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Does Firm-Level Productivity Predict Stock Returns?[★]

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Abstract

Contrary to the findings of previous U.S. studies, we show that the firm-level total factor productivity (TFP) of Japanese manufacturers positively predicts their future stock returns in the cross-section when controlling for relevant risk factors, including those of Fama and French (2015). Risks related to intangible expenditure, primarily those for research and development (R&D) and personnel, explain a substantial fraction of the predictive power of firm-level TFP, while bankruptcy, macroeconomic, and capital expenditure risks do not. More productive firms trade at a significant premium to less productive firms. This premium compensates investors for risks associated with innovation and human and organizational capital formation.

Keywords: Firm-level productivity, Total factor productivity (TFP), Cross-section of returns, Intangibles, Research and development (R&D), Organizational capital

JEL classification: D24, G12, G14, G17

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1. Introduction

Productivity plays a central role in both macroeconomic and corporate performance. Productivity growth is particularly exigent for the Japanese economy, given its declining labor force. The level of Japanese labor productivity is relatively low, at around 60% of U.S. labor productivity, according to Organization for Economic Co-operation and Development (OECD) data on value added per hour of work in 2018. Japan ranks 21st in labor productivity among 36 OECD members in the latest data and has had the lowest labor productivity of the Group of Seven (G7) economies since at least 1970 (Japan Productivity Center, 2019). Japan's productivity growth has been on a declining trend since at least the 1970s and has been relatively low compared to other OECD members over the last two decades. The average total factor productivity (TFP) of Japanese listed firms is also below that of both the U.S. and the OECD average (Nakamura et al., 2019).

At the same time, Japanese stocks have under-performed relative to other developed markets. The average annual return of the TOPIX index since 2000 is 3%, while that of MSCI Kokusai (the MSCI World Index excluding Japan) is 7.2%. Japanese corporate valuations are also comparatively low. Over the same period, the TOPIX average monthly price-to-book value ratio is 1.38, substantially below the MSCI Kokusai's 2.42. Further, 40% of the TOPIX 500 firms had a price to book ratio of less than one in November 2019 (Ministry of Economy Trade and Industry, 2019). A reasonable interpretation may be that the relatively low valuation of Japanese firms primarily reflects their low productivity. However, the literature contains little relevant empirical evidence to support this notion.

In contrast to the economic growth and business cycle literature, the asset pricing literature has made little use of productivity. A small number of recently published articles suggest a negative relationship between firm-level productivity and future stock returns in the United States. İmrohoroğlu and Tűzel (2014) demonstrate that low TFP firms earn a premium over high TFP firms in the year ahead. Low (high) TFP firms generally have small (large) market capitalization, high (low) book-to-market ratios and low (high) investment and hiring rates. Cross-sectional Fama and MacBeth (1973) regression of returns on lagged TFP produces a negative and significant coefficient estimate. However, controlling for market capitalization and the book-to-market ratio, two of the three Fama and French (1992) factors, erodes the significance of the TFP coefficient. Therefore, İmrohoroğlu and Tűzel (2014) argue that TFP is systematically related to market capitalization and the book-to-market ratio, and that TFP is not separate risk unrelated to well-known equity factors.

Using an alternative approach to estimate firm-level productivity, stochastic frontier analysis pioneered by Aigner et al. (1977), Nguyen and Swanson (2009) also show that a portfolio of highly inefficient firms significantly outperforms a portfolio of highly efficient firms in the US stock market. Ang et al. (2020) explain the return premium on inefficient firms as the reversal of mispricing. Investors initially underprice low productivity firms and overprice high productivity firms, and the future reversal of this mispricing explains the outperformance of low productivity firms.

To the best of our knowledge, the only study that analyzes the productivity of Japanese firms in relation to their stock returns is Ishikawa and Hasegawa (2019), who focus on labor productivity. They construct portfolios corresponding to labor productivity quintiles of the firms in the TOPIX 500 index. The lowest labor productivity quintile generates positive excess returns and the highest quintile generates negative excess returns. However, their estimates from a Fama-MacBeth regression including the Fama-French three factors are not significant.

We investigate the relationship between firm-level productivity, measured as estimated TFP, and future stock returns for listed Japanese manufacturing firms in the TOPIX index over the 20 fiscal years from 1999 to 2018. We find that productivity is positively related to future stock returns, in contrast to the negative relationship found in previous studies on US listed companies. Our results show that more productive firms trade at a significant premium over less productive firms in the year ahead.

Similar to İmrohoroğlu and Tűzel (2014), our TFP quintile portfolios show that high (low) TFP firms tend to have a large (small) market capitalization, low (high) book-to-market ratios, high (low) return on equity, high (low) asset growth and high (low) hiring. However, contrary to their results, the premium we find on high TFP firms cannot be attributed to the premia compensating investors for exposure to size, value or other common equity risk factors but instead reflects different risks. We evaluate and reject the mispricing hypothesis with limits-to-arbitrage as an explanation. We investigate alternative risk-based explanations of our result, examining bankruptcy, macroeconomic, capital and intangibles expenditure risks. We find that intangibles expenditure relating to research and development (R&D) and personnel explain a substantial fraction of the future return predictability due to TFP. The premium for highly productive firms compensates investors for risks related to innovation and human and organizational capital formation; innovation through R&D and the expansion of economic competencies through investment in human and organizational capital by expenditure on personnel.

We make two contributions to the asset pricing literature. Our first contribution is robust evidence that high TFP firms trade at a substantial premium to low TFP firms in Japan. We find a highly statistically significant and robust positive relationship between TFP and future returns while controlling for various firm characteristics including the Fama-French three and five factors (Fama and French, 1992, 2015), Carhart's (1997) four factors, Hou et al.'s (2015) q-factors and sector effects. The high TFP premium represents compensation for risk independent of the standard risk factors used in the finance literature. Our results contrast with previous research on U.S. listed firms. We use the same approach as İmrohoroğlu and Tűzel (2014) to estimate TFP, the same and more complex risk factor models, and similar Fama-MacBeth cross-sectional regressions including more control variables, but find a positive rather than negative relationship between returns and TFP.

Our second contribution is a new risk-based explanation for the substantial premium of high over low TFP stocks. Our results suggest that high intangibles expenditure, primarily that for R&D and personnel, is perceived as a risk in the marketplace. This risk, related to investment in innovation, human and organizational capital, has not been discussed in previous studies on the asset pricing implications of firm-level productivity.

The paper is organized as follows. Section 2 contains our estimation and empirical results, including description of the data, production function-based measurement of firm-level TFP, analysis of TFP-portfolios and firm characteristics, estimation of TFP-portfolio risk factor loadings and estimation of the relationship between future returns and TFP via Fama-MacBeth cross-sectional regressions. We evaluate alternative risk-based explanations for the predictive relationship between TFP and future returns in Section 3, including bankruptcy, macroeconomic, capital and intangible expenditure risks. We examine the reasons behind the explanatory power of TFP for future returns in Section 4. In Section 5 we check the robustness of our risk-based explanation by assessing the potential for mispricing due to limits-to-arbitrage to account for our results. We present the conclusions and implications of our research in Section 6.

2. Estimation and empirical results

2.1. Data

Our sample consists of manufacturing firms included in the TOPIX, an index of all large capitalization firms listed in the First Section of the Tokyo Stock Exchange (TSE). We use both monthly and annual data. Our explanatory variables include corporate financial data and cover the 20-year period from fiscal year (FY) 1999 (ending March 2000) to FY2018 (ending March 2019). We use stock return data over the period July 2000 to June 2020. All corporate financial data are obtained from Quick AstraManager unless otherwise noted. We use consolidated corporate data as consolidated financial data should determine stock prices. However, we resort to unconsolidated data for companies that do not disclose consolidated labor costs. Individual data series are described as they are used in the following sections. There are approximately 570 firm-level observations per year on average.

The manufacturing firms included in our data represent 12 major manufacturing sectors of the TOPIX.[1] We drop the TOPIX manufacturing sectors for which there are less than 400 annual observations, that is, sectors with less than an average of 20 observations per year. We include only companies that report based on a March year-end. The sectors included are chemicals, electronics, food, glass & ceramics, iron & steel, machinery, metal products, pharmaceuticals, precision instruments, textiles & apparel, transportation equipment and others.

[1] We focus on manufacturing firms because non-manufacturing firms' production function capital coefficient estimates are not stable across sectors. The term "sector" refers to the industry groups defined by the Japan Exchange Group for the TOPIX.

2.2. Firm-level TFP estimation

TFP is a standard measure of productivity, usually calculated as the difference between observed output and that predicted by a Cobb-Douglas production function. Estimating such a production function by ordinary least squares (OLS) yields biased estimates because it does not account for unobserved productivity shocks. Endogeneity arises because profit-maximizing firms respond to positive productivity shocks by expanding output, which requires inputs, while adverse shocks lead firms to pare back output, decreasing their input use.

Olley and Pakes (1996) introduce a semiparametric method to control for this bias, which allows the production function to be estimated consistently and provides a reliable productivity estimate by using investment as a proxy for the unobservable productivity shock. Levinsohn and Petrin (2003) argue that, as firm-level data suggests investment is lumpy, the investment proxy may not respond smoothly to the productivity shock, which violates the consistency condition. They propose an alternative method using intermediate inputs to solve the endogeneity problem. This method also avoids truncating zero investment firms from the estimation, as the investment proxy is only valid for companies reporting non-zero investment.

