Firm Level Productivity, Risk, and Return*

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Abstract

This paper documents a strong link between firm level total factor productivity (TFP) and several firm characteristics that are known to predict future stock returns, such as size, the book to market ratio, investment, and hiring rate. TFP is positively related to contemporaneous stock returns and negatively related to future excess returns and ex-ante discount rates. Low productivity firms on average earn a 6% annual premium over high productivity firms in the following year and the premium is countercyclical. We interpret the spread in the average returns across these portfolios as the risk premia associated with the higher risk of low productivity firms. A production-based asset pricing model with aggregate and idiosyncratic shocks accounts for most of these stylized facts.

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Total factor productivity (TFP) measures the efficiency with which inputs utilized in production are turned into output. There is vast evidence that TFP plays an important role in understanding economic fluctuations, economic growth and per capita income differences across countries.

In this paper we focus on the role of TFP in accounting for the differences in firm characteristics and returns. TFP is a fundamentally important economic variable which provides a more comprehensive gauge of firm level performance than some of the more conventional measures such as labor productivity or profitability alone.[1] While profitability captures only the part of the value added that goes to shareholders, labor productivity can be an inadequate measure of overall efficiency especially in capital intensive industries.[2]

We examine the link between firm characteristics, excess returns, and firm level total factor productivity for publicly traded firms in the U.S. We document that differences in measured firm level TFPs are strongly related to differences in certain firm characteristics such as size (market capitalization), the ratio of a firm's book value to market value, asset growth, investment to capital ratio, hiring rate, inventory investment rate, and real estate ratios of firms. Empirical research in finance has established significant differences in stock returns based on many of these characteristics.[3] These return relations, however,

[1]In corporate finance, similar TFP measures are utilized in different studies such as Schoar (2002) documenting that plants in diversified firms are more productive than plants in comparable single-segment firms; Maksimovic and Phillips (2002) comparing productivity between the different segments within a conglomerate, and McGuckin and Nguyen (1995) studying the productivity of plants that change owners.

[2]See Lieberman and Kang (2008) for a case study of the differences between TFP and profitability in measuring firm performance.

[3]These findings are documented in Fama and French (1992); Titman, Wei, and Xie (2003); Lyandres, Sun, and Zhang (2008); Cooper, Gulen, and Schill (2008); Bazdresch, Belo, and Lin (2010); Wu, Zhang, and Zhang (2010), Belo and Lin (2010); and Tüzel (2010). Many other papers document that firm

are puzzling because the connection between them and economic fundamentals is not well understood. Recently, a growing strand of literature has introduced equilibrium models to tie such differences in firm characteristics and returns to the optimal investment decisions of firms in response to changes in productivity and discount rates.[4] In this framework, low TFP firms turn out to be more vulnerable to business cycles, and end up being riskier than firms with high TFP. However, none of these papers has directly estimated firm level productivity. The main contribution of our work is to provide evidence of an empirical connection between TFP and firm characteristics and 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 each firm and year observation for publicly traded firms in the U.S.[5] We establish a set of stylized facts by examining the summary statistics of firms sorted into ten TFP portfolios between 1970 and 2007. Our findings indicate that 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 1.5. We find the relationship between firm size and TFP to be monotonic. The average size of the firms in the lowest TFP decile is 21% of the average size, whereas the size of firms in the highest TFP decile is 316% of the average firm size. In addition, the hiring rate, fixed investment to capital ratio, asset

characteristics are related to average stock returns including Ball (1978); Banz (1981); Basu (1983); De Bondt and Thaler (1985); Bhandari (1988); Jegadeesh and Titman (1993); Chan, Jegadeesh, and Lakonishok (1996); Sloan (1996); and Thomas and Zhang (2002).

[4] Some of the papers in this literature include Gomes, Kogan, and Zhang (2003); Zhang (2005); Gourio (2007); Bazdresch, Belo, and Lin (2010); Li, Livdan, and Zhang (2009); Tüzel (2010); and Belo and Lin (2010).

[5] Since firm level productivity is the major ingredient of our empirical work, its estimation is critical. An important advantage of the Olley and Pakes (1996) approach is its ability to control for selection and simultaneity biases. In our sensitivity analysis, we expand the basic production function in Olley and Pakes (1996) to include several different specifications.

growth, profitability, and inventory growth are all monotonically increasing in firm level TFP.

We find that TFP is positively and monotonically related to contemporaneous monthly stock returns and negatively related to future excess returns (equity returns and unlevered returns) and ex-ante discount rates. Low productivity firms on average earn a 6.3% annual premium over high productivity firms in the following year. There is significant variation in the TFP premium over business cycles. The return spread is about three times as high during NBER contractions as it is during expansions. We interpret the spread in the average returns across these portfolios as the risk premia associated with the higher risk of low productivity firms. Examination of Fama-MacBeth cross sectional regressions of monthly stock returns on lagged firm level TFP produce a negative and statistically significant average slope for TFP. Quantitatively, our regression results indicate about 2.5% higher expected returns for the firms in the lowest TFP decile compared to a firm with average TFP.

In addition to realized returns, we also look at ex-ante measures of discount rates proxied by two measures of the implied cost of capital. 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.

A number of additional results emerge from our firm level productivity estimation. We estimate the persistence of firm level TFP as 0.91 and the standard deviation of the

TFP shock as 0.14 at the quarterly frequency. These estimates provide empirical support for the productivity parameters used, for example, by Zhang (2005), Gomes (2001), and Hennessy and Whited (2005) where the parameters are calibrated so that the models used can match moments of some of the key variables.[6] We also document a two fold increase in the cross sectional dispersion of firm level productivity from approximately 0.25 in 1950s and 1960s to 0.50 in 2000s. This fact might be important in understanding the increase in the idiosyncratic volatility of stock returns documented by Campbell, Lettau, Malkiel and Xu (2001).

We propose a production-based asset pricing model to examine the link between productivity and expected returns similar to the models used in Zhang (2005) and Bazdresch, Belo, and Lin (2010). In this framework, firms are ex-ante identical but diverge over time due to 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 B/M ratio, and end up being smaller than the average firm in their industries. Firms that receive multiple good shocks end up being high TFP firms with high investment and hiring rates, low B/M ratio and end up being large firms. All firms in this economy 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 the ones with low firm level TFP. If recession deepens, these firms have the most pressure to scale back their investments and hence suffer the

[6] 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.

most from convex adjustment costs that result 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. Since the returns of low productivity firms fluctuate more closely with aggregate productivity in recessions, they are particularly riskier in recessions. The opposite happens in expansions. In the presence of frictions in adjusting capital, the negative relationship between a firm's productivity and its level of risk arises endogenously.

We calibrate the model to match the time series properties of aggregate stock returns and examine the cross section of firm characteristics and stock returns that are generated by the model economy. Our simulation results indicate that the model accounts for many of the cross sectional stylized facts documented in our empirical section. In particular, the dispersion in investment to capital ratio, hiring rate, book to market, size, and returns of low versus high TFP firms and its variation over the business cycle generated by the model captures the qualitative and some of the quantitative features of the data well. In other words, our simulation results indicate that differences in measured firm level TFPs can generate differences in certain firm characteristics and stock returns that resemble the data.

Overall our results provide an explanation to why firm characteristics can rationally predict returns. In our framework, 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 our model correctly describes firm behavior, characteristics such as size, B/M and investment/capital ratio should not have additional explanatory power vis-a-vis productivity, but should be determined by it. Return predictability regressions which incorporate these firm characteristics (together with TFP) should be interpreted with caution. 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, B/M or assets, which are observable, rather than estimated. As a result, in any return predictability regression which includes both firm productivity and other firm characteristics as forecasting variables, the better measured variables are expected to drive out productivity. Thus, our goal is not necessarily to come up with a variable that outperforms other firm characteristics in return predictability regressions, but rather to shed some light on why firm characteristics can rationally predict returns.

Section 1 summarizes the data and our empirical results. Section 2 presents the model and the numerical results for the calibrated economy. Section 3 concludes. The Appendix provides detailed information on the estimation of firm level productivities and sensitivity results.

1 Empirical Results

We start this section by examining the relationship between firm level TFP and certain firm characteristics that have been linked to stock returns by previous research in finance. We investigate the extent to which productivity, an economic fundamental, is linked to the cross sectional dispersion in firm characteristics and stock returns. First, we examine the relationship between firm level TFP and certain firm characteristics and returns by constructing portfolios sorted on firm level TFP. Next, we run Fama-MacBeth cross sectional regression of firm returns on firm level TFP and other control variables. Finally, we investigate the relationship between firm level TFP and ex-ante discount rates as measured by the implied cost of capital estimates for the firms.

1.1 Data

The key variables for estimating the firm level productivity for the benchmark case are the firm level value added, employment, and physical capital.[7] 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.[8] The sample is an unbalanced panel with approximately 12750 distinct firms spanning the years between 1953 and 2009. Some of the key variables are firm level capital stock (k_{it}) given by gross Plant, Property & Equipment (PPEGT)[9], deflated following Hall (1990) and

[7]Firms use many inputs in their production, such as raw materials, labor, different types of capital, energy, etc. In our specification, we focus on labor and physical capital as the main inputs. Consequently, firm's value added is defined as gross output net of expenditures on materials, as well as net of other expensed items such as advertisement, R&D expenditures and rental expenses. Hence our value added variable contains the contribution of labor and owned physical capital of the firm only.

[8]An alternative is to use the Longitudinal Research Database (LRD), which is a large panel data set of U.S. manufacturing plants developed by the U.S. Bureau of the Census. One major shortcoming of the LRD for our purposes is that it excludes data on headquarters, sales offices, R&D labs, and the other auxiliary units that service manufacturing establishments of the same company. Such data is available from the Auxiliary Establishment Survey, but only at 5 year intervals. Since our focus is on examining the link between annual firm level TFP and stock returns, missing a potentially important part of the firm activities is not desirable. Another shortcoming of the LRD data is that it is strictly limited to manufacturing establishments; hence the non-manufacturing sector, which is getting more important over time, is not represented at the LRD. Consequently, we use the Compustat data for measuring firm level TFP.

[9]In our estimation, we use the book value of capital, rather than proxy the market value of capital from the value of the firm. The market value of the firm includes the firm's growth options, which is

the stock of labor (l_{it}) given by the number of employees (EMP), both from Compustat. Firm level value added is computed using Compustat data on sales, operating income and employees, and then deflated using the output deflator. We employ the semi-parametric estimation procedure suggested by Olley and Pakes (1996) to obtain the firm level TFPs. In our TFP estimation, we use industry specific time dummies and take out the industry/year effect from firm TFPs. Hence our firm TFPs are free of the effect of industry or aggregate TFP in any given year. While we do not explicitly model the difference between embodied and disembodied technological change at the aggregate level, our use of industry specific time dummies and price deflators for investment remove the impact of possible embodied technological progress as modeled in Greenwood, Hercowitz, and Krusell (1997 and 2000) and Fernández-Villaverde and Rubio-Ramírez (2007).[10] Detailed information about the data, its computation, the measurement of TFP, and its properties are provided in the Appendix.[11]

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

unrelated to the firm's current output and inputs. See Philippon (2009).

[10] Examining cross sectional implications of investment specific technological change by introducing vintage capital as in Kogan and Papanikolaou (2011), or differences in exposure to investment shocks as in Garleanu, Panageas, and Yu (2011) are left for future research.

[11] Our TFP estimates and asset pricing results are not sensitive to alternative ways of measuring TFP, such as the inclusion of inventories in the definition of the capital stock, including organizational capital as another input to the production function, estimating the model with age as another variable, including R&D capital, using different deflators and prices (such as industry deflators), or carrying out the estimation at the industry level. The results are also not sensitive to carrying out the estimation with industry specific time dummies at 2, 3, and 4 digit SIC levels. The findings are also similar for manufacturing versus non-manufacturing firms. Many of these robustness results are available in the Appendix.

