansions and contractions, respectively. The empirical spread in contractions, -21.61% , falls within the 95% confidence interval around the model generated spread point estimate, whereas the empirical spread in expansions, -4.43% , does not. However, as in Lin and Zhang (2013), the model does not generate a significant spread in unconditional CAPM alphas, or Fama–French three-factor alphas, hence we do not tabulate them.

3.5. Comparative Statics and Properties

To understand the mechanism behind the results, we present comparative statics for most parameters of our model in Table 8. In each row we change one parameter at a time without recalibrating the model to match our targets.

As is standard in models with convex adjustment costs, the adjustment cost parameter η primarily affects the volatility and risk of investment. Lower η leads to higher investment volatility, lower risk, and lower expected returns in the economy. Expected returns decrease from 6.16% in the benchmark case to 4.22% with an η of 2. In the cross section, however, differences in investment behavior fueled by lower η leads to bigger dispersion between the low and high TFP firms.²⁸

Changing the pricing kernel parameters γ_0 and γ_1 yields predictable results. Although the two parameters play different roles, an increase in the absolute value of either parameter will raise the equity premium and return spreads. As a result of greater variation in expected returns, investment becomes slightly more volatile as well. The small and positive return

²⁸ Lower adjustment costs lead to bigger spreads in firm size and capital holdings, resulting in bigger spreads in the profits of low and high TFP firms (Equation (16)). This mechanism leads to bigger return spreads for TFP-sorted portfolios, despite an overall reduction in risk and level of expected returns.

Table 8 Comparative Statics

Case		Decile portfolio spreads in						
		$E(r^e)$	Std(I/K)	I/K	HR	Size	B/M	$E(r^e)$
Benchmark		6.16	15.66	0.30	2.85	1.60	-0.63	-8.00
Low η	$\eta = 2$	4.22	22.70	0.40	2.88	1.84	-0.83	-9.17
High η	$\eta = 7$	7.18	11.71	0.23	2.80	1.46	-0.66	-7.84
Low γ_0	$\gamma_0 = 3$	4.87	12.19	0.25	2.80	1.31	-0.51	-2.87
High γ_0	$\gamma_0 = 3.5$	7.80	19.45	0.35	2.88	1.72	-0.66	-15.38
Low γ_1	$\gamma_1 = 0$	1.72	9.30	0.23	2.78	1.20	-0.21	0.24
High γ_1	$\gamma_1 = 20$	15.83	18.13	0.32	2.87	1.72	-0.91	-17.37
Low ω	$\omega = 0$	6.49	15.93	0.30	2.85	1.60	-0.65	-7.94
High ω	$\omega = 1$	4.86	14.67	0.30	2.85	1.57	-0.58	-8.19
Fixed labor	$L_{it} = 1$	6.26	2.75	0.05	—	0.32	-0.13	-1.24

Notes. This table presents the comparative statics for our benchmark calibration. The top row shows moments from the calibrated model. The rows beneath show the moments that result from changing one parameter to the value given. The last row presents the results to fixed labor case, where labor is paid its marginal product in each firm. Moments include $E(r^e)$, the market risk premium; Std(I/K), the average firm-level volatility of investment; and the average spreads in investment to capital ratio, hiring rate (HR), size, B/M ratio, and mean excess returns on TFP-sorted portfolios. All results are obtained from 500 simulations of 4,000 firms for 50 periods (years).

spread in the $\gamma_1 = 0$ case (constant price of risk) demonstrates that countercyclical price of risk is a critical feature of the model to generate higher risk of low TFP firms.²⁹

Lowering the sensitivity of wages to aggregate productivity (lower ω) increases the risk and risk premia. This is because wages do not fall as far in recessions or rise as much in expansions, causing firms to make bigger adjustments to the quantity of labor and leading to larger fluctuations in firms' output and profits.