Simplifying the complicated two-step Levinsohn and Petrin (2003) procedure, Wooldridge (2009) suggests implementing Levinsohn and Petrin's moment condition and important extensions in a generalized method of moments (GMM) framework. Under this approach, fully robust standard errors are easy to obtain and GMM efficiently uses the moment conditions implied by the assumptions of Olley and Pakes (1996) and Levinsohn and Petrin (2003).

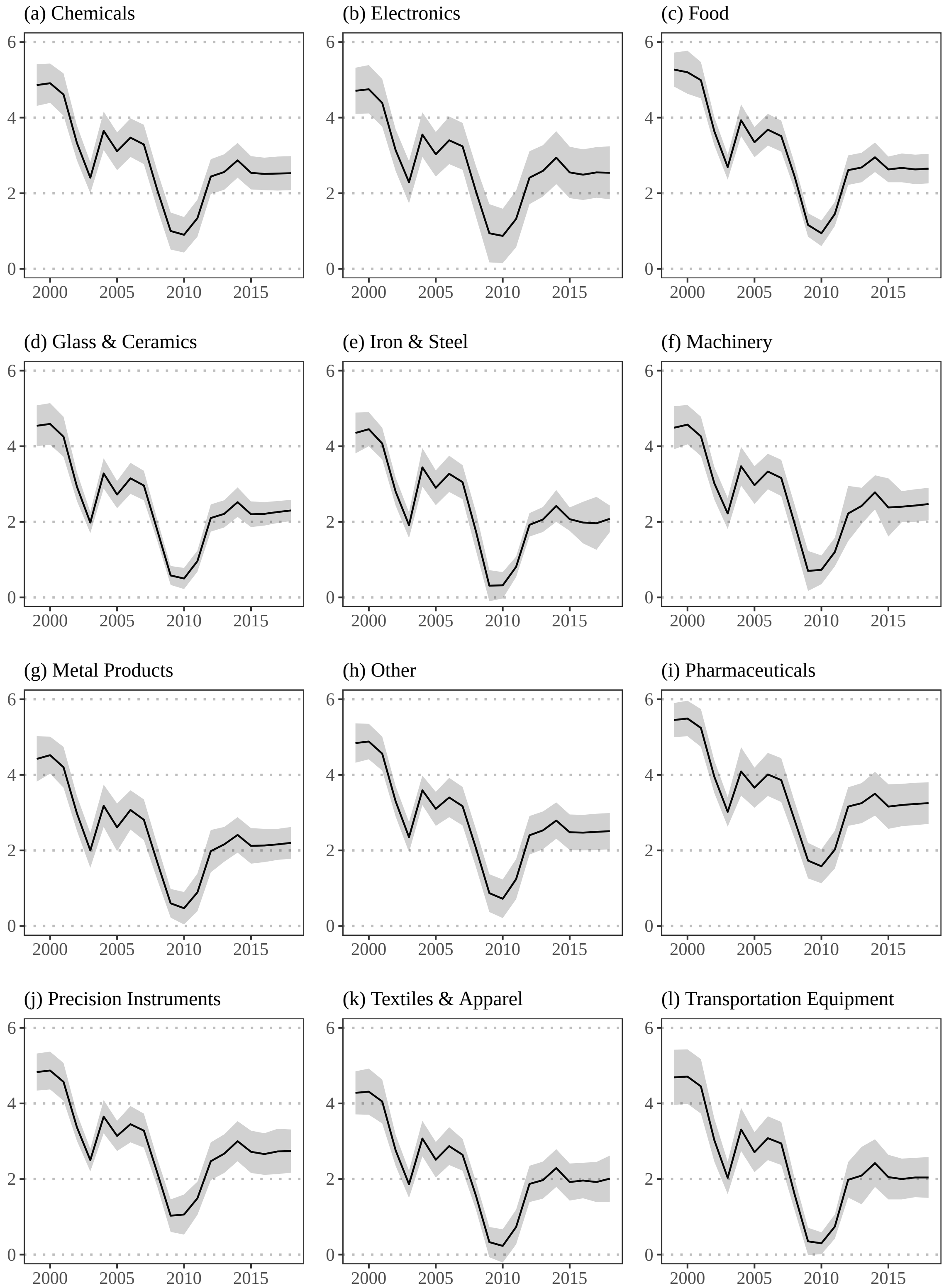
We generate firm-level TFP using the Levinsohn and Petrin (2003) control function approach, with intermediate inputs as proxy for unobservable productivity shocks, and estimate the production function using GMM following Wooldridge (2009) using annual data.

We estimate the following production function,

$$y_{i,t} = \alpha_0 + \alpha_k k_{i,t} + \alpha_l l_{i,t} + \omega_{i,t} + e_{i,t}, \tag{1}$$

where $y_{i,t}$ represents the log of value added for company i in year t, $k_{i,t}$ and $l_{i,t}$ are log indices of capital and labor inputs, respectively, $\omega_{i,t}$ is productivity, α_0, α_k and α_l are coefficients to be estimated and $e_{i,t}$ is a random error term. Value added is measured as gross output net of intermediate inputs, which is the sum of operating profit, total payroll, depreciation, welfare expense, rent for movables and real property, and taxes and duties. Labor is the sum of the number of regular employees at the end of the fiscal year and the average number of part-time workers. Capital stock is defined as tangible assets, which includes property, plant and equipment subject to depreciation, construction in progress, and land and other non-depreciable tangible assets. Intermediate inputs, as a proxy for productivity shocks, consists of the cost

Figure 1:
Mean and standard deviation of firm-level TFP by TOPIX sector.



Note: The TOPIX sectors shown contain firms classified under the 12 manufacturing industry groups as defined by the Japan Exchange Group for the index. The line in each chart represents the TOPIX sector mean of estimated firm-level TFP. The shaded region indicates ±1 standard deviation around the sector mean TFP.

of goods sold minus the sum of total payroll, depreciation, welfare expense, rent for movables and real property, and taxes and duties.

We estimate the production function recursively to mitigate potential look-ahead bias. Since estimation requires at least two years of annual data, the first set of estimates is generated using data for FY1999 and FY2000. Thereafter the parameters are estimated annually using data available up until that year. We estimate the production function 19 times using recursive samples that all begin with FY1999 and end with FY2000 to FY2018. This is the same estimation methodology as used by İmrohoroğlu and Tűzel (2014). The capital coefficient estimates have a mean of 0.375 and a standard deviation of 0.108, while the labor coefficient estimates have a mean of 0.498 and a standard deviation of 0.024.

Firm-level TFP is calculated using the production function estimates according to equation (2.2) to produce an annual time series of productivity estimates for each firm in our sample.

$$\omega_{i,t} = y_{i,t} - \hat{\alpha}_k\, k_{i,t} - \hat{\alpha}_l\, l_{i,t} \tag{2}$$

We use the estimates from the first recursive window to generate TFP for both FY1999 and FY2000 such that we obtain a total of 20 years of productivity estimates for FY1999 to FY2018.[2] We follow İmrohoroğlu and Tűzel (2014) in using the level of TFP as the measure of firm-level productivity rather than its change so that our results may be directly compared with theirs. Figure 1 shows the mean and standard deviation of TFP by TOPIX sector. The plots suggest the difference in TFP across manufacturing sectors is minor. The sector averages exhibit a very similar pattern over time.

2.3. TFP portfolios and firm characteristics

We sort all firms into quintile portfolios each fiscal year from FY1999 to FY2018 based on the firms' TFP for the respective year. Since we are interested in the variation of TFP within-sector rather than across sectors, we construct the quintiles using the TFP estimated in Section 2.2 demeaned by sector. Quintile one (Q1) represents the lowest TFP firms, within-sector, while quintile five (Q5) represents the highest. Table 1 shows the average values of various firm-level financial characteristics for each quintile portfolio over FY1999 to FY2018, assuming equally weighted portfolios. The last column of the table provides the financial characteristics for the spread between the high TFP (Q5) and low TFP (Q1) portfolios. In addition to portfolio TFP and returns, we show the following financial characteristics. ln(ME) is the natural logarithm of market capitalization in millions of yen. ln(B/M) is the natural logarithm of the book-to-market ratio. ROE represents the return on equity expressed as percent, AG is the percentage growth rate of assets and ln(L) is the natural logarithm of the number of employees including part-time workers.

[2] Although this involves a minor look-ahead bias for the first year of our sample, it does not materially affect our results.

Table 1:
TFP-quintile portfolios and firm characteristics, FY1999 to FY2018.