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 minimum of a six month gap between fiscal year-end and return tests. In other words, we match the productivities calculated using accounting data for fiscal year ending in year $t-1$ to stock returns from July of year t to June of year $t+1$. Similar to Fama and French (1993), in order to avoid the survival bias in the data, we include firms to our sample after they have appeared on Compustat for two years. Also following Fama and French (1993), we only include firms with ordinary common equity as classified by CRSP in our sample, excluding ADRs, REITs, and units of beneficial interest. In order to ensure that we have at least 1000 firms in our sample every year, we start our sample period in 1970 for Compustat Data (1970-2007) and match them to stock return data from CRSP (July 1971 - June 2009).

1.2 Productivity and Firm Characteristics

Table I presents summary statistics for firms sorted into 10 portfolios based on the level of TFP in year t. There are at least 100 firms, and on average 211 firms in each portfolio every year. The first row provides data on TFP levels of the firms in these portfolios where average TFP is normalized to be one. There is 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, while it is almost twice the average TFP in the highest TFP portfolio.

In order to gauge the sensibility of our TFP measure, we contrast some of its properties with those obtained from longitudinal micro-level data sets such as the Longitudinal Research Database (LRD), which is a large panel data set of U.S. manufacturing plants developed by the U.S. Bureau of the Census.[12] For example, using data for 4-digit textile industries, Dwyer (1997) finds the ratio of average TFP for plants in the ninth decile of the productivity distribution relative to the average in the second decile to be between about 2 and 4. Olley and Pakes (1996) find similar ratios in the telecommunications equipment industry. Using plant-level data from the 1977 Census of Manufactures, Syverson (2004) reports similar findings in four-digit manufacturing industries. The ratio of average TFPs between the high and low TFP portfolios obtained from our data set in Table I is 3.9. The ratio of the average TFP in the ninth decile to the average in the second decile is 1.8.

Results in Table I indicate a strong link between firm level TFP, 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 21% of the average size of all firms in that year, whereas the average size of firms in the highest TFP decile is 316% of the average size.[13] The B/M ratios of the firms monotonically decline with TFP indicating that high TFP firms are typically growth firms and low TFP firms are value firms.[14] This finding is consistent with the mechanisms in rational explanations of the

[12] Our baseline TFP estimation is performed using the entire Compustat sample, which includes both manufacturing and non-manufacturing firms. Estimations using only manufacturing data, or only non-manufacturing data yield very similar parameters for the production function and the TFP process. These results are provided in the Appendix.

[13] 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 $400 million in 1970 and $3.5 billion in 2008.

[14] The cross correlation between TFP and size is 0.33, and TFP and B/M is -0.35. These correlations are calculated cross-sectionally each year and then averaged across time.

value premium, such as Zhang (2005) and Gala (2006). These findings suggest that firm level productivity may be an important determinant of firm size and book to market ratios which are known to be strongly related to firm returns.

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.[15] The cross correlations between TFP and the hiring rate, investment to capital ratio, asset growth, and inventories are 0.18, 0.28, 0.26, and 0.12 respectively. The differences in these firm characteristics between the high and low TFP portfolios are highly statistically 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 35% for high productivity firms, whereas the ratio for organizational capital ranges between 40% to 66%. The results are similar for hiring rate, inventory growth and asset growth. The firms in the lowest productivity decile reduce their workforce by around 5% and their assets shrink on average 2%, whereas firms in the highest productivity decile increase their workforce by 16% and experience 40% asset growth. Inventory growth varies between 4% and 40%. These results are consistent with the frameworks used in Bazdresch, Belo, and Lin (2010); Li, Livdan, and Zhang (2009); and Belo and Lin (2010). The ratio of research and development expense (R&D) to the plant property & equipment (PPE) of the firm also tends to increase with TFP, but the relationship is not perfectly monotonic.[16] Table I also shows that the real estate ratio

[15] Fixed investment to capital ratio is given by firm level 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 change in the stock of labor from time $t-1$ to t. We measure organizational capital based on data on firm's reported sales, general, and administrative expenses. More details are provided in the Appendix.

[16] The data item for R&D expense is not populated for all firms. R&D expense can also be considered

of low productivity firms exceed the average in their industry whereas the real estate ratio of high productivity firms is lower than their industry average, consistent with the mechanism in Tüzel (2010). 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 (for example, Novy-Marx (2010), Gourio (2007)) where unobserved productivity is frequently proxied by measures of profitability.[17] We look at two profitability measures: Equity income / book equity from Fama and French (2008), which we call profitability, and gross profits / book assets from Novy-Marx (2010), which we label gross profitability. Both measures of profitability are monotonically and positively related to TFP, confirming that high productivity firms are also the most profitable. However, the cross correlation of TFP with gross profitability is quite modest (0.18), whereas its correlation with profitability is much higher (0.44). In untabulated results, Fama-MacBeth regressions of TFP on past 1-year and 3-year profit growth rates generate positive and significant coefficients for both profit measures, implying a positive relationship between past profit growth and current TFP. On the other hand, we find a strong negative relationship between current TFP and future profit growth.

as a type of investment; however, taking R&D as a seperate capital item would lead to the exclusion of a significant part of our sample. In untabulated results, we find that constructing a capital stock from R&D expense using the perpetual inventory method and adding that capital stock to the fixed capital leads to similar results.

[17]Even though productivity and profitability are expected to be related, their calculation and interpretation are different. Profits can be interpretated 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).

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.

Table I: Descriptive Statistics for TFP Sorted Portfolios, 1970-2007

	Low	2	3	4	5	6	7	8	9	High	High-Low
TFP	0.49	0.69	0.78	0.84	0.90	0.96	1.03	1.12	1.27	1.92	1.43
SIZE	0.21	0.32	0.50	0.66	0.80	1.08	1.42	1.78	2.09	3.16	2.94
											(18.07)
B/M	1.45	1.40	1.23	1.13	1.01	0.90	0.80	0.72	0.63	0.54	-0.90
											(-11.68)
I/K	0.10	0.09	0.10	0.11	0.12	0.14	0.16	0.18	0.23	0.35	0.25
											(32.38)
AG	-0.02	0.05	0.07	0.10	0.12	0.15	0.18	0.21	0.27	0.40	0.41
											(13.96)
HR	-0.05	0.01	0.03	0.04	0.06	0.08	0.11	0.13	0.16	0.16	0.22
											(18.72)
INV	0.04	0.08	0.08	0.11	0.14	0.15	0.20	0.23	0.37	0.40	0.36
											(11.36)
I_{OC}/OC	0.40	0.34	0.35	0.36	0.38	0.41	0.43	0.48	0.54	0.66	0.26
											(15.96)
RD/PPE	0.12	0.06	0.05	0.06	0.06	0.06	0.07	0.08	0.12	0.23	0.10
											(9.01)
RER	0.007	0.008	0.009	0.007	0.005	0.004	0.000	-0.002	-0.009	-0.015	-0.022
											(-5.45)
NS	-0.05	-0.03	-0.04	-0.04	-0.03	-0.04	-0.05	-0.06	-0.08	-0.13	-0.07
											(-6.37)
LEV	0.29	0.31	0.30	0.28	0.26	0.24	0.21	0.19	0.16	0.13	-0.16
											(-11.50)
PR	-0.24	-0.05	0.01	0.05	0.07	0.09	0.11	0.12	0.15	0.17	0.41
											(32.13)
GPR	0.33	0.38	0.41	0.43	0.45	0.47	0.47	0.48	0.49	0.49	0.17
											(16.67)
AGE	15.24	17.62	18.18	18.33	18.05	17.79	17.00	16.14	14.91	12.75	-2.49
											(-11.30)

Note: For each variable, averages are first taken over all firms in that portfolio, then over years. On average, there are 211 firms in each portfolio every year. 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, where investment is measured from capital expenditures deflated by the price deflator for investment, and capital is the gross plant, property and equipment, deflated following Hall (1990). AG is the change in the natural log of assets from year $t-1$ to year t. HR is the change in the natural log of number of employees from year $t-1$ to year t . INV is the change in the natural log of total inventories 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 following Eisfeldt and Papanikolau (2009). RD/PPE is the ratio of research and development expenses to gross plant, property and equipment in year t. RER is the ratio of buildings +capital leases to plant, property and equipment in year t , adjusted for industries, following Tüzel (2010). 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. PR is the equity income in year t divided by book equity for year t. GPR is the gross profits in year t divided by book assets for year t. AGE is computed in year t as 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. Appendix 4.1 gives more detailed definitions of the variables.

1.3 Asset Pricing Implications

1.3.1 Returns of TFP-sorted portfolios

The relationships between firm characteristics and returns documented in prior research, when combined with the stylized facts presented in Table I, imply a positive relationship between firm TFP and contemporaneous returns, while implying a negative relationship between TFP and future returns. In Table II, we investigate if there is indeed a 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 confirm that TFP is positively and monotonically related to contemporaneous stock returns. The difference between the returns of high and low TFP firms is 27.7%

for equal-weighted portfolios and 17.9% for value-weighted portfolios, and both spreads are highly statistically significant. The relationship between the level of TFP and future excess returns is equally striking for equal-weighted portfolios: low productivity firms on average earn 6.3% annual premium over high productivity firms in the following year, and the return spread is statistically significant. The unconditional return spread is not significant for value-weighted portfolios.

In order to understand the relationship between TFP and future returns over the business cycles, we separate our sample to expansionary and contractionary periods as defined by the NBER (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. Both the average level of expected returns (approximately 7% versus 27%), and the spread between the returns of high and low TFP portfolios (approximately 5% versus 15%) are much higher during contractions. For value-weighted portfolios, similar to the unconditional returns, there is no significant spread in returns during expansions. However, there is a significant negative relationship between TFP and expected value-weighted returns during contractions. The spread between the value-weighted low and high TFP portfolio expected returns is 18% and is highly significant over 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.

Table II: Excess Returns for TFP Sorted Portfolios (%, annualized)

	Low	2	3	4	5	6	7	8	9	High	High-Low
	Contemporaneous Returns, January 1970 - December 2007										
r^e_{EW}	-4.26	3.38	6.97	9.97	11.43	13.69	15.26	17.12	19.19	23.47	27.73
	(-1.01)	(0.98)	(2.08)	(3.07)	(3.52)	(4.19)	(4.58)	(5.00)	(5.42)	(5.98)	(13.60)
σ^e_{EW}	25.95	21.21	20.66	20.03	20.02	20.17	20.55	21.11	21.84	24.21	12.57
r^e_{VW}	-8.49	0.07	3.67	4.51	4.61	6.75	4.01	6.58	5.80	9.35	17.85
	(-2.02)	(0.02)	(1.24)	(1.54)	(1.58)	(2.44)	(1.47)	(2.52)	(2.19)	(3.22)	(6.18)
σ^e_{VW}	25.96	21.25	18.26	18.07	18.01	17.01	16.79	16.09	16.36	17.88	17.81
	Future Returns, July 1971 - June 2009										
	All states, 456 months										
r^e_{EW}	13.15	13.10	10.99	10.68	10.09	9.64	8.77	8.04	7.36	6.83	-6.33
	(3.07)	(3.52)	(3.24)	(3.20)	(3.00)	(2.90)	(2.59)	(2.39)	(2.06)	(1.79)	(-3.07)
σ^e_{EW}	26.45	22.91	20.90	20.58	20.76	20.52	20.87	20.73	21.98	23.56	12.69
r^e_{VW}	4.82	6.90	8.00	5.62	5.92	6.08	4.76	5.52	4.81	5.17	0.35
	(1.21)	(1.95)	(2.55)	(1.77)	(1.98)	(2.16)	(1.69)	(2.00)	(1.75)	(1.69)	(0.15)
σ^e_{VW}	24.55	21.82	19.33	19.55	18.47	17.35	17.35	16.99	16.98	18.88	14.28
	Expansions, 396 months										
r^e_{EW}	10.16	10.39	8.10	8.17	7.10	6.81	6.02	5.74	4.68	5.15	-5.01
	(2.33)	(2.85)	(2.46)	(2.51)	(2.19)	(2.09)	(1.82)	(1.73)	(1.33)	(1.36)	(-2.30)
σ^e_{EW}	25.06	20.94	18.89	18.71	18.62	18.71	19.00	19.11	20.23	21.72	12.49
r^e_{VW}	2.74	5.57	6.81	4.30	4.78	4.82	4.20	4.94	5.07	5.87	3.13
	(0.67)	(1.58)	(2.21)	(1.46)	(1.65)	(1.72)	(1.48)	(1.85)	(1.87)	(1.98)	(1.26)
σ^e_{VW}	23.58	20.27	17.74	16.88	16.68	16.13	16.32	15.29	15.55	17.05	14.26
	Contractions, 60 months										
r^e_{EW}	32.92	30.99	30.05	27.26	29.82	28.37	26.93	23.20	25.04	17.90	-15.02
	(2.17)	(2.11)	(2.19)	(2.04)	(2.15)	(2.15)	(1.99)	(1.78)	(1.81)	(1.20)	(-2.43)
σ^e_{EW}	33.93	32.88	30.72	29.94	31.03	29.47	30.19	29.11	30.92	33.31	13.81
r^e_{VW}	18.59	15.71	15.84	14.35	13.46	14.37	8.42	9.39	3.07	0.60	-17.99
	(1.38)	(1.16)	(1.28)	(1.00)	(1.09)	(1.34)	(0.81)	(0.82)	(0.28)	(0.05)	(-3.01)
σ^e_{VW}	30.16	30.22	27.70	32.11	27.61	23.91	23.17	25.70	24.59	28.28	13.36