Finally, the last row of Table 8 presents the results for the fixed labor case in order to isolate the role of labor in the model. In this exercise the labor channel in the model is shut down by setting each firm's employees equal to 1, and paying labor its marginal product. This special case is almost equivalent to Zhang's (2005) model without the fixed costs. In this specification the same TFP shocks lead to very small spreads in I/K , size and B/M, and -1.24% spread in expected returns.³⁰ So, the model

²⁹ This is a well-known result since Zhang (2005). As partially discussed before, Zhang (2005) includes two additional mechanisms (asymmetric adjustment costs and fixed costs that disproportionately effect low TFP firms) that introduce asymmetry into the model, in addition to the countercyclical price of risk. In the absence of these mechanisms, low TFP firms are not riskier than high TFP firms.

³⁰ Small cross-sectional differences in firms' investment behavior also lead to low volatility in firm investment with benchmark parameter values. Recalibrating the model with lower adjustment costs and higher volatility in the pricing kernel increases firm's investment volatility, but still leads to relatively small cross-sectional spreads.

without labor requires an additional mechanism (such as fixed costs) to boost the cross-sectional dispersion in returns.

Model parameters, calibrated as described in §3.3, often have implications for other statistics as well. The parameter γ_1 governs the degree of countercyclicality of the market price of risk and also has implications on the degree of predictability in stock returns. To test whether our benchmark value of -13.32 implies a realistic amount of predictability, we run return predictability regressions where annual excess stock returns are predicted by our state variable, aggregate TFP. We find that aggregate TFP predicts stock returns with 9.4% R^2 at annual horizon, which is in line with the stock predictability regression R^2 's reported in the literature (Jones and Tüzel 2013b).

The adjustment cost parameter η also has additional implications for the economy. Lower adjustment costs would imply higher elasticity of investment rate to Tobin's q . Our benchmark value of 4.45 generates an investment— q elasticity of 2.8 around the steady state. Because of the poor empirical fit of the neoclassical investment equation, it is hard to find good empirical estimates for this elasticity. The results in Cummins et al. (2006) imply an elasticity around 1.2. Hence, our elasticity of 2.8 indicates a relatively low adjustment cost. With this calibration, the fraction of output that is lost because of capital adjustment costs is around 5%.

The functional form we assume for the equilibrium wage rate has implications for the cyclical behavior of aggregate employment in the economy. To compare the cyclical behavior generated by our model to the data, we compute the correlation of total employment growth with output growth, and the volatility of employment growth relative to output. We find that the moments generated by the model measure up to the data well. In the postwar U.S. data, this correlation is 0.9, and the relative volatility of employment growth is 1.1, whereas both of these numbers are around 1 using the simulated data.

4. Conclusion

This paper provides new evidence about the link between TFP and stock returns, offering an explanation to how firm characteristics can rationally predict returns. We estimate firm-level TFP and show that it is strongly related to several firm characteristics such as size, the book-to-market ratio, investment, and hiring rate. TFP is negatively related to future stock returns, as well as ex ante discount rates. A production-based asset pricing model calibrated to match the estimated TFP distribution can replicate the empirical relationship between TFP, firm characteristics, and stock returns reasonably well. Firms that

receive repeated bad shocks (low TFP firms) end up being small firms and are characterized by low investment and hiring rates, and high B/M ratio. High TFP firms are large firms with high investment and hiring rates, and low B/M ratio. Low TFP firms end up being riskier than high TFP firms. Thus, differences in TFP generates the observed relationships between characteristics and stock returns.

Even though we consider frictions in the real side of the economy, the paper abstracts from financial frictions, which are known to be important for the valuation and investment behavior of firms. Further research integrating financing frictions into the firm's investment framework would provide a more realistic and comprehensive view of the firm's economic environment than what this simple model portrays.³¹

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³¹ See, for example, Livdan et al. (2009), who study the effect of financial constraints on risk and expected returns by extending the standard investment-based asset pricing framework.

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