	(Low)		TFP Quintiles		(High)	(High-Low)
	Q1	Q2	Q3	Q4	Q5	Q5-Q1
TFP	2.005	2.415	2.659	2.918	3.373	1.368
Contemp. return (%)	7.467	9.760	12.474	13.490	12.689	5.222
Future return (%)	7.349	9.058	8.638	8.292	7.863	0.514
ln(ME)	9.990	10.548	10.998	11.551	12.371	2.381
ln(B/M)	0.159	0.056	-0.023	-0.186	-0.383	-0.542
ROE (%)	1.697	4.201	5.051	6.172	7.364	5.667
ROE_{t+1} (%)	2.398	4.167	5.297	6.261	6.918	4.521
Net Income/Sales (%)	1.031	2.467	3.422	4.267	5.165	4.134
Net Income/$Sales_{t+1}$ (%)	1.316	2.554	3.570	4.282	4.993	3.678
Net Income/MV (%)	-0.251	2.743	2.921	4.099	3.655	3.905
Net Income/MV_{t+1} (%)	0.192	2.471	3.784	3.680	3.863	3.671
AG (%)	2.185	2.540	2.764	3.701	4.020	1.835
ln(L)	7.548	7.824	8.042	8.361	8.795	1.247
Observations	2,366	2,235	2,229	2,235	2,329	

Note: This table shows the average values of various financial characteristics for each TFP-quintile portfolio assuming the portfolios are equally weighted. Q1 is the lowest TFP-quintile and Q5 is the highest. The contemporaneous return is defined as the one-year return over the fiscal year t, that is, from the beginning of April to the end of March. The future return is the one-year return beginning three months after the fiscal year, that is, from the beginning of July to the end of June for the portfolio formed in year t. ln(ME) is the natural logarithm of market capitalization in millions of yen. ln(B/M) is the natural logarithm of the book-to-market ratio. ROE represents the return on equity expressed as percent. Net Income/Sales is the ratio of net income to sales as a percentage. Net Income/MV is the ratio of net income to market value as a percentage. Values without a time subscript, except for the future return, are calculated for the year of portfolio formation, year t. Those with the subscript t+1 represent the financial characteristics of the year t portfolios in the year following the year of portfolio formation. AG is the percentage growth rate of assets. ln(L) is the natural logarithm of the number of employees including part-time workers. The total number of firm-level observations across all quintiles is 11,394.

We consider two return measures, contemporaneous and future. Contemporaneous returns are calculated over the same fiscal year that TFP is measured, that is, from April to March. Future returns are calculated for a one-year period beginning after firms have reported their financial results for the fiscal year, that is, from July following the fiscal year end to June the next year. Calculating future returns beginning three months after the end of the fiscal year is sufficient to avoid look-ahead bias for Japanese firms since the TSE requires financial statement disclosure within 45 days of firms' fiscal year-end, while the Ministry of Finance requires disclosure within three months.[3]

Neither contemporaneous nor future returns display a monotonic pattern over the TFP quintiles. Ordering our quintile portfolios from lowest to highest contemporaneous return gives Q1, Q2, Q3, Q5 and

[3]Our empirical results for future returns defined as beginning a more conservative six months after the fiscal year-end are qualitatively similar to those for three months and available on request. İmrohoroğlu and Tűzel (2014) measure one year-ahead returns from six months after the fiscal year-end, citing the approach of Fama and French (1992, 1993). According to Fama and French (1992), on average 19.8% of U.S. firms do not comply with the U.S. Securities and Exchange Commission's (SEC) requirement that 10-K reports be filed within 90 days of the end of the fiscal year. Even for those firms with a December year-end that do comply with the 90-day rule, 40% file on the last day of March and their reports are not public until April. Taking this into account, Fama and French (1992) impose a six-month gap between fiscal year-end and their return tests.

Q4, while ordering by future return yields Q1, Q5, Q4, Q3 and Q2. Our results contrast with the monotonically increasing pattern in contemporaneous returns with respect to TFP observed by İmrohoroğlu and Tűzel (2014), and the monotonically decreasing pattern in future returns noted by both İmrohoroğlu and Tűzel (2014) and Ang et al. (2020).

The TFP-sorted portfolios suggest a positive relationship between TFP and market capitalization and a negative relationship between TFP and book-to-market valuation. High TFP firms tend to be large growth firms with a book-to-market ratio around 0.7, while low TFP firms tend to be small value firms with book-to-market of about 1.2. This positive relationship between TFP and firm size and the negative relationship with value for Japanese stocks is consistent with the previous literature on the US firms. High TFP firms generally have greater return on equity, net income to sales and net income to market value ratios, both in the year of portfolio formation and the following year. Thus, high TFP firms have better operating performance than low TFP firms. High TFP firms have higher asset growth and have more employees.

2.4. TFP portfolio risk factor loadings

In this section, we investigate whether Japanese stock returns exhibit TFP-related alpha while controlling for a variety of widely-recognized risk factors. Table 2 shows the risk factor loading for each TFP-quintile portfolio, as well as for the spread between Q5 and Q1 portfolio returns, according to four prominent factor models. We use the annually rebalanced equal weighted TFP-quintile portfolios constructed in Section 2.3, monthly portfolio returns and monthly factor returns to estimate the factor models.

The dependent variable for each of regressions (1) to (5) is the future monthly excess portfolio return, calculated as the quintile portfolio return minus the future 1-month certificate of deposit (CD) yield. The dependent variable for regression (6) is the spread between the future excess returns on portfolios Q5 and Q1. To avoid look-ahead bias, the future monthly portfolio excess returns are calculated for the period July to June following the March end of the fiscal year for which each portfolio was constructed. This provides a total of 240 monthly time series excess return observations covering the 20-year period from July 2000 to June 2020 for each quintile portfolio. The future monthly portfolio excess returns are regressed on risk factor returns.[4]

We estimate four risk factor models that are standard in the literature. Table 2 Panel (a) shows the loadings for the Fama-French three-factor model (Fama and French, 1993) which includes the market

[4]The risk factor data was provided by Hitoshi Takehara. The Fama-French three factors, MKT, SMB, and HML, are computed by applying the same method similar to that of Fama and French (1993). The UMD factor is calculated by constructing six (=2×3) portfolios by firm size and realized returns at the end of each month based on realized returns over the past year. The "one-year momentum anomaly" is not observed in the Japanese market and the UMD factor has a negative coefficient signifying contrarian investor behavior (Chou et al., 2007). The RMW and CMA portfolio factors are constructed in the same way as Fama and French (2015). The $r_{I/A}$ and r_{ROE} factors in the q-factor model are constructed using the same methodology as Hou et al. (2015) but, due to data limitations, realized ROE is used instead of expected ROE.

Table 2:
Risk factor loadings for the TFP quintile portfolios.

	Dependent variable: future monthly excess portfolio return					
	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) Q5	(6) Q5-Q1
(a) Fama-French 3-Factor						
MKT	1.179***	1.119***	1.107***	1.076***	1.022***	-0.158***
	(0.026)	(0.027)	(0.024)	(0.023)	(0.025)	(0.028)
SMB	0.961***	0.750***	0.663***	0.434***	0.230***	-0.731***
	(0.051)	(0.042)	(0.041)	(0.037)	(0.044)	(0.067)
HML	0.539***	0.456***	0.388***	0.241***	0.110**	-0.429***
	(0.049)	(0.043)	(0.042)	(0.041)	(0.044)	(0.059)
Alpha	-0.109	0.054	0.084	0.172**	0.200**	0.309**
	(0.111)	(0.097)	(0.098)	(0.083)	(0.094)	(0.136)
Adj. R^2	0.925	0.923	0.923	0.927	0.924	0.506
(b) Carhart 4-Factor						
MKT	1.159***	1.106***	1.090***	1.062***	1.008***	-0.151***
	(0.024)	(0.027)	(0.024)	(0.022)	(0.023)	(0.029)
SMB	1.018***	0.789***	0.710***	0.474***	0.269***	-0.749***
	(0.046)	(0.040)	(0.035)	(0.036)	(0.045)	(0.067)
HML	0.509***	0.436***	0.364***	0.220***	0.090**	-0.420***
	(0.051)	(0.044)	(0.046)	(0.041)	(0.042)	(0.061)
UMD	-0.146***	-0.098**	-0.119**	-0.101***	-0.099***	0.047
	(0.051)	(0.042)	(0.050)	(0.036)	(0.033)	(0.045)
Alpha	-0.121	0.046	0.074	0.164**	0.192**	0.313**
	(0.101)	(0.094)	(0.091)	(0.078)	(0.091)	(0.134)
Adj. R^2	0.931	0.926	0.928	0.931	0.928	0.507
(c) Fama-French 5-Factor						
MKT	1.156***	1.103***	1.092***	1.063***	1.022***	-0.134***
	(0.030)	(0.031)	(0.029)	(0.026)	(0.026)	(0.026)
SMB	0.913***	0.732***	0.639***	0.419***	0.232***	-0.680***
	(0.048)	(0.046)	(0.043)	(0.038)	(0.044)	(0.063)
HML	0.442***	0.424***	0.343***	0.212***	0.115**	-0.327***
	(0.049)	(0.050)	(0.041)	(0.044)	(0.048)	(0.067)
RMW	-0.238**	-0.182**	-0.156	-0.143	-0.001	0.237**
	(0.111)	(0.084)	(0.100)	(0.088)	(0.080)	(0.119)
CMA	0.053	-0.086	-0.020	-0.058	-0.018	-0.071
	(0.102)	(0.098)	(0.090)	(0.079)	(0.075)	(0.113)
Alpha	-0.059	0.088	0.115	0.199**	0.200**	0.259**
	(0.106)	(0.096)	(0.100)	(0.082)	(0.094)	(0.130)
Adj. R^2	0.931	0.924	0.925	0.928	0.923	0.539
(d) q-factor						
MKT	1.191***	1.126***	1.115***	1.082***	1.022***	-0.169***
	(0.030)	(0.029)	(0.026)	(0.024)	(0.026)	(0.028)
r_{ME}	0.911***	0.741***	0.653***	0.428***	0.217***	-0.694***
	(0.055)	(0.048)	(0.044)	(0.040)	(0.045)	(0.066)
$r_{I/A}$	0.227**	0.051	0.064	0.001	-0.031	-0.259***
	(0.089)	(0.079)	(0.073)	(0.061)	(0.066)	(0.096)
r_{ROE}	-0.422***	-0.397***	-0.371***	-0.318***	-0.121	0.301***
	(0.123)	(0.102)	(0.105)	(0.087)	(0.081)	(0.106)
Alpha	-0.015	0.154	0.164	0.231***	0.235**	0.250*
	(0.117)	(0.102)	(0.101)	(0.083)	(0.096)	(0.138)
Adj. R^2	0.912	0.915	0.920	0.929	0.923	0.481

Note: The dependent variable for each of regressions (1) to (5) is the future monthly quintile portfolio return minus the future 1-month CD yield, that is, the future monthly excess portfolio return. The dependent variable for regression (6) is the difference between the future excess returns on portfolios Q5 and Q1. MKT is the market excess return defined as the return on the TOPIX minus the 1-month CD yield. SMB and HML represent the Fama and French (1993) size and value factors, respectively. UMD is Carhart's (1997) momentum factor. RMW and CMA are the Fama and French (2015) profitability and asset growth factors, respectively. r_{ME}, $r_{I/A}$ and r_{ROE} are the Hou et al. (2015) size, investment and profitability factors, respectively. The alphas represent the intercepts. Each model is estimated by ordinary least squares using 240 monthly observations. Newey-West Standard errors are provided in parentheses. ***, **, and * indicate significant at the 1%, 5% and 10% levels, respectively.