Note: r^e_{EW} is equal-weighted monthly excess returns (excess of risk free rate). r^e_{VW} is value-weighted monthly excess returns, annualized, averages are taken over time (%). σ^e_{EW} and σ^e_{VW} 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 (%). $t-$ statistics are in parentheses. Expansion and contraction periods are designated in June of each year based on whether that month is an NBER expansion or contraction. Returns over the expansions and contractions are measured from July of that year, to June of the following year.

As we demonstrate in Table I, TFP is significantly related to size and B/M at the firm level. Hence, we would like to investigate how returns of TFP sorted portfolios covary with SMB and HML and whether these factors can capture the variation in excess returns of TFP sorted portfolios.[18] Table III presents the alphas and betas of TFP sorted portfolios with respect to MKT, SMB, and HML factors (Fama and French, 1992, 1993, among others). 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. We find that low TFP portfolios load heavily on HML and SMB, whereas the loading of the high TFP portfolios are low, even negative in some cases. The three factors capture most of the variation in excess returns. The equal-weighted portfolios that are long in high TFP portfolio and short in low TFP portfolio (High-Low) have an alpha around -4%, which is statistically significant. The spread in alphas of value-weighted portfolios is positive, but not statistically significant. Our takeaway from these results is not necessarily that TFP is a separate risk factor that is not captured by SMB and HML but rather that TFP is systematically related to SMB and HML, which we further investigate empirically and through a model economy.

[18] 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.

Table III: Alphas and Betas of Portfolios Sorted on TFP (%, annualized)
Dependent Variable: Excess Returns, July 1971 - June 2009

	Low	2	3	4	5	6	7	8	9	High	High-Low
					Equal-weighted Portfolios						
alpha	4.66	4.02	2.39	2.11	1.52	1.80	0.98	1.03	0.43	0.66	-4.00
	(2.07)	(2.50)	(2.03)	(1.93)	(1.48)	(1.69)	(0.95)	(1.06)	(0.38)	(0.51)	(-2.13)
MKT	1.12	1.07	1.03	1.04	1.07	1.07	1.09	1.09	1.13	1.20	0.08
	(26.14)	(35.02)	(46.18)	(50.34)	(54.91)	(52.57)	(56.03)	(58.92)	(52.80)	(49.08)	(2.27)
HML	0.38	0.55	0.51	0.50	0.49	0.37	0.34	0.22	0.16	-0.02	-0.40
	(5.88)	(11.75)	(15.07)	(16.00)	(16.49)	(12.15)	(11.53)	(7.76)	(5.00)	(-0.55)	(-7.42)
SMB	1.07	0.93	0.85	0.80	0.79	0.71	0.71	0.66	0.70	0.63	-0.44
	(17.87)	(21.65)	(26.98)	(27.41)	(28.96)	(25.10)	(25.85)	(25.74)	(23.51)	(18.46)	(-8.77)
					Value-weighted Portfolios						
alpha	-1.98	0.18	1.18	-1.90	-0.06	0.80	-0.36	0.89	1.20	1.98	3.96
	(-0.97)	(0.11)	(0.92)	(-1.53)	(-0.06)	(0.71)	(-0.34)	(0.95)	(1.30)	(1.91)	(1.87)
MKT	1.25	1.17	1.11	1.14	1.08	1.00	1.01	1.00	0.98	1.04	-0.22
	(32.27)	(39.15)	(45.54)	(48.23)	(52.91)	(46.45)	(49.58)	(56.16)	(55.95)	(52.71)	(-5.34)
HML	0.09	0.15	0.25	0.35	0.14	0.09	0.06	-0.01	-0.15	-0.29	-0.38
	(1.58)	(3.38)	(6.75)	(9.67)	(4.49)	(2.76)	(1.95)	(-0.23)	(-5.77)	(-9.66)	(-6.23)
SMB	0.37	0.37	0.18	0.21	0.14	0.07	0.04	-0.03	-0.13	-0.07	-0.44
	(6.78)	(8.80)	(5.38)	(6.29)	(4.83)	(2.45)	(1.31)	(-1.32)	(-5.26)	(-2.55)	(-7.77)

Note: The table presents the regressions of equal-weighted and value-weighted excess portfolio returns on FF factor returns. The portfolios are sorted on TFP. Alphas are annualized (%). Returns are measured from July 1971 to June 2009. $t-$statistics are calculated by dividing the slope coefficient by its time series standard error and presented in parentheses.

1.3.2 Fama-MacBeth Regressions

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.

Table IV reports the time series averages of cross-sectional regression slope coefficients and their time-series t-statistic (computed as in Newey-West with 4 lags) obtained from the Fama-MacBeth regressions. In all specifications, the dependent variable is the excess monthly stock returns, annualized to make the magnitudes comparable to the results in Table II. The first specification in Table IV shows the relationship between the level of TFP and future excess returns. The cross sectional regression, where log TFP is the only explanatory variable, produces a negative and statistically significant average slope. The magnitude of the effect is significant as well. The -5.00 average regression coefficient in this setting translates into approximately 2.5% higher expected returns for the firms in the lowest TFP decile compared to an average TFP firm.[19]

In specifications II-XIII, we examine the marginal predictive power of TFP after controlling for several firm level characteristics that are known to predict stock returns and/or found to systematically vary with TFP in Table I. We include these return predictors in addition to our productivity variable as it is relatively standard to control for most of these variables in such predictability regressions. However, it is not clear that these are the right control variables in our setting. As we discuss in Section 2, our model generates cross sectional variations in characteristics such as B/M, size, hiring rate, and investment rate as a result of differences in firm level productivity (though the relationship does not have to be linear as assumed in the Fama-MacBeth regressions). To the extent that our model is valid, and the variables of interest are correctly measured, many

[19] To examine if the industry concentration may play a role in these results, we merged our data with the Herfindahl indexes published by the Census Bureau which are calculated from establishment level data for 4-digit SIC codes (for manufacturing firms only). We separated the sample into above and below median concentration levels and found stronger results for the sample of firms from industries with lower concentration. Fama-MacBeth regression coefficient is -3.8 ($t-$ statistic is 1.8) for firms in high concentration industries, versus -6.7 ($t-$ statistic is 3.5) for firms in low concentration industries.

of these variables should be correlated. With this caveat in mind, we summarize the findings.

Table IV: Fama-MacBeth Regressions with Other Predictors (%, annualized)

	Int	TFP	BM	SIZE	I/K	HR	INV	AG	PR	GPR	NS	LEV	AGE
I	9.51	-5.00											
	(2.5)	(-3.21)											
II	10.66	-1.02	4.63										
	(2.80)	(-0.82)	(4.82)										
III	5.95	-1.86		-1.81									
	(1.76)	(-1.61)		(-3.72)									
IV	10.99	-3.36			-9.29								
	(3.08)	(-2.02)			(-3.71)								
V	10.05	-3.91				-4.58							
	(2.71)	(-2.50)				(-4.83)							
VI	10.00	-4.09					-2.94						
	(2.70)	(-2.54)					(-5.93)						
VII	10.89	-2.74						-7.21					
	(2.94)	(-1.80)						(-7.21)					
VIII	9.76	-3.76							-4.70				
	(2.48)	(-3.04)							(-1.76)				
IX	6.54	-5.56								6.45			
	(1.74)	(-3.51)								(3.15)			
X	9.43	-5.00									-1.25		
	(2.49)	(-3.19)									(-1.37)		
XI	7.90	-3.83										5.30	
	(2.15)	(-2.75)										(1.61)	
XII	10.63	-5.24											-0.08
	(2.23)	(-3.20)											(-0.96)
XIII	7.44	3.10	2.85	-1.12	-6.04	-0.18	-1.34	-3.97	-3.83	5.88	-5.77	0.43	0.02
	(2.05)	(3.24)	(3.31)	(-2.69)	(-2.27)	(-0.21)	(-3.03)	(-4.19)	(-1.43)	(2.89)	(-3.24)	(0.16)	(0.45)

Note: The table presents the average slopes and their $t-$statistics from monthly cross-section regressions to predict excess stock returns. Results are reported for the whole sample period of July 1973 to June 2007. The $t-$statistics for the average regression slopes use the time-series standard deviations of the monthly slopes (computed as in Newey-West with 4 lags) and presented in parentheses. Excess returns are predicted for July of year $t+1$ to June of $t+2$. Average TFP each year is normalized to be 1. SIZE is the log 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, where investment is measured from capital expenditures deflated by the price deflator for investment, and capital is the gross plant, property and equipment, deflated following Hall (1990). AG is the change in the natural log of assets from year $t-1$ to year t. HR is the change in the natural log of number of employees from year $t-1$ to year t . INV is the change in the natural log of total inventories from year $t-1$ to year t. 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. PR is the equity income in year t divided by book equity for year t. GPR is the gross profits in year t divided by book assets for year t. AGE is computed in year t as the number of years since the firm first shows up in Compustat. Excess returns are annualized (%).

Specification (II) considers firm's B/M, (III) considers size, (IV) considers investment to capital ratio, (V) considers hiring rate, (VI) considers inventory growth, (VII) considers asset growth, (VIII) considers profitability, (IX) considers gross profitability, (X) considers net share issues, (XI) considers leverage, and (XII) considers firm age. The definitions of these variables are available in Appendix, Section 4.1. In the last specification, XIII, we consider all the return predictors jointly. We observe that the cross sectional regressions in specifications I to XII produce negative and statistically significant average slopes for TFP except for the specifications in II, III, and VII where including book to market (in II), size (in III), and asset growth (in VII) erodes the significance of TFP.

Specifications VIII and IX, where we investigate the marginal predictive power of profitability and gross profitability together with TFP, warrant some discussion. Measures of profitability are often used to proxy for unobserved productivity in asset pricing context; hence it is essential to understand how they relate to TFP and future returns. Section 1.2 reports that TFP is modestly correlated with gross profitability, whereas the correlation between TFP and profitability is more substantial. Specification VIII shows that profitability and TFP both predict returns with a negative sign. However, the coefficient for TFP is significant, whereas the one for profitability is not.[20] In specification IX we consider TFP and gross profitability together. We find that TFP predicts future returns with a negative sign, whereas gross profitability predicts with a positive sign and both coefficients are highly significant. Hence, out of the two profitability measures considered, TFP is more closely related to profitability. Gross profitability, as also argued by Novy-Marx, is quite different from profitability, and its information content is dissimilar to that of TFP.

1.3.3 Ex-Ante Discount Rates of TFP-Sorted Portfolios

Both the portfolio approach and the Fama-MacBeth regressions reported in the previous section 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, Lee, and Swaminathan (GLS, 2001), rely on analyst forecasts of future earnings. However analyst forecasts are not available in the first few years of our sample period, and earnings forecasts

[20] It is well known in the literature that the relationship between profitability and future returns is not very robust (Fama and French, 2008).

of many firms in our sample are not available.[21] As an alternative, Hou, van Dijk, and Zhang (HDZ, 2010) use a statistical model to forecast earnings, hence are not constrained by the analyst coverage of firms. We look into ICC estimates following both approaches, calculated as described in GLS and HDZ.

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 forecasts made at the previous fiscal year end. We match the ICC estimates of individual firms with these firms' most recent total factor productivity estimates. Higher risk of low TFP firms would imply higher ICC estimates for these firms.

Table V presents the average implied cost of capital estimates for portfolios sorted on productivity. The relationship between TFP and the cost of capital measured from both ICC measures is negative and quite monotonic. The firms with low productivity have contemporaneously higher discount rates (ICC) than firms with high productivity using both ICC measures and both for equal and value weighted portfolios. Using the GLS measure, value-weighted portfolio returns range between 19.15% for the low TFP firms and 6.75% for the high TFP firms. The equal-weighted portfolio returns are 9.14% for the low TFP firms, and 8.55% for the high TFP firms. Both spreads are highly statistically significant. Using the HDZ measure, value-weighted portfolio returns are 10.77% for the low TFP firms and 8.86% for the high TFP firms. The equal-weighted portfolio returns are 13.18% for the low TFP firms and 9.86% for the high TFP firms.

[21] Even though analyst forecast data becomes available in late 1970s, the intersection of firms that have both analyst forecast data and TFP data is too small until 1983. Starting in 1983, the sample grows to at least 800 firms per year. Hence, we start looking at analyst-forecast based implied cost of capital estimates in 1983.

Again, both spreads are highly statistically significant, implying that firms with low productivity have higher ex-ante discount rates, hence are riskier than high productivity firms.[22] Furthermore, similar to the results based on average realized returns in Table II, both the levels of implied cost of capital and the spread between the low and high TFP portfolios are countercyclical. The spread between the discount rates of low and high TFP portfolios increases from 3.04% to 5.58% for equal-weighted portfolios, and from 1.8% to 2.81% for value-weighted portfolios as the economy moves from expansions to contractions, as defined by the NBER.[23] During recessions, firms with low productivity are hit particularly hard and thus bear more risk than firms with high TFPs.

[22] We have 36 years of implied cost of capital data following HDZ, and 23 years of data following GLS. In addition, GLS sample spans the "Great Moderation" period, with no severe recessions in the sample period. Hence, the level of ICCs from both methods are not directly comparable.

[23] Since the GLS sample includes only two short and relatively mild recessions, we report expansion and contraction ICCs with only the HDZ measure.

Table V: **Implied Cost of Capital for TFP Sorted Portfolios (%, annualized)**

	Low	2	3	4	5	6	7	8	9	High	High-Low
	Gebhardt, Lee, Swaminathan (2001) Measure, 1983-2005										
ICC_{EW}	9.14	9.77	9.64	9.53	9.33	9.21	9.14	8.97	8.76	8.55	-0.58
											(-5.81)
ICC_{VW}	19.15	17.41	13.65	12.20	10.70	9.35	9.26	8.22	7.77	6.75	-12.41
											(-6.52)
	Hou, van Dijk, Zhang (2010) Measure, 1970-2005										
	All states										
ICC_{EW}	13.18	14.81	14.07	13.36	12.75	12.19	11.54	10.99	10.37	9.86	-3.32
											(-7.80)
ICC_{VW}	10.77	11.02	10.40	9.98	9.86	9.43	9.38	8.95	8.82	8.86	-1.91
											(-4.99)
	Expansions										
ICC_{EW}	12.53	14.25	13.59	12.93	12.25	11.80	11.11	10.62	10.01	9.50	-3.04
											(-7.05)
ICC_{VW}	10.22	10.69	9.92	9.53	9.48	9.18	8.96	8.67	8.43	8.42	-1.80
											(-4.45)
	Contractions										
ICC_{EW}	18.35	19.31	17.95	16.77	16.78	15.30	14.99	14.01	13.20	12.77	-5.58
											(-4.22)
ICC_{VW}	15.13	13.66	14.16	13.65	12.85	11.44	12.77	11.18	11.95	12.31	-2.81
											(-2.53)

Note: ICC_{EW} is equal-weighted implied cost of capital, ICC_{VW} is value-weighted implied cost of capital, annual, averages are taken over time (%). ICC data based on Gebhardt, Lee, Swaminathan (2001) method is matched to TFP data from 1982 to 2005. ICC data based on Hou, van Dijk and Zhang (2010) method is matched to TFP data from 1970 to 2005. $t-$ statistics are in parentheses. Expansion and contraction periods are designated in June of each year (when ICCs are computed) based on whether that month is an NBER expansion or contraction.

1.3.4 Robustness Checks

We perform several additional tests to check the robustness of the results to different production function specifications, use of different data samples, concerns related to leverage and in-sample versus out-of-sample forecasts of stock returns. We report the results with unlevered returns and out-of-sample forecasts in this section, and discuss the remaining robustness results in the Appendix.

Empirical Analysis with Unlevered Returns The characteristics of TFP sorted portfolios in Table I show that firms with lower TFP have higher leverage (LEV), which is measured as 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. Since the equity returns of low TFP firms are more levered, it is possible that financial leverage may explain some of the effect of TFP on the cost of equity. Our first attempt to isolate the effect of TFP from leverage was specifically controlling for firm leverage in the Fama-MacBeth regressions (Table IV, specification XI), where we found TFP to be still significantly related to returns. In this section we reconfirm that differences in leverage is not the underlying reason for the spread between the low and high TFP equity returns by unlevering the equity returns and investigating the relationship between TFP and unlevered firm returns. Working with the unlevered cost of equity eliminates concerns that financial leverage might alter our results.

We compute the unlevered cost of equity from the standard weighted average cost of capital formula. Unlike equity returns, firm debt returns are not readily available. We compute debt returns following Liu, Whited and Zhang (2009). The computation involves imputing bond ratings for all firms/years in our sample following the procedure in Blume, Lim and MacKinlay (1998) and assigning the corporate bond returns for a given credit rating as the debt returns to all firms with the same credit rating. The details of the computation are available in the Data section of the Appendix.

We repeat our basic tests using the unlevered future excess returns as our cost of capital measure. The sample gets slightly shorter in these exercises since the bond return data starts in January 1973. The Fama-MacBeth regressions of monthly unlevered excess returns on lagged firm level TFP reveal an average cross-sectional regression slope coefficient of -2.87 (annualized) with a Newey-West adjusted t-statistic of -2.17, which translates into approximately 1.5% higher expected unlevered returns for the firms in the lowest TFP decile compared to an average TFP firm.

TFP sorted portfolio returns also yield a similar result. Table VI presents the equal-weighted contemporaneous and future excess unlevered returns of decile portfolios sorted on TFP. The slightly smaller, but still highly significant spreads in average unlevered contemporaneous and future excess returns (21.7% and -4.1%, respectively) confirm that the effect of TFP on the cost of equity we document is not driven by financial leverage. In the untabulated results, we verify that the value-weighted returns and returns during expansions and recessions are qualitatively similar to the benchmark case for levered returns as well.

Table VI: Excess Unlevered Returns for TFP Sorted Portfolios (%, annualized)

	Low	2	3	4	5	6	7	8	9	High	High-Low
					Contemporaneous Returns						
r^e_{EW}	1.56	6.10	8.34	10.25	11.32	12.99	14.48	16.52	18.60	23.21	21.65
	(0.46)	(2.33)	(3.29)	(4.07)	(4.40)	(4.88)	(5.16)	(5.56)	(5.82)	(6.30)	(11.87)
σ^e_{EW}	19.90	15.47	15.02	14.90	15.21	15.74	16.60	17.59	18.92	21.79	10.79
					Future Returns						
r^e_{EW}	10.03	9.42	8.37	7.88	7.60	7.81	7.24	6.67	6.43	5.93	-4.10
	(2.92)	(3.30)	(3.20)	(2.98)	(2.80)	(2.84)	(2.53)	(2.27)	(2.02)	(1.67)	(-2.35)
σ^e_{EW}	20.76	17.23	15.80	15.98	16.37	16.63	17.25	17.72	19.22	21.47	10.53

Note: r^e_{EW} is equal-weighted monthly excess unlevered returns (excess of risk free rate), annualized, averages are taken over time (%). σ^e_{EW} is 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 (%). $t-$ statistics are in parentheses.

Out-of-Sample Tests One possible concern about the return forecasting results presented above is the potential for "look-ahead" bias due to the fact that the coefficients in TFP estimation (production function parameters) are estimated using the full sample. This concern may be addressed by performing out-of-sample forecasts where the production function parameters are reestimated every year, using only data available at the time of the return forecast. In this section, we reestimate the production function parameters every year using all data available up until that year and compute TFPs for each year using that year's data and the corresponding production function estimates. We label these TFPs as "rolling TFPs" to distinguish them from the benchmark TFPs. This procedure leads to only minor differences in TFP estimates compared to the benchmark case where we use all available data to estimate the production function parameters.[24]

We replicate our empirical tests using the rolling TFP estimates. We find that results are almost identical to the bechmark case. The Fama-MacBeth regressions of monthly excess returns on lagged firm level TFP reveal an average cross-sectional regression slope coefficient of -4.97 (annualized) with a Newey-West adjusted t-statistic of -3.06, which translates into approximately 2.5% higher expected returns for the firms in the lowest TFP decile compared to an average TFP firm. Table VII presents the equal-weighted

[24] In Appendix (Section 4.2), we provide estimates of the production function for several different time periods. Overall, production function estimates are fairly stable across different sub-periods. Hence, it is not surprising to have rolling TFP estimates that are similar to the benchmark estimates.

contemporaneous and future excess returns of decile portfolios sorted on TFP. We also verify that the remaining findings (value-weighted returns, ex-ante discount rates, returns over the business cycles, Fama-MacBeth regression results) are very similar to the benchmark case, hence are not tabulated for brevity.

Table VII: Excess Returns for Rolling TFP Sorted Portfolios (%, annualized)

	Low	2	3	4	5	6	7	8	9	High	High-Low
					Contemporaneous Returns						
r^e_{EW}	-4.55	3.14	7.60	9.61	11.72	13.80	15.24	17.33	18.79	23.32	27.87
	(-1.08)	(0.91)	(2.27)	(2.93)	(3.59)	(4.15)	(4.60)	(5.07)	(5.32)	(6.00)	(13.61)
σ^e_{EW}	25.95	21.34	20.61	20.23	20.11	20.50	20.41	21.06	21.77	23.96	12.62
					Future Returns						
r^e_{EW}	13.60	12.74	10.99	10.38	9.76	9.32	9.15	8.35	7.50	6.87	-6.73
	(3.13)	(3.42)	(3.23)	(3.07)	(2.93)	(2.77)	(2.74)	(2.44)	(2.10)	(1.83)	(-3.08)
σ^e_{EW}	26.78	22.94	21.00	20.83	20.57	20.72	20.59	21.08	21.97	23.14	13.46

Note: r^e_{EW} is equal-weighted monthly excess returns (excess of risk free rate), annualized, averages are taken over time (%). σ^e_{EW} is 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 (%). $t-$ statistics are in parentheses.

2 Model

In this section we investigate whether a 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 in Table I and Table II. 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, Green, and Naik (1999);

Zhang (2005); and Gomes and Schmid (2010) and Bazdresch, Belo and Lin (2010), we assume that the model is populated with many competitive firms that take the pricing kernel and the stochastic wage rate as given. We calibrate the model using the firm level TFP estimates summarized in the Appendix and examine the resulting firm level characteristics and firm returns generated by the model economy.