(MKT), size (small-minus-big, SMB) and value (high-minus-low, HML) factors. We define the excess return on the market as the return on the TOPIX minus the 1-month CD yield. Panel (b) shows the results for the Carhart four-factor model (Carhart, 1997), which adds momentum (up-minus-down, UMD) to the factors included in the Fama-French three-factor model. Panel (c) provides the estimates for the Fama-French five-factor model (Fama and French, 2015), which adds profitability (robust-minus-weak, RMW) and investment (conservative-minus-aggressive, CMA) to their earlier three-factor model. The advantage of the five-factor model is that it allows for the observed positive relationship between profitability and returns (Novy-Marx (2013) and others) and the negative relationship between asset growth and returns (Cooper et al., 2008; Titman et al., 2004). Panel (d) gives the estimated loadings for Hou et al.'s (2015) q-factor theory which includes the excess return on the market, and size (r_{ME}), investment ($r_{I/A}$) and profitability (r_{ROE}) factors constructed differently to those in the Fama-French models. Hou et al. (2015) argue their risk factors better explain the returns associated with significant market anomalies than other commonly used factor models.

Our empirical results are broadly similar across the four risk factor models. Table 2 shows that the estimated alphas for each risk factor model increase monotonically over the low to high TFP quintile regressions. All alpha estimates for quintiles Q4 and Q5, the higher TFP firms are positive and significant. The positive and significant Q5 minus Q1 spread alpha estimates indicate that a portfolio of high minus low TFP firms generates a positive return that is not explained by standard risk factors. Our results contrast with those of İmrohoroğlu and Tűzel (2014) who find larger Fama-French three-factor model intercepts for lower productivity firms.

Our results suggest low productivity firms are more exposed to the market than high productivity firms. We also find that low productivity firms are more exposed to the size and value factors than high productivity firms, consistent with the results of İmrohoroğlu and Tűzel (2014) and Ang et al. (2020). The negative and significant UMD coefficients indicate that the portfolios are contrarian (Chou et al., 2007). Low productivity firms load more negatively on the q-factor model's return on equity factor. However, the Fama-French profitability coefficient estimates are not significant in the models for the Q3, Q4 and Q5 portfolios. Furthermore, none of the Fama-French asset growth coefficients are significant. Our results concur with those of Kubota and Takehara (2018) who find the profitability and asset growth factors are not significant in standard cross-section asset pricing tests for Japanese stocks.

2.5. Fama-MacBeth cross-sectional regressions

We investigate the relationship between firm-level TFP and future returns using Fama-MacBeth cross-sectional regressions of annual future stock returns on firm-level TFP, the Fama-French risk factors and sector dummy variables. Equation (2.5) shows the general model estimated.

Table 3:
Fama-MacBeth regressions of year-ahead returns on TFP.

	Dependent variable: future return, $r_{i,t+1}$			
	(1)	(2)	(3)	(4)
β	0.973	0.448	0.769	0.224
	(2.490)	(1.926)	(2.378)	(1.835)
ln(ME)	-0.933	-1.001	-0.876	-0.947
	(0.840)	(0.895)	(0.781)	(0.822)
ln(B/M)	5.235***	5.087***	4.902***	4.718***
	(1.513)	(1.340)	(1.620)	(1.409)
ROE			-0.123**	-0.128***
			(0.046)	(0.043)
AG			-0.013	-0.023
			(0.037)	(0.034)
TFP	3.893***	3.730***	4.068***	3.983***
	(1.083)	(1.188)	(1.103)	(1.138)
Sector dummies	No	Yes	No	Yes
Observations	10,739	10,739	10,580	10,580
Adj. R^2	0.093	0.143	0.101	0.149

Note: The dependent variable for each model is the future return for company i, $r_{i,t+1}$, defined as the one-year return from three months after the fiscal year-end. β is sensitivity to TOPIX, calculated over the 60 months prior to each fiscal year-end. ln(ME) is the natural logarithm of market capitalization in millions of yen. ln(B/M) is the natural logarithm of the book-to-market ratio. ROE represents the return of equity expressed as percent. AG is the percentage growth rate of assets. ln(L) is the natural logarithm of the number of employees including part-time workers. TFP is is total factor productivity measured at fiscal year-end. There are 12 sectors and we include 11 sector dummies in models (2) and (4). Standard errors are in parentheses. The intercepts are not displayed. ***, **, and * indicate significant at the 1%, 5% and 10% levels, respectively.

$$\begin{aligned} r_{i,t+1} &= \gamma_0 + \gamma_1 \beta_{i,t} + \gamma_2 \ln(ME)_{i,t} + \gamma_3 \ln(B/M)_{i,t} + \gamma_4 ROE_{i,t} + \gamma_5 AG_{i,t} + \gamma_6 TFP_{i,t} \\ &\quad + \textstyle\sum_{j=1}^{11} \chi_j DS_j + \epsilon_{i,t+1} \end{aligned} \tag{3}$$

The dependent variable, $r_{i,t+1}$, is the one-year future return for firm i. Recall that future returns, with the time subscript $t+1$, are calculated for the period July to June following the end of the fiscal year in March. We include the Fama and French (2015) five factors as control variables in addition to firm-level TFP. The time subscript, t, refers to the fiscal year that ends in March. $\beta_{i,t}$ is the market beta of firm i at time t, defined as its sensitivity to the TOPIX index over the previous 60 months. The variables $\ln(ME)_{i,t}$ and $\ln(B/M)_{i,t}$ represent the natural logarithms of firm i's fiscal year-end market capitalization in millions of yen and the book-to-market ratio, respectively. $ROE_{i,t}$ is the return on equity for firm i at the end of the fiscal year and $AG_{i,t}$ is the asset growth rate over the fiscal year. Our variable of interest, $TFP_{i,t}$, represents firm i's total factor productivity at fiscal year-end. Sector dummies, DS_j, account for differences over the j sectors. We include dummies for all but one of the 12 sectors to avoid multicollinearity. $\epsilon_{i,t}$ is a random error term. The Fama-MacBeth procedure conveniently adjusts for cross-sectional dependence and we use Newy-West heteroskedasticity and autocorrelation consistent standard errors to account for time-series dependence.

Given the lack of support for the Fama-French profitability and investment factors in models of Japanese stock returns discussed in the previous section, we specify models that control for three and five factors. We also specify models with and without sector dummy variables. The sector dummies control for potential sector-wide shocks so we can identify the within-sector cross-sectional differences in the impact of TFP on future stock returns.

Table 3 provides our estimates for the four Fama-MacBeth regressions. The TFP coefficient estimates are positive and highly significant in all models and their magnitudes are similar across the four specifications. The TFP coefficient estimates are not sensitive to the choice of three or five Fama-French factors, nor the exclusion of sector dummies.

Among the control variable coefficient estimates, those for book-to-market are positive and significant for all models while the market capitalization coefficients are negative but not significant. Fama and French (1992) note that firms with smaller market capitalization and higher book-to-market are perceived to reflect a distress risk, for which investors demand premium. The beta coefficients in all four models are not significant, consistent with Fama and French's (1992) and others' findings that beta has no explanatory power for average returns in the cross-section. The estimated coefficients of return on equity and asset growth are negative for models (3) and (4), and only the return on equity estimates are significant.

Our results suggest that TFP has explanatory power for the future returns of Japanese manufacturing firms beyond the accepted stock risk factors. TFP is positively and significantly related to future returns in the presence of the market capitalization and book-to-market controls in contrast to İmrohoroğlu and Tűzel's (2014) results for U.S. firms. Our results appear robust to various specifications, accounting for sector differences and controlling for widely accepted stock risk factors.

3. What risk explains the relationship between future returns and TFP?

What risk does the productivity related excess return compensate investors for bearing? In this section, we investigate three risk-based explanations for the return premium provided by high TFP stocks relative to low TFP stocks: bankruptcy risk, macroeconomic risk, and capital and intangible expenditure risks.

Previous research on firm-level productivity and stock returns has examined risk-based explanations for the relationship, including financial distress or bankruptcy risk and business cycle or macroeconomic risk. İmrohoroğlu and Tűzel (2014) conclude that the return premium they find for unproductive firms may compensate investors for the relatively high distress risk of firms that are less efficient. They also find that the returns on low TFP firms have greater sensitivity to macroeconomic shocks, particularly during economic downturns. This may suggest their risk premium for low TFP stocks reflects the exposure to business cycle risks.