2.1 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:

$$\begin{aligned} Y_{it} &= F(A_t, Z_{it}, K_{it}, L_{it}) \\ &= A_t Z_{it} K_{it}^{\alpha_k} L_{it}^{\alpha_l}. \end{aligned}$$

K_{it} denotes the beginning of period t capital stock of firm i. 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:

$$a_{t+1} = \rho_a a_t + \varepsilon^a_{t+1} \tag{1}$$

where $\varepsilon^a_{t+1} \sim$ i.i.d. $\mathrm{N}(0, \sigma_a^2)$. 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:

$$z_{i,t+1} = \rho_z z_{it} + \varepsilon^z_{i,t+1} \tag{2}$$

where $\varepsilon^z_{i,t+1} \sim$ i.i.d. $\mathrm{N}(0, \sigma_z^2)$. $\varepsilon^z_{i,t+1}$ and $\varepsilon^z_{j,t+1}$ 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},

$$g\left(I_{it}, K_{it}\right) = \frac{1}{2}\eta\left(\frac{I_{it}}{K_{it}} - \delta\right)^2 K_{it} \tag{3}$$

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 Bazdresch, Belo, and Lin (2010). The equilibrium wage rate is assumed to be increasing with aggregate productivity

$$W_t = exp(a_t). \tag{4}$$

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,

$$\begin{aligned} F_{L_{it}} &= F_L(A_t, Z_{it}, K_{it}, L_{it}) \\ &= W_t. \end{aligned}$$

Dividends to shareholders are equal to

$$D_{it} = Y_{it} - [I_{it} + g_{it}] - W_t L_{it}. \tag{5}$$

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

$$V_{it} = \max_{\{I_{i,t+k}, L_{i,t+k}\}} E_t \left[\sum_{k=0}^{\infty} M_{t,t+k} D_{i,t+k} \right], \tag{6}$$

subject to (Eq.1-4), where $M_{t,t+k}$ is the stochastic discount factor between time t and $t+k$. V_{it} is the cum-dividend value of the firm.

The pricing equations for the firm's optimization problem are:

$$1 = \int \int M_{t,t+1} R^I_{i,t+1} p_{z_i}(z_{i,t+1}|z_{it}) p_a(a_{t+1}|a_t) d_{z_i} d_a \tag{7}$$

where the returns to investment are given by

$$R^I_{i,t+1} = \frac{F_{K_{i,t+1}} + (1-\delta) q_{i,t+1} + \frac{1}{2}\eta \left(\left(\frac{I_{i,t+1}}{K_{i,t+1}} \right)^2 - \delta^2 \right)}{q_{it}} \tag{8}$$

and where

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

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

$$q_{it} = 1 + \eta \left(\frac{I_{it}}{K_{it}} - \delta \right). \tag{9}$$

The pricing equation (Eq.7) 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 as

$$R^S_{i,t+1} = \frac{V_{i,t+1}}{V_{it} - D_{it}}. \tag{10}$$

2.2 The Stochastic Discount Factor

Following Berk, Green, and Naik (1999) and Zhang (2005), we directly parameterize the pricing kernel without explicitly modeling the consumer's problem. We follow Jones and

Tüzel (2010a,b) and modify the pricing kernel specification in Zhang (2005) as

$$\log M_{t+1} = \log \beta - \gamma_t \epsilon^a_{t+1} - \frac{1}{2}\gamma_t^2 \sigma_a^2 \quad (11)$$
$$\log \gamma_t = \gamma_0 + \gamma_1 a_t$$

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

Our model 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^a_{t+1}, 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. As in Zhang, this volatility takes higher values following business cycle contractions and lower values following expansions, implying a countercyclical price of risk as the result.[25] 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, 2010a; among many others). Our empirical results in Table II and Table V, 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.

[25] A countercyclical price of risk is endogenously derived in Campbell and Cochrane (1999) from time varying risk aversion; in Barberis, Huang, and Santos (2001) from loss aversion; in Constantinides and Duffie (1996) from time varying cross sectional distribution of labor income; in Barberis, Shleifer, and Vishny (1998) from time varying investor sentiment; in Guvenen (2009) from limited participation; in Bansal and Yaron (2004) from time varying economic uncertainty; and in Piazzesi, Schneider, and Tuzel (2007) from time varying consumption composition risk.

Two differences with Zhang (2005) are worth noting. One is that the riskless rate is constant in our specification. This follows the inclusion of the term $-\frac{1}{2}\gamma_t^2\sigma_a^2$ in the pricing kernel. This ensures that the pricing kernel has a constant expectation and implies that the riskless rate is equal to $-\log\beta$ in every period. The second difference is the exponential rather than linear specification of γ_t. It is desirable to have a pricing kernel whose variance is globally decreasing in the level of productivity. The exponential guarantees positivity of γ_t, which prevents the relationship between M_{t+1} and ϵ_{t+1} from becoming perversely positive for high values of a_t.

2.3 Calibration and Quantitative Results

Solving our model generates solutions for 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 in the state space. Our primary interest is in understanding the relationship between firm level productivity, firm characteristics, and expected returns.

Similar to Zhang (2005), 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. All risk derives from the firm's 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 due to 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[26], they incur adjustment costs when they change their capital stock.[27] In states of low aggregate productivity, a bad aggregate shock has 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. Due to the convexity in adjustment costs, low TFP firms sustain a higher cost while reducing their capital stock in a recession than high TFP firms. A positive aggregate shock, on the other hand, results in a bigger 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.[28] As in Zhang (2005), we assume that the volatility of the pricing kernel is a decreasing function of aggregate productivity; hence, Sharpe ratios (and discount rates) are higher in bad times. Risk is defined as the covariation of the returns with the pricing

[26] This is an assumption to keep the model as simple as possible. Bazdresch, Belo, and Lin (2010) consider an economy with labor adjustment costs, in addition to the usual capital adjustment costs, and find qualitatively similar results.

[27] 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.

[28] For simplicity, we assume symmetric adjustment costs, but asymmetric adjustment costs would also break this symmetry. Zhang (2005) and Tuzel (2010), for example, use asymmetric adjustment costs under which reducing the capital stock is more costly than increasing it. This asymmetry leads to differences in the risk levels of firms with low and high investment and will cause firms that are disinvesting to be more sensitive to aggregate productivity shocks. This mechanism would strengthen our results.

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 higher risk. The highest expected returns therefore tend to come from low productivity firms reducing their capital stock during economic downturns. 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. Without the countercyclical price of risk, the model could neither generate the average level of risk premia nor the spread between the returns of the high and low TFP firms. However, the model that is calibrated to match the average level and volatility of the aggregate risk premia (through the calibration of the pricing kernel) is capable of matching many of the cross sectional properties.

To capture the business cycle movements, we calibrate the model at quarterly frequency but report annualized moments to match our annual empirical results. Table VIII presents the parameters used in the calibration, which correspond to quarterly frequency.[29] We derive the parameters of the firm level productivity process from the production function estimations in the Appendix. The persistence of the firm productivity process, ρ_z, is 0.911 $(= 0.69^{\frac{1}{4}})$. The conditional volatility of firm productivity, σ_z, is computed from ρ_z and the cross sectional standard deviation of firm productivity as 0.145 $\left(= 0.4 \times \sqrt{1-0.69^2} \times 0.5\right)$.[30] The parameters of the production function, α_k and α_l, are

[29]Calibrations of the model economy based on alternative TFP estimation results presented in the Appendix yields qualitatively and quantitatively very similar asset pricing results.

[30]The dispersion of firm productivity rises over time, from 0.23 in 1953 to 0.52 in 2009. In this

roughly equal to our estimates presented in the Appendix. Even though our production function estimates imply an almost constant returns to scale production technology, we model technology as slightly decreasing returns to scale, with $\alpha_k + \alpha_l = 0.95$. It is well known that firm size is indeterminate with constant returns to scale technology. Decreasing returns to scale technology makes studying the relationship between firm size and productivity possible.

We take the parameters of the aggregate productivity from King and Rebelo (1999). Their point estimates for σ_a and ρ_a are 0.979 and 0.0072, respectively, using quarterly data. The depreciation rate for fixed capital is set to eight percent annually ($\delta = 0.02$ quarterly), which is roughly the midpoint of values used in other studies. Cooley and Prescott (1995) use 1.6%; Boldrin, Christiano, and Fisher (2001) use 2.1%; and Kydland and Prescott (1982) use a 2.5% quarterly depreciation rate.

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 0.995, which implies an annual risk free rate of 2%. γ_0 and γ_1 are 3.24 and -19.05, respectively, and generate annual excess mean returns and standard deviation of 6.3% and 17%, respectively. Finally, the adjustment cost parameter, η, is set to 11.3 to replicate the value-weighted average (annual) volatility of investment to capital ratio of 0.143 in our data.

calibration, we take the cross sectional standard deviation to be 0.35, which is the average dispersion over this time period.

Table VIII: Model Parameter Values

Parameter	Description	Value
α_k	Capital share	0.24
α_l	Labor share	0.71
β	Discount factor	0.995
γ_0	Constant price of risk parameter	3.24
γ_1	Time varying price of risk parameter	-19.05
δ	Capital depreciation rate	0.02
η	Adjustment cost parameter	11.3
ρ_a	Persistence of aggregate productivity	0.98
σ_a	Conditional volatility of aggregate productivity	0.007
ρ_z	Persistence of firm productivity	0.911
σ_z	Conditional volatility of firm productivity	0.145

Table IX presents the average firm characteristics and expected returns for TFP sorted portfolios using simulated data from the model economy. The results indicate that the model is able to match the data presented in Table I and Table II 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. Firm TFP is a state variable in the model; 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. However, the magnitude of the dispersion in investment to capital ratios and hiring rates of low versus high productivity firms is higher than the dispersion found in the data.[31]

[31] The model-generated dispersion in I/K is approximately twice as high as the dispersion in the data. However, the model overshoots the dispersion in hiring rate significantly more. This problem could be alleviated by introducing adjustment costs in hiring/firing, which is currently assumed to be costless.

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}).[32] Tobin's q is linear in investment to capital ratio (Eq. 9), which is monotonically increasing in TFP. Likewise, the amount of capital, K_{t+1} is increasing in TFP due to 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_{it+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 q (q_{it}) in the model.[33] This leads to a negative relationship between B/M and TFP. The model is quite successful in matching the magnitude of the dispersion in size and B/M observed in the data. These results confirm that the model can qualitatively, and to a significant extent quantitatively, generate the relationship between productivity and these firm characteristics found in the data.

Table IX also reports that the expected returns of TFP sorted portfolios decline monotonically with TFP. The spread in expected returns, -11.2%, is higher than the empirical spread of 6.33% reported in Table II. 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

Adjustment costs in hiring would reduce the volatility in hiring rate, hence reduce the dispersion in the hiring rate of the most productive and least productive firms.

[32] 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 $q_t K_{t+1}$.

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

this exercise, we define periods where aggregate productivity is more than one standard deviation lower than the mean 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 (60 out of 456 months in our sample period). The model generates approximately 3.5% expected average returns, and 10% spread in TFP sorted portfolios in expansions (7% and 5% in the data, respectively), whereas the average returns are approximately 40%, and the spread is 18% in contractions (27% and 15% in the data).