Recent studies highlight intangible expenditure as a key driver of corporate productivity and performance. Corrado et al. (2005) propose treating tangible and intangible investment equivalently given that both involve foregoing current production to increase future production. They classify intangible capital into three categories: computerized information, innovative property and economic competencies. Computerized information consists of knowledge embedded in software and databases, innovative property consists of R&D and other inventive processes, and economic competencies include advertising and market research, organizational structures such as management, and training of employees. Lin and Lo (2015) demonstrate that intangible investment has a positive impact on productivity at the firm level for Taiwanese manufacturers. In a study spanning 36 countries, Montresor and Vezzani (2016) find that larger scale investment in intangibles contributes to more innovation in manufacturing firms, and that investing in 'technological' intangibles, such as R&D, software and design, supports greater innovation than investing in 'non-technological' intangibles, such as training, advertising and branding, and business processes. Their results are consistent with a substantial literature dating back to Scherer (1982) and others that links R&D with productivity. On the other hand, Chappell and Jaffe (2018) find that firm-level intangible investment does not contribute positively to productivity or profitability in New Zealand.

Intangible expenditure is related to the development of organizational capital, which a small number of recent studies have shown plays an important role in improving firm productivity (Tronconi and Vittucci Marzetti, 2011; Lev and Radhakrishnan, 2005). Evenson and Westphal (1995) define organizational capital as "the knowhow used to combine human skills and physical capital into systems for producing and delivering want-satisfying products." Human and organizational capital are related in that part of a firm's organizational capital is the knowledge of how to utilize its human capital, and that like human capital, organizational capital may be embodied in a firm's employees (Atkeson and Kehoe, 2002). Prescott and Visscher (1980) identify three examples of ways in which a firm may invest in organizational capital: improving the matches between employees and jobs, improving the match between employees in teams and improving the human capital of the firm's employees through on-the-job training. Firms' personnel expenditure may enhance both organizational and human capital, leading to improved productivity. Lev and Radhakrishnan (2005) consider organizational capital as a characteristic of the firm itself and defining it as "an agglomeration of technologies – business practices, processes and designs, and incentive and compensation systems – that together enable some firms to consistently and efficiently extract from a given level of physical and human resources a higher value of product than other firms find possible to attain." They find that employee efficiency can be improved through expenditure that proxies for organizational capital investment.

We evaluate whether bankruptcy, macroeconomic and capital and intangibles expenditure risks explain the high TFP premium in Sections 3.1, 3.2 and 3.3, respectively. Following Corrado et al.'s (2005) taxonomy, we consider intangibles expenditures on R&D as primarily related to innovative property while expenditures contributing to the development of human and organizational capital as primarily related to economic competencies. We are unable to investigate computerized information because data on software is only available for one third of the firms in our sample and that data is measured as stocks rather than the flow measures we use in our analysis. Lev and Radhakrishnan (2005) note that information technology enables organizational capital and measures of organizational capital should correlate with information technology investment.

For a particular risk to lie behind our empirical result that high TFP stocks command a risk premium, the following two conditions must be satisfied: i) the risk is positively correlated with firm-level TFP, and ii) the impact of firm-level TFP on returns increases as the risk increases. We investigate these conditions for each type of risk in the following sections.

3.1. Bankruptcy risk

Fama and French (1993) find that firms with high book-to-market ratios are less profitable and more financially distressed than firms with low book-to-market ratios. Small firms are more leveraged and have greater earnings uncertainty. Accordingly, the size and value factors reflect a risk premium for financially distressed firms. Vassalou and Xing (2004) show that for U.S. stocks, size and value contain default-related information. A bankruptcy risk premium consistent with the size and value factors should be large for low TFP firms and small for high TFP firms. This is the opposite of the TFP premium that we find, which is small for low productivity firms and large for high productivity firms. However, there may be bankruptcy risk among high productivity firms that is not immediately obvious from the financial characteristics discussed in our TFP-quintile portfolio and factor loading analyses. Bankruptcy risk warrants a closer examination.

In contrast to Fama and French (1993), empirical analyses such as Dichev (1998) and Campbell et al. (2008) find a negative relationship between bankruptcy risk and returns. Dichev (1998) measures bankruptcy risk using Altman's (1968) Z-score and Ohlson's (1980) O-score and shows that bankruptcy risk cannot explain the size and value effects. Campbell et al. (2008) calculate a measure of bankruptcy risk using profit and market information, and demonstrate a negative relationship between bankruptcy risk and returns. They show that the negative relationship between bankruptcy risk and returns is stronger for firms with large information asymmetries and those facing arbitrage limitations. This explains the existence of anomalies caused by pricing errors as a result of bankruptcy risk that is not properly reflected in market prices, suggesting bankruptcy risk is not compensated by a positive return premium. Using a probability measures derived from options prices, Gharghori et al. (2009) find that default risk is negatively related to returns on Australian stocks while Liu et al. (2019) find that default risk is positively associated with expected stock returns for small and non-state owned Chinese firms.

The two main approaches to estimating the probability of corporate bankruptcy involve either determining the credit quality of a company based on accounting information (for example, Altman (1968)) or predicting corporate failure based on market information (for example, Merton (1974)). Numerous recent studies estimate bankruptcy models that incorporate market information, such as Campbell et al. (2008), Gharghori et al. (2009), Liu et al. (2019) and Shumway (2001). However, the market information approach is inappropriate for explaining the return premium associated with TFP. We examine two accounting information-based measures of bankruptcy likelihood, Altman's (1968) Z-score and Ohlson's (1980) O-score.[5] Xu and Zhang (2009) demonstrate that the Z-score and O-score measures are useful in assessing the bankruptcy risk of listed Japanese firms.[6]

Table 4:
Descriptive statistics for the Z-scores and O-scores.

	Obs.	Mean	S.D.	Min	Max
Z-score	10,854	3.128	2.169	-0.897	28.597
O-score	10,409	-5.600	15.118	-732.883	168.628

Note: Altman's (1968) Z-score is a measure of credit strength and Ohlson's (1980) O-score is a measure of credit weakness.

Table 4 shows the descriptive statistics for the bankruptcy scores calculated for each firm in each year of our sample. The Z-score is a measure of credit strength while the O-score is a measure of credit weakness. We run Fama-MacBeth regressions of TFP on the Z-scores and O-scores to evaluate on the cross-sectional relationships between TFP and each bankruptcy score. The estimates are shown in Table 5. The positive and significant estimate for the Z-score coefficient in model (1) suggests that high TFP firms have a low probability of bankruptcy, although the magnitude of the coefficient is not large. The

[5] Altman's (1968) Z-score is defined as:

$$\text{Z-score} = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5$$

where X_1 is working capital divided by total assets, X_2 is retained earnings divided by total assets, X_3 is earnings before interest and taxes divided by total assets, X_4 is the market value of equity divided by the book value of total liabilities, and X_5 is sales divided by total assets.

Ohlson's (1980) O-score is defined as:

$$\begin{aligned}\text{O-score} = & -1.32 - 0.407log(TA_t/GNP_t) + 6.03(TL_t/TA_t) - 1.43(WC_t/TA_t) + 0.0757(CL_t/CA_t) - 1.72(X) \\ & - 2.37(NI_t/TA_t) - 1.83(FFO_t/TL_t) + 0.285(Y) - 0.521(NI_t - NI_{t-1})/(|NI_t| - |NI_{t-1}|)\end{aligned}$$

where TA_t represents total assets, GNP_t is the gross national product price-index level, TL_t is total liabilities, WC_t is working capital, CL_t represents current liabilities, CA_t is current assets, X is one if total liabilities exceed total assets and is zero otherwise, NI_t is net income, FFO_t is funds provided by operations, and Y is one if net income was negative for the last two years and is 0 otherwise.

[6] To the best of our knowledge there are no recent published articles examining the relationship between bankruptcy risk and stock returns for the Japanese market. Suzuki and Wright (1985) find that for Japanese stocks in the 1970s, measures of a company's social importance and the strength of its bank relationship may be better indicators of bankruptcy risk than accounting information.

Table 5:
Fama-MacBeth regressions of TFP on the bankruptcy scores.

	Dependent variable: total factor productivity, $TFP_{i,t}$	
	(1)	(2)
Z-score	0.106^{***}	
	(0.007)	
O-score		3.49e-04
		(0.001)
Constant	2.300^{***}	2.633^{***}
	(0.253)	(0.243)
Observations	10,843	10,399
Adj. R^2	0.144	0.005

Note: The dependent variable for each model is total factor productivity (TFP) measured at fiscal year-end. Altman's (1968) Z-score is a measure of credit strength and Ohlson's (1980) O-score is a measure of credit weakness. Sector dummy variables are included. Standard errors are in parentheses. ***, **, and * indicate significant at the 1%, 5% and 10% levels, respectively.

O-score coefficient estimate in model (2) is not significant. The models provide no indication that TFP is positively related to bankruptcy risk. Next we examine the relationship between the TFP premium and bankruptcy risk controlling for common equity risk factors.

We perform regressions based on equation (2.5) adding a bankruptcy score by TFP interaction term. We estimate separate models for the Z-score by TFP and O-score by TFP interaction terms, both with and without the TFP variable itself. The regressions control for the five Fama-French factors and include sector dummies. If bankruptcy risk explains the relationship between TFP and future returns, then future returns should be more sensitive to TFP as the probability of bankruptcy increases. This implies the coefficient of the interaction between the Z-score and TFP should be negative while the coefficient for the interaction between the O-score and TFP should be positive.

The estimates in Table 6 do not support our priors required for bankruptcy risk to explain the relationship between TFP and future returns. The estimated coefficients of the interaction terms in equations (1) to (4) are not significant, implying there is no role for bankruptcy risk in explaining the TFP premium. Recall that our TFP portfolio analyses of Sections 2.3 and 2.4 that suggest high (low) TFP firms have large (small) market capitalization, low (high) book-to-market ratios and high (low) returns on equity. Higher TFP-quintile firms are likely to be more profitable and thus relatively creditworthy.

Table 6:
Fama-MacBeth regressions of year ahead returns and TFP including TFP-bankruptcy interaction terms.

	Dependent variable: future return, $r_{i,t+1}$			
	(1)	(2)	(3)	(4)
β	0.537	0.255	0.707	0.094
	(1.823)	(1.860)	(1.955)	(2.050)
ln(ME)	-0.723	-0.226	-0.753	-0.154
	(0.827)	(0.734)	(0.824)	(0.712)
ln(B/M)	4.747***	4.742***	4.374***	4.070**
	(1.365)	(1.405)	(1.442)	(1.517)
ROE	-0.134***	-0.124**	-0.130***	-0.112**
	(0.046)	(0.046)	(0.045)	(0.044)
AG	-0.015	-0.027	-0.026	-0.036
	(0.035)	(0.034)	(0.038)	(0.036)
TFP	3.153***		3.563***	
	(1.012)		(1.050)	
TFP × Z-score	0.052	0.150		
	(0.096)	(0.111)		
TFP × O-score			0.014	-0.005
			(0.024)	(0.028)
Observations	10,107	10,107	10,053	10,053
Adj. R^2	0.143	0.138	0.142	0.136

Note: Altman's (1968) Z-score is a measure of credit strength and Ohlson's (1980) O-score is a measure of credit weakness. The dependent variable for each model is the future return for company i, $r_{i,t+1}$, defined as the one-year return from three months after the fiscal year-end. β is sensitivity to TOPIX, calculated over the 60 months prior to each fiscal year-end. ln(ME) is the natural logarithm of market capitalization in millions of yen. ln(B/M) is the natural logarithm of the book-to-market ratio. ROE represents the return of equity expressed as percent. AG is the percentage growth rate of assets. TFP is is total factor productivity measured at fiscal year-end. Sector dummy variables are included. Standard errors are in parentheses. The intercepts are not displayed. ***, **, and * indicate significant at the 1%, 5% and 10% levels, respectively.

3.2. Macroeconomic risk

We examine whether macroeconomic risk explains the premium for high TFP stocks by analyzing the relationship between the business cycle, TFP and future returns. We use the diffusion index of actual (current) business conditions for large manufacturing firms (DI) from the Bank of Japan's Tankan survey as our business cycle indicator. The Tankan is a comprehensive quarterly national economic survey of enterprises, considered to provide the most reliable business conditions indicators for Japan. The DI is based on survey responses from large manufacturing firms and is thus an appropriate indicator for the firms in our sample.

Table 7 shows the correlation between fiscal year-end TFP and the average of the quarterly business conditions DI for each fiscal year by the TFP-quintile portfolios constructed in Section 2.3. There is no significant correlation between TFP and business conditions for any quintile or the spread between Q5 and Q1.

Table 7:
Correlation between TFP and the business conditions DI.

	Correlation with DI
Q1	0.001
Q2	0.005
Q3	0.002
Q4	0.000
Q5	-0.001
Q5-Q1	-0.024

Note: Q1 to Q5 refer to the TFP-quintiles shown in Table 1. Q1 is the lowest TFP quintile and Q5 is the highest TFP quintile. TFP is the cross-sectional average of firm-level TFP in each quintile at the end of each financial year. DI is the average of the quarterly Tankan diffusion index of actual (current) business conditions for large manufacturing firms for each fiscal year. Q5-Q1 shows the correlation between the average of the quarterly Tankan diffusion index of actual (current) business conditions for large manufacturing firms for each fiscal year and the difference in Q5 and Q1 TFP. ***, **, and * indicate significant at the 1%, 5% and 10% levels, respectively.

Table 8 shows the average future return to each quintile portfolio corresponding to the fiscal years of macroeconomic expansions and contractions, as well as for both macroeconomic states. Expansions are defined as fiscal years in which the average of quarterly Tankan DIs is positive and contractions where the average is negative. This gives 13 years of expansions and seven years of contractions. Future returns are greater for contractions than expansions for all quintile portfolios. The future returns of low TFP firms are more sensitive to the business cycle than those of high TFP firms. The average future return of the Q1 portfolio is 1.4% for expansions and 18.4% for contractions, while the average future return for the Q5 portfolio is 3.9% for expansions and 14.6% for contractions. The Q5 minus Q1 spread is lower for contractions and than for expansions. In these respects, the future return characteristics of our TFP sorted portfolios over the business cycle correspond with the findings of İmrohoroğlu and Tűzel (2014) for U.S. stocks. Our data also suggests that the future returns of high TFP firms outperform low TFP

Table 8:
Quintile portfolio future returns, macroeconomic expansions and contractions (%).

	(Low)		TFP Quintiles		(High)	(High-Low)
	Q1	Q2	Q3	Q4	Q5	Q5-Q1
All states, 20 fiscal years	7.364	9.150	8.571	8.223	7.659	0.294
Expansions, 13 fiscal years	1.427	3.367	3.436	3.482	3.937	2.510
Contractions, 7 fiscal years	18.391	19.889	18.107	17.027	14.570	-3.821

Note: Q1 to Q5 refer to the TFP-quintile portfolios shown in Table 1. Q1 is the lowest TFP quintile and Q5 is the highest TFP quintile. The return to each TFP quintile portfolio is the annual future return beginning three months after the end of fiscal year. We examine the response of TFP portfolio future returns to business conditions. Expansions are defined as fiscal years in which the average of quarterly Tankan DIs is positive and contractions where the average is negative.

firms for expansions while low TFP firms outperform high TFP firms for contractions. If macroeconomic risk explained the relationship between future returns and TFP, we would expect high TFP firms to trade at a premium over low TFP firms following contractions because of their relatively high risk. However, Table 8 shows that for unconditioned portfolio future returns, this is not the case.

Table 9:
Descriptive statistics and correlations for business conditions and future returns.

	Obs.	Mean	S.D	Min	Max	Correlations		
						DI	Q1	Q5
DI	20	2.813	17.112	-31.250	23.250	1.00		
Q1	20	7.364	20.347	-21.524	50.310	-0.33	1.00	
Q5	20	7.659	21.571	-25.815	47.722	-0.09	0.89***	1.00
Q5-Q1	20	0.294	9.931	-25.022	15.703	0.48**	-0.12	0.35

Note: DI is the Tankan diffusion index of actual (current) business conditions for large manufacturing firms for the last quarter of each fiscal year. Q1 and Q5 refer to the TFP-quintile portfolios shown in Table 1. Q1 is the lowest TFP quintile and Q5 is the highest TFP quintile. The table shows statistics for the future return for Q1 and Q5 portfolios. Spread is the difference in future return between the Q5 and Q1 portfolios. ***, **, and * indicate significant at the 1%, 5% and 10% levels, respectively.

Table 9 provides descriptive statistics for the business conditions DI, the Q1 and Q5 future returns and their spread. The correlation between the DI and the unconditioned Q5 minus Q1 spread is positive and significant. This is consistent with our results presented in Table 8 and with those of İmrohoroğlu and Tűzel (2014).[7] However, the low and high TFP portfolios have substantially different risk factor loadings as demonstrated in Tables 1 and 2, and the risks associated with the standard equity factors may be correlated with the business cycle. We condition for known factors to better isolate the TFP effect. Figure 2 shows the DI and the future return spread between the Q5 and Q1 portfolios conditioned on the Fama-French three, Carhart four, Fama-French five and q-factors. The conditioned spreads have little correlation with the business cycle, supporting our conclusion that macroeconomic risk does not explain the TFP premium.[8]

[7]İmrohoroğlu and Tűzel (2014) discuss the TFP effect as a premium on low TFP firms while we express the TFP effect as a premium on high TFP firms. Our (unconditioned) high minus low spread has the same positive correlation with the business cycle as theirs if they measure the spread in the same way.

[8]The correlations between the DI and the Q5 minus Q1 spread conditioned on the Fama-French three, Carhart four, Fama-French five and q-factor loadings as estimated in Table 2 are 0.03, 0.05, 0.06 and 0.10, respectively.

Figure 2:
DI and future return spread between 5th and 1st quintile portfolios conditioned on risk factors.

Note: The DI shown in the figure is the Tankan diffusion index of actual (current) business conditions for large manufacturing firms averaged over the four quarters of each fiscal year. The conditioned future return spreads shown represent the difference between the Q5 and Q1 future returns conditioned on factor loadings according to the Fama-French three factor (FF3), Carhart four factor (CHT4), Fama-French five factor (FF5) and q-factor (qfactor) models. The conditioned future return spreads are aligned temporally with the DI. For example, the DI shown for the date 1999 represents the average quarterly DI over the period April 1999 to March 2000 and the conditioned future return spreads shown for the same date refer to the 1-year return spreads calculated for July 2000 to June 2001.

3.3. Capital and intangibles expenditure risks

We consider capital and intangibles expenditure risks as potential explanations for the existence of a premium for high TFP firms.[9] We hypothesize that high TFP firms are more likely to undertake capital and intangibles expenditure and that future returns are higher for firms that take on the greater risks associated with this higher expenditure. Previous studies on the relationship between firm-level productivity and stock returns do not consider these risks.