Table IX: Model Implied Characteristics and Excess Returns for TFP Sorted Portfolios

	Low	2	3	4	5	6	7	8	9	High	High-Low Model	High-Low Data
TFP	0.54	0.70	0.79	0.88	0.96	1.05	1.15	1.27	1.45	1.85	1.31	1.43
I/K	-0.19	-0.09	-0.05	-0.02	0.02	0.05	0.09	0.14	0.21	0.39	0.58	0.25
HR	-0.41	-0.07	0.09	0.26	0.40	0.57	0.72	0.88	1.15	1.74	2.15	0.22
Size	0.38	0.49	0.58	0.66	0.75	0.85	0.99	1.18	1.50	2.60	2.22	2.94
B/M	1.56	1.35	1.27	1.21	1.13	1.06	0.99	0.89	0.78	0.67	-0.89	-0.90
							Future Returns					
	All states											
r^e	14.47	12.48	11.35	10.45	9.62	8.81	7.92	6.94	5.69	3.23	-11.24	-6.33
σ^e	28.78	27.22	26.28	25.81	24.76	23.94	23.00	22.08	20.73	18.01	13.30	12.69
	Expansions											
r^e	8.27	6.47	5.46	4.66	3.91	3.18	2.40	1.53	0.42	-1.78	-10.05	-5.01
σ^e	22.38	21.06	20.31	19.94	19.27	18.85	18.30	17.53	16.82	15.07	10.16	12.49
	Contractions											
r^e	48.36	45.30	43.56	42.09	40.80	39.52	38.10	36.49	34.48	30.59	-17.77	-15.02
σ^e	49.08	46.61	44.90	44.07	41.99	40.06	38.08	36.36	33.52	27.82	23.50	13.81

3 Conclusion

This paper examines the relationship between firm level TFP and certain firm characteristics and returns. We find that high TFP firms are typically large growth firms. The hiring rate, fixed investment to capital ratio, asset growth, and inventory growth are all monotonically increasing in firm level TFP. We also show that TFP is positively and monotonically related to contemporaneous stock returns and negatively related to future returns, as well as ex-ante discount rates. The unconditional return spread is sizable, approximately 6% in realized returns and 3% in implied cost of capital. However, there is significant variation in the spread over the business cycles; the spread is about three times as high during NBER contractions as it is during expansions. We interpret the spread in the average returns across these portfolios as the risk premia associated with the higher risk of low productivity firms. We show that a production-based asset pricing model with aggregate and idiosyncratic shocks is able to account for most of these stylized facts quantitatively.

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4 Appendix: Measuring TFP

The main contributions to measuring firm level TFP are by Olley and Pakes (1996) and Levinsohn and Petrin (2003). The key difference between the two methods is that Olley and Pakes (1996) use investment whereas Levinsohn and Petrin (2003) use materials used in production as a proxy for TFP. Since data on investment is readily available and often non-zero at the firm level but data on materials is not, we follow Olley and Pakes (1996) to estimate firm level productivities. The major advantage of this approach over more traditional production function 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. The static OLS production function estimates reveal that within firm residuals, which are the productivity estimates in that setting, are serially correlated. The simultaneity bias arises if the firm's factor input decision is influenced by the TFP that is observed by the firm. This means that the regressors and the error term in an OLS regression are correlated, resulting in biased estimates of the production function parameters. The selection bias in the OLS regressions arises due to firms exiting the sample used in estimating the production function parameters. If the exit probability is correlated with productivity, not accounting for the selection issue may bias the production function parameter estimates.

In our benchmark case, we estimate the production function based on labor and physical capital as inputs to the production of the firm.

Assume that the production technology is represented by a production function that relates output to inputs and productivity.

$y_{it} = F(l_{it}, k_{it}, \omega_{it})$ where y_{it} is log output for firm i in period t. l_{it}, k_{it} are log values of labor, and capital of the firm. ω_{it} is the productivity and η_{it} is an error term not known by the firm or the econometrician. Specifically,

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \omega_{it} + \eta_{it}. \tag{12}$$

Olley and Pakes assume that productivity, ω_{it}, is observed by the firm before the firm makes some of its factor input decisions, which gives rise to the simultaneity problem. Labor, l_{it}, is the only variable input, i.e., its value can be affected by current productivity, ω_{it}. The other input, k_{it} is a fixed input at time t and its value is only affected by the conditional distribution of ω_{it} at time $t-1$. Consequently, ω_{it} is a state variable that affects firms' decision making where firms that observe a positive productivity shock in period t will invest more in capital, i_{it}, and hire more labor, l_{it}, in that period. The solution to the firm's optimization problem results in the equations for i_{it},

$$i_{it} = i\left(\omega_{it}, k_{it}\right) \tag{13}$$

where both i and j are strictly increasing in ω. The inversion of the equations yield

$$\omega_{it} = h(i_{it}, k_{it})$$

where h is strictly increasing in i_{it}.

Define

$$\phi_{it} = \beta_0 + \beta_k k_{it} + h(i_{it}, k_{it}). \tag{14}$$

Using equations (12) and (14), we can obtain

$$y_{it} = \beta_l l_{it} + \phi_{it} + \eta_{it} \tag{15}$$

where we approximate ϕ_{it} with a second order polynomial series in capital and investment.[34] This first stage estimation results in an estimate for $\widehat{\beta}_l$ that controls for the simultaneity problem.[35] In the second stage, consider the expectation of $y_{i,t+1} - \widehat{\beta}_l l_{i,t+1}$ on information at time t and survival of the firm[36]:

$$\begin{aligned} E_t\left(y_{i,t+1} - \widehat{\beta}_l l_{i,t+1}\right) &= \beta_o + \beta_k k_{i,t+1} + E_t(\omega_{it+1}|\omega_{it}, survival) \\ &= \beta_o + \beta_k k_{i,t+1} + g(\omega_{it,} \widehat{P}_{survival,t}) \end{aligned} \tag{16}$$

where $\widehat{P}_{survival,t}$ denotes the probability of firm survival from time t to time $t+1$. The survival probability is estimated via a probit of a survival indicator variable on a polynomial expression containing capital and investment. We fit the following equation by nonlinear least squares:

$$y_{i,t+1} - \widehat{\beta}_l l_{i,t+1} = \beta_k k_{i,t+1} + \rho\omega_{it} + \tau\widehat{P}_{survival,t} + \eta_{i,t+1} \tag{17}$$

[34] Approximating with a higher order polynomial instead does not significantly change the results.

[35] Since our data set covers different industries with different market structures and factor prices, in our benchmark case, we estimate equation (15) with industry specific time dummies.

[36] We also take out the effects of industry specific time dummies at this stage.

where ω_{it} is given by $\omega_{it} = \phi_{it} - \beta_0 - \beta_k k_{it}$ and is assumed to follow an AR(1) process.[37] At the end of this stage, $\widehat{\beta}_l$ and $\widehat{\beta}_k$ are estimated.

Finally, productivity is measured by[38]

$$P_{it} = \exp(y_{it} - \widehat{\beta}_o - \widehat{\beta}_l l_{it} - \widehat{\beta}_k k_{it}). \tag{18}$$

4.1 Data

The main data source for firm level productivity estimation is Compustat. We use the Compustat fundamental annual data from 1953 to 2009. We delete observations of financial firms (SIC classification between 6000 and 6999) and regulated firms (SIC classification between 4900 and 4999).[39] Our sample for production function estimation is comprised of all remaining firms in Compustat that have positive data on sales, total assets, number of employees, gross plant property equipment, depreciation, accumulated depreciation, and capital expenditures. The sample period starts in 1953; however, there are relatively few observations in the early years of the sample. The sample is an unbalanced panel with approximately 12750 distinct firms; the total number of firm-year

[37] Estimating an AR(2) process has almost no impact on the estimated labor and capital shares $(\widehat{\beta}_l, \widehat{\beta}_k)$.

[38] We again take out the effects of industry specific time dummies while calculating the TFPs. In another specification, we compute firm level TFPs without using these industry dummies in our first stage estimation. We analyze the industry adjusted TFPs of firms, which are the log TFPs in excess of their industry averages. The stylized facts generated from that framework are both qualitatively and quantitatively very similar to our benchmark results even though the production function estimates for labor and capital are somewhat different.

[39] We exclude financial firms and regulated firms since it is standard to do in this literature. Keeping these firms in the sample does not change the results in any material way. The production function estimates for the financial firms are quite similar to the production function estimates for the non-financial firms.

observations is approximately 131000.[40]

The key variables for estimating the firm level productivity in our benchmark case are the firm level value added, employment, and physical capital. Firm level data is supplemented with price index for Gross Domestic Product as deflator for the value added and price index for private fixed investment as deflator for investment and capital, both from the Bureau of Economic Analysis; and national average wage index from the Social Security Administration.

Value added (y_{it}) is computed as Sales - Materials, deflated by the GDP price deflator.[41] Sales is net sales from Compustat (SALE).[42] Materials is measured as Total expenses minus Labor expenses. Total expenses is approximated as [Sales - Operating Income Before Depreciation and Amortization (Compustat (OIBDP))]. Labor expenses is calculated by multiplying the number of employees from Compustat (EMP) by average wages from the Social Security Administration).[43] The stock of labor (l_{it}) is measured by the number of employees from Compustat (EMP). These steps lead to our value added definition which is proxied by Operating Income Before Depreciation and Amortization + labor expenses.

[40] At this stage, we do not require the firms to be in CRSP database. Hence, our sample size gets somewhat smaller later when we merge our dataset with CRSP data.

[41] Measures of productivity based on firm revenues typically confound idiosyncratic demand and factor price effects with differences in efficiencies. Foster, Haltiwagner, and Syverson (2008) show that demand factors can be important in understanding industry dynamics and reallocation. Measures of productivity that incorporate demand factors require data on producers' physical outputs as well as product prices which is not available at the firm level. However, they also show that revenue based productivity measures, such as the one used in this study, are highly correlated with their physical productivity.

[42] Net sales are equal to gross sales minus cash discounts, returned sales, etc.

[43] Compustat also has a data item called staff expense (XLR), which is sparsely populated. Comparing our labor expense series with the staff expense data available at Compustat reveals that our approximation yields a relatively correct and unbiased estimate of labor expenses.

Capital stock (k_{it}) is given by gross Plant, Property & Equipment (PPEGT) from Compustat, deflated by the price deflator for investment following the methods of Hall (1990) and Brynjolfsson & Hitt (2003).[44] Since investment is made at various times in the past, we need to calculate the average age of capital at every year for each company and apply the appropriate deflator (assuming that investment is made all at once in year [current year - age]). Average age of capital stock is calculated by dividing accumulated depreciation (Gross PPE - Net PPE, from Compustat (DPACT)) by current depreciation, from Compustat (DP). Age is further smoothed by taking a 3-year moving average.[45] The resulting capital stock is lagged by one period to measure the available capital stock at the beginning of the period.[46]

Fixed investment to capital ratio is given by firm level real capital investment divided by the beginning of the period real capital stock. Investment to capital ratio for organizational capital is obtained similarly. Asset growth is the percent change in total assets (TA) from Compustat. Hiring rate at time t is the change in the stock of labor (EMP) from time $t-1$ to t. Inventory growth is the percent change in inventories (INVT)

[44] Hulten (1990) discusses many complications related to the measurement of capital. The principal options are to look for a direct estimate of the capital stock, K, or to adjust book values for inflation, mergers, and accounting procedures; or to use the perpetual inventory method to construct the capital stock from data on investments. There are problems associated with either method and most of the time, the choice between these methods is dictated by the availability of data. Our results are insensitive to the treatment of inventories as a part of the capital stock.

[45] If there are less than three years of history for the firm, the average is taken over the available years.

[46] We do not have detailed deflators and wages for individual industries in our current benchmark estimation using the general Compustat sample. For the sample of manufacturing firms, detailed deflators and wages at the 4-digit SIC code level are available from the NBER-CES Database. Even though it is arguably better to use industry level deflators, the downside of this approach would be limiting the sample to 5700 manufacturing firms, and the time frame to 1959-2005.

In our estimation we use industry specific time dummies, which lessens the potential problems with using broad deflators to a great extent. In Section 4.2.1 we provide the results for the sample of manufacturing firms, complemented with industry level deflators / wages from the NBER-CES database. These results are very similar to our benchmark results in the paper.

from Compustat. R&D/PPE is the research and development expenditures (XRD from Compustat) divided by gross plant property and equipment. Real estate ratio for each firm is calculated by dividing the real estate components of PPE (sum of buildings and capitalized leases) by total PPE. Firm size is the market value of the firm's common equity (number of shares outstanding times share price from Center for Research in Security Prices (CRSP)). B/M, net stock issues (NS), and Profitability (PR) are defined as in Fama and French (2008). Gross profitability is gross profits / total book assets, as defined in Novy-Marx (2010). Leverage is calculated by dividing long-term debt holdings (DLTT in Compustat) by firm's total assets calculated as the sum of their long-term debt and the market value of their equity. Firm age (AGE) is proxied by the number of years since the firm's first year of observation in Compustat.

We compute firm debt returns following Liu, Whited and Zhang (2010) and use them to unlever equity returns. The computation involves imputing bond ratings for all firms/years in our sample following the procedure in Blume, Lim and MacKinlay (1998) and assigning the corporate bond returns for a given credit rating as the debt returns to all firms with the same credit rating. Since data on credit ratings (Compustat annual item SPLTICRM) is often missing, in order to impute bond ratings we first estimate an ordered probit model that relates credit ratings to observed explanatory variables using all the firms that have data on credit ratings and explanatory variables. We then impute the credit ratings for all firms in our sample using the estimated model parameters. The bond return data is from Barclays Capital U.S. Long Term Corporate Bond Returns for the rating categories Aaa, Aa, A, Baa and High Yield (downloaded from Morningstar).

Data on all rating categories start in January 1973, except for High Yield, which starts in June 1983. Returns on high yield bonds are backfilled to 1973 using data from Ibbotson Associates. We assign the corporate bond returns for a given credit rating to all the firms with the same credit ratings. The ordered probit model contains the following explanatory variables: interest coverage, the ratio of operating income after depreciation (item OIADP) plus interest expense (item XINT) to interest expense; the operating margin, the ratio of operating income before depreciation (item OIBDP) to sales (item SALE), long-term leverage, the ratio of long-term debt (item DLTT) to assets (item AT); total leverage, the ratio of long-term debt plus debt in current liabilities (item DLC) plus short-term borrowing (item BAST) to assets; the natural logarithm of the market value of equity (item PRCC_C times item CSHO) deflated to 1973 by the consumer price index; as well as the market beta (CRSP data item BETAV) and standard deviation of returns (CRSP data item SDEVV).

4.2 Estimation and Properties of TFP

The estimates for the production function and the standard errors are given in Table A-I. The results for the benchmark case spanning between 1953 and 2009, presented in column two, indicate a labor share of 0.751 and a capital share of 0.240. The estimates for the persistence and the standard deviation of the TFP shock, at the annual frequency, are 0.69 and 0.29 respectively. We also document an increase in the cross sectional dispersion of firm level productivity from 0.23 in 1953 to 0.52 in 2009. As a part of our robustness check we provide estimates of the production function for manufacturing and non-manufacturing industries separately as well as for different time periods. Overall, production function estimates are fairly stable across manufacturing and non-manufacturing sectors and different sub-periods. In our benchmark empirical analysis we estimate predictive regressions based on TFP estimates recovered using the entire sample period.[47] Therefore, having stable production function estimates for different sub-periods is reassuring. Unstable production function estimates could potentially induce a look-ahead bias in the TFP estimates. Even if we use the production function estimates from the 1953-1969 period in our asset pricing tests, which start in 1970, our asset pricing results remain virtually identical to our benchmark results.

Table A-I: Production Function Parameters

	All Industries					Manuf	Non-manuf
	Benchmark 1953-2009	1970-2009	1953-1969	1970-1989	1990-2009	1953-2009	1953-2009
Labor	0.751	0.754	0.709	0.770	0.748	0.785	0.725
	(0.002)	(0.002)	(0.004)	(0.002)	(0.003)	(0.003)	(0.003)
Capital	0.240	0.238	0.254	0.211	0.254	0.211	0.265
	(0.002)	(0.002)	(0.008)	(0.004)	(0.003)	(0.003)	(0.003)
Autocorr	0.687	0.685	0.704	0.710	0.643	0.685	0.662
	(0.008)	(0.008)	(0.040)	(0.012)	(0.014)	(0.010)	(0.013)

Note: Table reports the Cobb-Douglas shares of labor and physical capital in the production function. Autocorrelation of TFP is reported at the bottom of the table. Standard errors are presented in parentheses.

One method used in summarizing the evolution of productivity is the transition probability matrix, which shows the probability of a plant/firm moving from a certain productivity percentile in a period to other percentiles in the next period. Table A-II presents the transition probability matrix for the firms sorted into decile TFP portfolios in our

[47]We also perform additional out-of-sample analysis by reestimating the production function every year using only data available at that time and report corresponding results in the paper. The results are very similar regardless of whether the analysis is performed in or out-of-sample.

sample for the benchmark case. The probabilities of staying in the lowest or the highest TFP portfolios are about 50%. The higher probabilities along the diagonal shows that there is some persistence in productivity. The table also reports the probability that a firm in a given portfolio will disappear from our sample in the next year. The drop-off may be the result of either firm failure or a missing data item in the following year. The probability of drop-off ranges from 8-9% for the firms in the higher TFP portfolios to 15% for the firms in the lowest TFP portfolio. The negative relationship between drop-off rates and TFP shows that low productivity firms are more likely to disappear from our sample where the difference in the drop-off rates can be interpreted as the higher likelihood of failure for low TFP firms.

Table A-II: Portfolio Transition Probabilities

		Year t										
	TFP	Low	2	3	4	5	6	7	8	9	High	Drop-off
	Low	0.46	0.19	0.08	0.04	0.02	0.02	0.02	0.01	0.01	0.01	0.15
	2	0.18	0.32	0.18	0.09	0.05	0.03	0.02	0.01	0.01	0.00	0.11
	3	0.07	0.18	0.26	0.18	0.09	0.05	0.03	0.02	0.01	0.01	0.10
	4	0.04	0.09	0.18	0.23	0.18	0.10	0.05	0.03	0.01	0.00	0.10
Year	5	0.04	0.06	0.09	0.17	0.23	0.17	0.09	0.04	0.02	0.01	0.09
$t-1$	6	0.02	0.03	0.06	0.10	0.18	0.23	0.17	0.08	0.03	0.01	0.09
	7	0.02	0.02	0.04	0.06	0.10	0.18	0.25	0.17	0.07	0.02	0.08
	8	0.02	0.02	0.02	0.03	0.05	0.10	0.18	0.29	0.17	0.04	0.08
	9	0.02	0.02	0.02	0.02	0.02	0.04	0.08	0.20	0.37	0.13	0.09
	High	0.02	0.01	0.01	0.01	0.01	0.02	0.02	0.05	0.17	0.60	0.09

Various papers examine the persistence of productivity at the plant level. For example, Bartelsman and Dhrymes (1998) examine transition probabilities of plant level TFPs in three industries over 1972-1986.[48] They report a great deal of persistence where about 50 to 70% of the plants in the lowest and highest deciles tend to stay in the same bin for all the three industries. Their drop-off rates also decline with the TFP decile.

[48]The industries examined are Machinery except Electrical; Electrical and Electronic Equipment and Supplies; and Measuring Instruments.

Baily, Hulten, and Campbell (1992) reach similar conclusions in twenty three 4-digit SIC industries.

Lastly, we construct an aggregate productivity measure based on firm level productivities obtained for our benchmark case and study its characteristics. First, we compute the average industry level TFP and find the industry level TFP growth rates.[49] Then, the industry level productivity growth rates are aggregated using an industry's share in total sales. In figure A1, the resulting aggregate TFP growth is compared with the U.S. industrial TFP growth rate provided by EU KLEMS Growth and Productivity Accounts (2009). The higher volatility produced by our data is somewhat expected since it provides an aggregation over a smaller number of firms compared to the EU KLEMS data.

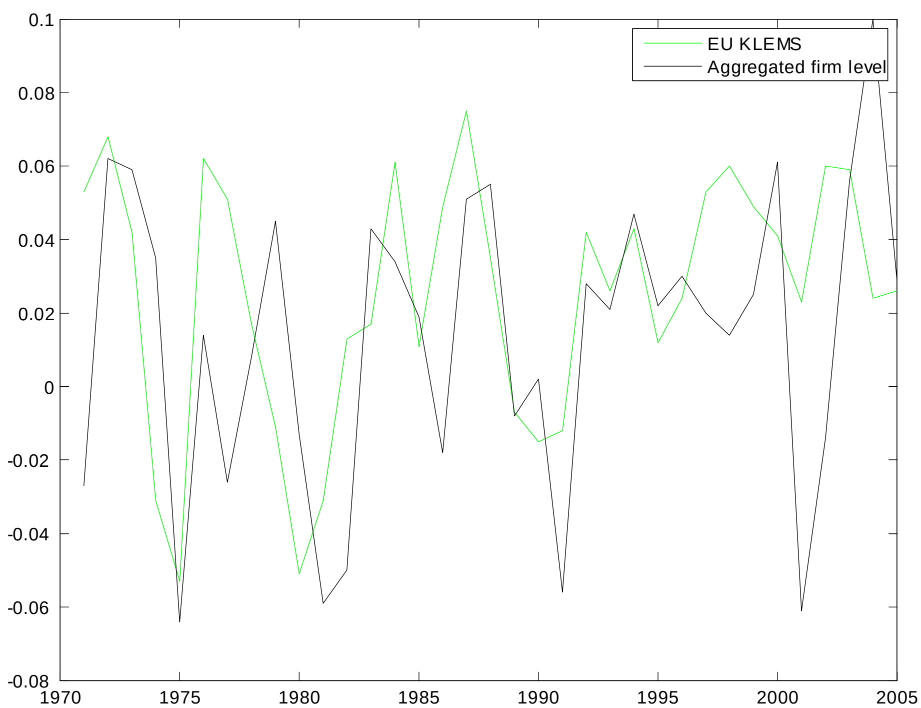

Figure A1: Aggregate TFP Comparisons

[49] In order to find the industry TFPs, we measure and aggregate firm TFPs without subtracting the effects of industry specific time dummies in equation 18.

Overall, we conclude that the firm level TFP series estimated using the Compustat data have reasonable properties.

4.2.1 Results with Alternative Estimations

In this section we present results for two different cases. In the first case, we use data from the manufacturing industry only. In the second case we extend the Olley and Pakes method to include organization capital as another input to the production function.

Manufacturing Sector Results We use firm level data for firms in the manufacturing sector from Compustat and supplement it with industry level data from the NBER-CES Manufacturing Industry Database.[50] Similar to our findings for the benchmark case, results in Table A-III indicate a strong link between firm level TFP, 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 17% of the average size of all firms in that year, whereas the average size of firms in the highest TFP decile is 289% of the average size. The B/M 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 hiring rate and fixed investment to capital ratio are monotonically increasing in firm level TFP. These results are very similar, both qualitatively and quantitatively, to our benchmark results that contain both manufacturing and non-manufacturing industries.

[50] The sample is an unbalanced panel with approximately 5700 distinct firms spanning the years between 1958 and 2005 for 4-digit SIC manufacturing industries. Firm level value added is computed using Compustat data on sales, operating income and employees, and then deflated using industry deflators. Capital stock is given by gross Plant, Property & Equipment from Compustat, deflated by the price deflator for investment for the matching industry from the NBER-CES Database (PIINV) following the methods of Hall (1990) and Brynjolfsson & Hitt (2003).

Table A-III: Descriptive Statistics for TFP Sorted Portfolios

	Low	2	3	4	5	6	7	8	9	High	High-Low
TFP	0.55	0.73	0.81	0.87	0.92	0.97	1.03	1.11	1.24	1.77	1.22
SIZE	0.17	0.28	0.48	0.67	0.75	0.98	1.18	1.61	2.29	2.89	2.72
											(18.11)
B/M	1.47	1.39	1.21	1.08	0.99	0.91	0.82	0.73	0.64	0.52	-0.95
											(-11.40)
I/K	0.09	0.09	0.09	0.10	0.11	0.12	0.14	0.17	0.21	0.32	0.23
											(21.01)
HR	-0.06	0.01	0.02	0.04	0.05	0.08	0.08	0.11	0.12	0.16	0.22
											(18.72)
N	121.86	122.62	122.78	122.80	122.61	122.90	122.98	122.69	122.92	122.48	

Note: 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. HR is the change in the natural log of number of employees from year $t-1$ to year t . N is the average number of firms in each portfolio in year t.

Asset Pricing Implications Similar to our benchmark results, TFP is positively and monotonically related to contemporaneous stock returns and negatively related to future returns, given in Table A-IV. The difference between the returns of high and low TFP firms is 28.7%, and it is highly statistically significant. A positive productivity shock leads both to high TFP and high stock returns in that year. Low productivity firms on average earn 4.9% annual premium over high productivity firms in the following year, and the return spread is statistically significant.