A substantial literature shows that US firms realize abnormally low stock returns subsequent to increases in capital investment (Berk et al., 1999; Baker et al., 2003; Titman et al., 2004). However, Titman et al. (2009) find there is no significant negative relationship between capital investment and subsequent stock returns for Japanese companies, which may be because characteristics of corporate financing limit

[9]Capital expenditure refers to funds used by a firm to acquire, improve and maintain long-term physical assets that improve the productive efficiency or capacity of the firm. Such expenditure is capitalized on the firm's balance sheet and may also referred to as capital investment.

over-investment.

Fama and French (2015) include asset growth as a risk factor to proxy capital investment after Cooper et al. (2008) identified the negative relationship between asset growth and U.S. stock returns. Despite this, empirical evidence suggests a significant asset growth-return relationship does not exist for Japanese stocks. Our models in Sections 2.4 and 2.5 that include the Fama-French five factors show that the coefficient on asset growth is not significant, consistent with Kubota and Takehara's (2018) results indicating that asset growth is not important for returns in the Japanese market. Asset growth is a broad measure of the financing raised by a firm that includes retained earnings or debt accumulated as cash and may not necessarily correlate with capital investment. More specific measures of capital investment may still play a role in explaining the premium on high TFP firms and we proceed with data on reported capital expenditure itself.

Intangibles such as R&D expenditure have also been shown to influence stock returns. A vast literature has documented evidence in both U.S. and non-U.S. markets that R&D-intensive firms have high market value and high stock returns subsequent to their R&D expenditure. Early work by Lev and Sougiannis (1996) reports that R&D intensity predicts returns and profitability after controlling for size, the book-to-market ratio and survivorship bias. Bae and Kim (2003) find a positive and significant relationship between R&D expenditure and the market value of firms in US, Germany and Japan. Hou et al. (2021) note two potential explanations for the R&D effect on returns: a risk premium that arises because R&D investments create growth options and may increase firms' exposure to unspecified systematic risk factors and mispricing as pessimism regarding the value of R&D may lead investors to over-discount related expected future cash flows.

Two recent papers address the relationship between organizational capital and stock returns. Eisfeldt and Papanikolaou (2013) note that organizational capital is often embodied in firms' key employees and postulate that the mobility of senior talent involves and additional risk for shareholders. Key employees may demand an increase in compensation, equaling the value of their outside option, that would reduce the cash flows to shareholders from organizational capital. Thus shareholders demand a premium for their exposure to this risk. Eisfeldt and Papanikolaou measure firm-level organizational capital stock as accumulated SGA expenses, and show this correlates highly with managerial quality. Their findings show that US firms with more organizational capital provide investors with a premium over those with less organizational capital. Similarly, Leung et al. (2018) find that firms with greater organizational capital have significantly higher stock returns for a sample spanning 20 developed economies. They use the same measure of organizational capital and argue it captures the qualitative characteristics of organizational capital since firms with higher accumulated SGA have higher productive and managerial efficiency, and are more innovative.

In one of the few papers examining the relationship between personnel expenditure and asset returns, Palacios (2015) develops a general equilibrium framework to infer the value and riskiness of human capital. Although studies including Fama and Schwert (1977) and Heaton and Lucas (2000) show little evidence for comovement between wages and returns, Palacios's model suggests a role for human capital as a return factor even when the correlation between wages and returns is small. In related work, Santos and Veronesi (2006) provide evidence that, at the macroeconomic level, the ratio of labor income to consumption forecasts stock returns. This implies that deviations in labor income from its long run relationship with consumption contain useful information about returns, both in the time series and the cross-section. At a firm-level, Donangelo et al. (2019) show that companies with a high labor share have operating profits that are more sensitive to economic shocks and have higher expected returns. Accordingly, we examine personnel expenditure as a separate source of intangibles risk.

Table 10:
Descriptive statistics for the capital and intangibles expenditure variables.

	Obs.	Mean	S.D.	Min	Max
ln(CE)	11,294	8.373	1.729	0.000	15.219
ln(RD)	11,217	7.780	1.890	0.000	13.878
ln(PE)	10,979	8.673	1.377	1.386	13.679
ln(AD)	4,534	6.711	2.296	0.000	13.133
ln(SGAexRD)	11,405	9.814	1.441	5.602	14.665
ln(SGAexRDPEAD)	11,405	9.318	1.490	5.050	14.478

Note: Natural logarithms of the following variables, measured in millions of yen, are used. CE, RD, PE and AD represent capital, R&D, personnel and advertising expenditure, respectively. SGAexRD is selling, general and administrative expenditure minus R&D expenditure. SGAexRDPEAD is selling, general and administrative expense minus R&D, personnel and advertising expenditure.

Table 10 provides descriptive statistics for the natural logarithms of the following capital and intangible expenditure variables in levels, measured in millions of yen: capital expenditure (CE), R&D expenditure (RD), personnel expenditure (PE), advertising expenditure (AD), selling, general and administrative expense minus R&D expenditure (SGAexRD), and selling, general and administrative expense minus R&D, personnel and advertising expenditure (SGAexRDPEAD). These variables proxy for firms' exposure to capital and intangibles expenditure risks. Specifically, R&D expenditure provides a proxy of exposure to investment in innovative property. Personnel and selling, general and administrative expenditure proxy investment in human and organizational capital. Personnel expenditure includes salaries and items such as bonuses, allowances and welfare expenses. SGA covers a variety of expenditure not usually broken down in detail, and may include employee training, brand enhancement, systems and strategy consultant and information technology outlays (Tronconi and Vittucci Marzetti, 2011).

Although SGA expenditure usually includes R&D, whether or not to report R&D in SGA is left to the discretion of the company. Some firms with large R&D expenditure, such as pharmaceuticals, do not include R&D in SGA but disclose it as a separate account in the income statement. We uniformly exclude R&D from SGA by using SGAexRD for all firms to avoid overlap among the different types of intangible expenditure. Similarly we exclude advertising and personnel expenditure from SGA in SGAexRDPEAD. We use flow measures for all capital and intangibles variables to avoid the substantial difficulties and arbitrary choices involved in measuring stocks that are related to initial stock levels and depreciation rates.

Table 11:
Fama-MacBeth regressions of TFP on capital and intangibles expenditure.

	Dependent variable: total factor productivity, $TFP_{i,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
ln(CE)	0.089***					
	(0.016)					
ln(RD)		0.143***				
		(0.011)				
ln(PE)			0.226***			
			(0.019)			
ln(AD)				0.055***		
				(0.004)		
ln(SGAexRD)					0.075***	
					(0.004)	
ln(SGAexRDPEAD)						0.075
						(0.004)
Constant	1.991***	1.623***	0.751***	2.436***	2.001***	2.039***
	(0.122)	(0.164)	(0.085)	(0.229)	(0.210)	(0.217)
Observations	11,285	11,206	10,969	4,526	11,394	11,394
Adj. R^2	0.099	0.228	0.296	0.048	0.035	0.037

Note: The dependent variable for each model is total factor productivity (TFP) measured at fiscal year-end. Natural logarithms of the following variables, measured in millions of yen, are used. CE, RD, PE and AD represent capital, R&D, personnel and advertising expenditure, respectively. SGAexRD is selling, general and administrative expenditure minus R&D expenditure. SGAexRDPEAD is selling, general and administrative expense minus R&D, personnel and advertising expenditure. Sector dummy variables are included. Standard errors are in parentheses. ***, **, and * indicate significant at the 1%, 5% and 10% levels, respectively.

The regression results shown in Table 11 indicate that TFP is positively related to capital and intangibles expenditure. All estimates are significant except for that for SGAexRDPEAD. Personnel and R&D expenditures in models (3) and (2), respectively, have the largest adjusted R^2, followed by capital expenditure. These results suggest the intangibles expenditure variables potentially reflect risks that may lie behind the premium for high TFP firms.

To examine whether the impact of TFP on returns increases along with capital and intangibles expenditure risks, we run Fama-MacBeth regressions of future returns on TFP and interaction terms between TFP and quintile dummy variables for our capital and intangibles risk proxies, controlling for the Fama-French five factors. We run one regression for each of the six capital or intangibles risk proxies. Quintile

Table 12:
Fama-MacBeth regressions of year ahead returns on capital and intangibles expenditure risks.