The negative relationship between TFP and expected returns persists both in expansions and in contractions. Both the average level of expected returns (approximately 10% versus 34%), and the spread between the returns of high and low TFP portfolios (approximately 4% versus 13%) are much higher in contractions.

Table A-IV: Excess Returns for TFP Sorted Portfolios (%, annualized)

	Low	2	3	4	5	6	7	8	9	High	High-Low
	Contemporaneous Returns, January 1972 - December 2005										
r^e	-3.95	3.80	8.76	10.92	11.60	14.75	16.37	16.27	20.52	24.75	28.70
	(-0.88)	(1.03)	(2.50)	(3.11)	(3.31)	(4.12)	(4.57)	(4.55)	(5.27)	(5.79)	(12.60)
σ^e	26.16	21.40	20.40	20.47	20.42	20.87	20.89	20.86	22.72	24.94	13.28
	Future Returns, July 1973 - June 2007										
	All states, 408 months										
r^e	15.21	16.86	13.31	13.66	12.87	12.72	12.33	11.10	10.70	10.30	-4.90
	(3.43)	(4.45)	(3.86)	(4.00)	(3.73)	(3.83)	(3.56)	(3.17)	(2.92)	(2.53)	(-2.22)
σ^e	25.88	22.09	20.08	19.90	20.11	19.39	20.20	20.39	21.32	23.77	12.87
	Expansions, 360 months										
r^e	11.94	13.59	10.06	10.11	9.64	9.85	9.62	8.11	8.05	8.16	-3.78
	(2.59)	(3.46)	(2.83)	(2.92)	(2.73)	(2.89)	(2.75)	(2.27)	(2.15)	(1.97)	(-1.61)
σ^e	25.24	21.50	19.44	18.97	19.33	18.68	19.14	19.56	20.49	22.72	12.81
	Contractions, 48 months										
r^e	39.72	41.36	37.65	40.27	37.13	34.24	32.63	33.51	30.52	26.36	-13.36
	(2.69)	(3.28)	(3.22)	(3.25)	(3.05)	(2.94)	(2.47)	(2.67)	(2.32)	(1.73)	(-2.02)
σ^e	29.58	25.22	23.41	24.74	24.36	23.33	26.38	25.12	26.35	30.40	13.22

Similar to our findings for the benchmark case, Fama-MacBeth regressions presented in Table A-V produce negative and statistically significant average slopes for TFP except for the specifications in II, III, and VII where including book to market (in II), size (in III), and asset growth (in VII) erodes the significance of TFP.

Table A-V: **Fama-MacBeth Regressions with Other Predictors (%, annualized)**

	Int	TFP	BM	SIZE	I/K	HR	INV	AG	PR	NS	LEV	AGE
I	12.61	-6.11										
	(3.43)	(-3.11)										
II	13.85	-1.43	4.84									
	(3.84)	(-0.90)	(4.44)									
III	8.29	-2.15		-1.79								
	(2.55)	(-1.19)		(-4.35)								
IV	13.56	-4.76			-6.43							
	(4.02)	(-2.27)			(-1.84)							
V	12.97	-4.37				-7.92						
	(3.63)	(-2.28)				(-5.96)						
VI	13.18	-4.67					-4.25					
	(3.69)	(-2.35)					(-5.04)					
VII	13.93	-3.12						-9.23				
	(3.93)	(-1.66)						(-7.04)				
VIII	12.82	-5.03							-3.07			
	(3.42)	(-2.74)							(-2.29)			
IX	12.45	-6.25								-3.79		
	(3.40)	(-3.15)								(-3.20)		
X	11.01	-4.57									5.96	
	(3.01)	(-2.77)									(1.45)	
XI	14.83	-6.46										-0.14
	(3.08)	(-3.14)										(-1.68)
XII	11.45	3.55	2.09	-1.73	-3.46	-1.28	-2.05	-3.42	-1.20	-8.23	-1.19	0.01
	(3.13)	(2.67)	(2.09)	(-4.00)	(-1.06)	(-0.93)	(-2.39)	(-2.43)	(-0.96)	(-3.02)	(-0.36)	(0.27)

Note: The table presents the average slopes and their $t-$statistics from monthly cross-section regressions to predict excess stock returns.

Ex-Ante Discount Rates of TFP-Sorted Portfolios Table A-VI presents the average implied cost of capital estimates for portfolios sorted on productivity. The relationship between TFP and the cost of capital measured from both ICC measures is negative and quite monotonic. The firms with low productivity have contemporaneously higher discount rates (ICC) than firms with high productivity: 13.72% versus 9.95% with HDZ, 9.59% versus 8.53% with GLS, per annum. The spreads of 3.77% and %1.06 are both highly significant, implying that firms with low productivity have higher ex-ante discount rates, hence are riskier than high productivity firms. Furthermore, both the levels of implied cost of capital, and the spread between the low and high TFP portfolios are countercyclical. The spread between the discount rates of low and high TFP portfolios increases from 3.47% to 6.00% as the economy moves from expansions to contractions, as defined by the NBER.

Table A-VI: Implied Cost of Capital for TFP Sorted Portfolios (%, annualized)

	Low	2	3	4	5	6	7	8	9	High	High-Low
	Gebhardt, Lee, Swaminathan (2001) Measure, 1982-2005										
ICC	9.59	9.80	9.66	9.54	9.43	9.20	9.10	8.88	8.65	8.53	-1.06
											(-9.98)
	Hou, van Dijk, Zhang (2010) Measure, 1972-2005										
	All states										
ICC	13.72	14.92	13.75	13.06	12.57	12.04	11.75	11.35	10.63	9.95	-3.77
											(-7.76)
	Expansions										
ICC	13.10	14.44	13.38	12.60	12.08	11.62	11.37	10.96	10.23	9.63	-3.47
											(-6.82)
	Contractions										
ICC	18.34	18.54	16.57	16.50	16.27	15.14	14.63	14.23	13.62	12.34	-6.00
											(-7.56)

Note: ICC is equal-weighted implied cost of capital, annual, averages are taken over time (%). ICC data based on Gebhardt, Lee, Swaminathan (2001) method is matched to TFP data from 1982 to 2005. ICC data based on Hou, van Dijk and Zhang (2010) method is matched to TFP data from 1972 to 2005. $t-$ statistics are in parentheses. Expansion and contraction periods are designated in June of each year (when ICCs are computed) based on whether that month is an NBER expansion or contraction.

Model Results The estimation of TFP obtained for this specification results in a different calibration of the parameters that are needed for the model economy. Since the calibration requires certain targets to be satisfied, we end up with a new set of parameters that are summarized in Table A-VII.

Table A-VII: Model Parameter Values

Parameter	Description	Value
α_k	Capital share	0.17
α_l	Labor share	0.79
β	Discount factor	0.995
γ_0	Constant price of risk parameter	4.12
γ_1	Time varying price of risk parameter	-7.1
δ	Capital depreciation rate	0.02
η	Adjustment cost parameter	43
ρ_a	Persistence of aggregate productivity	0.98
σ_a	Conditional volatility of aggregate productivity	0.007
ρ_z	Persistence of firm productivity	0.915
σ_z	Conditional volatility of firm productivity	0.121

Table A-VIII presents the average firm characteristics and expected returns for TFP sorted portfolios using simulated data from the model economy for this calibration. Similar to our benchmark results, investment to capital ratio and hiring rate both increase monotonically with TFP. TFP is also monotonically and positively related to size and negatively related to B/M. The spread in expected returns, -15.6%, is higher than the empirical spread of 4.90%.[51] Overall, this alternative calibration also indicates that a model where firms are subject to aggregate and idiosyncratic shocks can reasonably account for the cross sectional relationship between firm productivity, several important firm characteristics and firm returns.

[51] Since the return data for the sensitivity analysis carried out in this section spans between July 1973 and June 2007, the reported future returns for the data in Table A-IX are slightly different from those in the benchmark case.

Table A-VIII: Model Implied Characteristics and Excess Returns for TFP Sorted Portfolios

	Low	2	3	4	5	6	7	8	9	High	High-Low Model	High-Low Data
TFP	0.60	0.70	0.82	0.90	0.97	1.04	1.13	1.23	1.37	1.70	1.10	1.22
I/K	-0.14	-0.05	-0.01	0.02	0.05	0.09	0.12	0.17	0.23	0.40	0.54	0.23
HR	-0.91	-0.55	-0.40	-0.22	-0.07	0.09	0.25	0.45	0.68	1.31	2.22	0.22
Size	0.27	0.37	0.47	0.56	0.67	0.80	0.97	1.21	1.62	3.05	2.78	2.72
B/M	1.57	1.49	1.39	1.27	1.18	1.10	1.01	0.93	0.85	0.75	-0.82	-0.95
						Future Returns						
	All states											
r^e	22.14	17.70	15.56	14.09	12.84	11.70	10.62	9.52	8.26	6.51	-15.63	-4.90
σ^e	30.21	25.56	23.33	22.10	21.49	20.41	19.48	18.29	18.07	17.10	22.62	12.87
	Expansions											
r^e	20.12	16.12	14.18	12.83	11.69	10.65	9.66	8.65	7.49	5.84	-14.28	-3.78
σ^e	28.57	24.40	22.47	21.36	20.66	19.65	18.56	17.94	17.67	16.00	21.41	12.81
	Contractions											
r^e	39.20	31.11	27.31	24.73	22.50	20.61	18.75	16.89	14.85	12.15	-27.05	-13.36
σ^e	40.26	32.77	29.38	26.79	26.15	25.03	25.32	20.75	20.52	19.77	30.68	13.22

Results with Organizational Capital In this specification, we examine the role of including organizational capital in production function estimation, and study the resulting relationship between productivity and returns. There is a large and growing literature on organizational capital (intangible capital) and its implications for the macroeconomy.[52] This extensions involves broadening the Olley and Pakes method to include organization capital as another input to the production function. We calculate organizational capital from the Sales, General, and Administrative Expenses from Compustat (XSGA) and following Eisfeldt and Papanikolau (2009), construct it by using the perpetual inventory method.[53]

[52] See Hall (2000, 2001); Corrado, Hulten, and Sichel (2005); and McGrattan and Prescott (2005).

[53] Following Atkeson and Kehoe (2005), Lev and Radhakrishnan (2005), and Evenson and Westphal (1995), organizational capital is viewed as a firm-specific capital good that is embodied in the organization itself. Sales, general and administrative expenses are considered as investment in organizational capital, deflated by the price deflator for investment for the matching industry from the NBER-CES Database (PIINV) and assumed to depreciate by 20% per year.

Similar to our benchmark results, we find that TFP is positively and monotonically related to contemporaneous stock returns and negatively related to future returns, as can be seen from Table A-IX.[54]

Table A-IX: Excess Returns with Organization Capital

	Low	2	3	4	5	6	7	8	9	High	High-Low
					Contemporaneous Returns (Year t)						
r^e	-4.02	4.85	7.37	9.99	12.34	14.49	15.54	16.44	20.07	26.34	28.70
	(-0.92)	(1.32)	(2.22)	(2.92)	(3.51)	(4.18)	(4.40)	(4.45)	(4.94)	(5.87)	(12.60)
σ^e	25.34	21.52	19.31	19.93	20.50	20.22	20.59	21.53	23.68	26.17	13.28
					Future Returns (Year $t+1$)						
r^e	15.23	15.48	13.34	14.78	12.68	11.80	13.17	11.29	10.60	10.15	-4.90
	(3.48)	(4.23)	(3.98)	(4.42)	(3.74)	(3.46)	(3.87)	(3.17)	(2.81)	(2.39)	(-2.22)
σ^e	25.50	21.32	19.56	19.52	19.79	19.87	19.86	20.79	22.01	24.82	12.87

[54] Additional results based on portfolio sorts, Fama-MacBeth regressions and ex-ante discount rates are similar to the benchmark results and can be obtained from the authors.