	Dependent variable: future return, $r_{i,t+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
β	-0.036	-0.204	-0.134	0.589	0.279	0.220
	(1.791)	(1.769)	(1.823)	(1.970)	(1.829)	(1.833)
ln(ME)	-2.029**	-2.034*	-2.014**	-1.564*	-1.054	-0.993
	(0.950)	(0.993)	(0.874)	(0.859)	(0.839)	(0.837)
ln(B/M)	4.437***	4.318***	4.344***	4.007	4.705***	4.704***
	(1.399)	(1.379)	(1.359)	(2.318)	(1.400)	(1.411)
ROE	-0.124***	-0.119**	-0.110**	-0.277***	-0.127***	-0.128***
	(0.042)	(0.042)	(0.041)	(0.089)	(0.043)	(0.043)
AG	-0.024	-0.014	-0.014	0.054	-0.022	-0.023
	(0.035)	(0.033)	(0.034)	(0.059)	(0.033)	(0.034)
TFP	3.841***	2.366*	1.708	4.929***	3.238**	3.243**
	(1.116)	(1.267)	(1.378)	(1.657)	(1.152)	(1.176)
TFP × CE Dummy 2	-0.564					
	(0.367)					
TFP × CE Dummy 3	0.792					
	(0.459)					
TFP × CE Dummy 4	1.536**					
	(0.667)					
TFP × CE Dummy 5	1.679**					
	(0.616)					
TFP × RD Dummy 2		0.783				
		(0.577)				
TFP × RD Dummy 3		0.919				
		(0.570)				
TFP × RD Dummy 4		2.050***				
		(0.660)				
TFP × RD Dummy 5		2.403***				
		(0.767)				
TFP × PE Dummy 2			0.669			
			(0.594)			
TFP × PE Dummy 3			0.642			
			(0.516)			
TFP × PE Dummy 4			1.885**			
			(0.729)			
TFP × PE Dummy 5			2.859***			
			(0.915)			
TFP × AD Dummy 2				-0.324		
				(0.587)		
TFP × AD Dummy 3				1.132		
				(0.676)		
TFP × AD Dummy 4				1.423*		
				(0.723)		
TFP × AD Dummy 5				0.405		
				(0.632)		
TFP × SGAexRD Dummy 2					0.812**	
					(0.331)	
TFP × SGAexRD Dummy 3					0.870	
					(0.506)	
TFP × SGAexRD Dummy 4					1.094***	
					(0.370)	
TFP × SGAexRD Dummy 5					1.217*	
					(0.623)	
TFP × SGAexRDPEAD Dummy 2						0.899**
						(0.347)
TFP × SGAexRDPEAD Dummy 3						0.941*
						(0.489)
TFP × SGAexRDPEAD Dummy 4						1.082**
						(0.451)
TFP × SGAexRDPEAD Dummy 5						0.995*
						(0.565)
Observations	10,580	10,580	10,580	4,169	10,580	10,580
Adj. R^2	0.160	0.159	0.159	0.236	0.156	0.156

Note: The dependent variable for each model is the future return for company i, $R_{i,t+1}$, defined as the one-year return from three months after the fiscal year-end. β is sensitivity to TOPIX, calculated over the 60 months prior to each fiscal year-end. ln(ME) is the natural logarithm of market capitalization in millions of yen. ln(B/M) is the natural logarithm of the book-to-market ratio. ROE represents the return of equity expressed as percent. AG is the percentage growth rate of assets. TFP is is total factor productivity measured at fiscal year-end. Dummy variables represent the quintiles of the natural logarithms of the following variables measured in millions of yen: capital expenditure (CE), R&D expenditure (RD), personnel expenditure (PE), advertising expenditure (AD), selling, general and administrative expense minus R&D expenditure (SGAexRD), and selling, general and administrative expense minus R&D, personnel and advertising expenditure (SGAexRDPEAD). Standard errors are in parentheses. The intercepts are not displayed. ***, **, and * indicate significant at the 1%, 5% and 10% levels, respectively.

dummies are used to avoid multicollinearity since interaction terms constructed with levels are highly correlated with TFP. The dummies for each capital or intangibles expenditure variable correspond with quintiles of firms ordered by the respective variable. The number in the dummy name indicates the quintile. Quintile one represents the lowest values and quintile five represents the highest. For example, CE Dummy 2 is the dummy variable for the second-lowest quintile of firms with respect to capital expenditure. The first dummy is excluded from each model.

Table 12 reports the results for the six Fama-MacBeth regressions. Our priors suggest that the coefficients of the interaction terms should be positive and should increase with the dummy variable quintiles. This is broadly the case for the models including capital (1), R&D (2) and personnel expenditure (3), but is less clear for the models including advertising expenditure (4), SGAexRD (5) and SGAexRDPEAD (6). The coefficient estimates for both the Dummy 4 and Dummy 5 interaction terms are positive and significant in all models except that for advertising expenditure (4). The significant fourth and fifth quintile estimates are large relative to first and second quintile estimates, and compared with the TFP coefficient estimates, in models (1), (2) and (3). TFP has a relatively great impact on returns for firms in the high capital, R&D and personnel expenditure quintiles. Overall these results provide support for capital, R&D and personnel expenditure risks as explanations for the premium on high TFP stocks. The evidence for advertising expenditure, SGAexRD and SGAexRDPEAD risks is less convincing, although not sufficient grounds to rule out the possibility that these intangibles expenditure types play a role in explaining the high TFP premium.

4. Decomposing the predictive power of TFP

In this section we investigate the extent to which capital and intangibles expenditure risks explain the premium for high TFP firms. We examine the six candidate variables in logarithmic form as ln(CE), ln(RD), ln(PE), ln(AD), ln(SGAexRD) and ln(SGAexRDPEAD). Our regressions in the previous section consider the role of each candidate separately. In the explanatory decompositions that follow, we consider each candidate variable individually in univariate analyses and all candidates jointly in two multivariate models.

We use the method proposed by Hou and Loh (2016) to calculate the extent to which the candidate risks explain the predictive power of TFP for future returns. The analysis consists of the following four steps which we illustrate using the univariate procedure. The equations for the analogous multivariate procedure can be found in Appendix A of Hou and Loh (2016). Stage one involves running the same firm-level cross-sectional Fama-MacBeth regression of future returns on TFP as shown in Equation (2.5), controlling for the Fama-French five factors and sector effects. We obtain the estimated coefficient of $TFP_{i,t}$, γ_6, which is shown in the top panel of Table 13 for the univariate analyses and Table 14 for the multivariate models.

In stage two, we add the candidate variable, represented by $C_{i,t}$, to the model of stage one. We regress future returns on TFP, the candidate and control variables as shown in Equation (4) to obtain estimates of the coefficients of TFP and the candidate, ψ_6 and ψ_7, respectively. As the candidate variables are measured in levels, controlling for firm size is particularly important because larger firms are likely to have greater expenditure. The multivariate version of the procedure includes all candidates jointly in this regression. The coefficients estimated in this step are shown in the second panel of Tables 13 and 14.

$$\begin{aligned} r_{i,t+1} &= \psi_0 + \psi_1 \beta_{i,t} + \psi_2 \ln(ME)_{i,t} + \psi_3 \ln(B/M)_{i,t} + \psi_4 ROE_{i,t} + \psi_5 AG_{i,t} \\ &\quad + \psi_6 TFP_{i,t} + \psi_7 C_{i,t} + \textstyle\sum_{j=1}^{11} \widetilde{\chi}_j DS_j + \nu_{i,t+1} \end{aligned} \tag{4}$$

A candidate risk should be contemporaneously correlated with TFP if it is to explain the premium for high TFP firms. Stage three of the procedure evaluates the relationship between TFP and the candidate using Equation (4) to obtain the estimated coefficient for the candidate, δ_1, as shown in the third panel of Tables 13 and 14.

$$TFP_{i,t} = \delta_0 + \delta_1 C_{i,t} + \xi_{i,t} \tag{5}$$

Stage four provides the explanatory power of the candidate risk for the premium on high TFP firms. The coefficient of TFP obtained in stage one, γ_6, can be decomposed into two parts as demonstrated by Equation (4). The first part is the covariance between the portion of TFP that can be explained by the candidate and future returns, ϕ^C. The second part is the covariance between the unexplained portion of TFP and future returns, ϕ^υ. The adjusted return, $Adj.r_{i,t+1}$, refers to the future return controlled for the five Fama-French firm characteristics and sector dummies.

$$\begin{aligned} \gamma_6 &= \frac{Cov(Adj.r_{i,t+1}, TFP_{i,t})}{Var(TFP_{i,t})} = \frac{Cov(Adj.r_{i,t+1}, (\delta_0 + \delta_1 C_{i,t} + \xi_{i,t}))}{Var(TFP_{i,t})} \\ &= \frac{Cov(Adj.r_{i,t+1}, \delta_1 C_{i,t})}{Var(TFP_{i,t})} + \frac{Cov(Adj.r_{i,t+1}, (\delta_0 + \xi_{i,t}))}{Var(TFP_{i,t})} \\ &= \phi^C + \phi^\upsilon \end{aligned} \tag{6}$$

ϕ^C can be calculated as shown in Equation (4). The ratio ϕ^C/γ_6 measures the fraction of the TFP-future return relation that is explained by the candidate risk, while ϕ^υ/γ_6 is the fraction unexplained by the candidate risk. The decompositions of the stage one TFP coefficient for the candidate risks are shown in the last panel of Tables 13 and 14.

$$\phi^C = \left(\frac{\psi_7}{\delta_1} + \psi_6\right) \frac{Var(\delta_1 C_{i,t})}{Var(TFP_{i,t})} \tag{7}$$

Table 13:
Decomposing TFP for individual candidates.

Stage	Description		Coefficient					
1	$r_{i,t+1}$ on TFP	TFP	3.983^{***}					
			(1.138)					
			Candidates					
			ln(CE)	ln(RD)	ln(PE)	ln(AD)	ln(SGA exRD)	ln(SGA exRDPEAD)
2	$r_{i,t+1}$ on TFP and Candidate	TFP	4.130^{***}	3.626^{***}	3.261^{**}	5.775^{***}	3.971^{***}	3.965^{***}
			(0.994)	(1.099)	(1.221)	(1.578)	(1.134)	(1.137)
		Candidate	0.752	0.965	1.620^{*}	0.536^{**}	0.595^{**}	0.544^{**}
			(0.659)	(0.564)	(0.894)	(0.244)	(0.258)	(0.245)
3	TFP on Candidate	Candidate	0.089^{***}	0.143^{***}	0.226^{***}	0.055^{***}	0.075^{***}	0.075^{***}
			(0.016)	(0.011)	(0.019)	(0.004)	(0.005)	(0.004)
4	Decompose Stage-1 Coefficient	Explained	0.206	0.525	0.699	0.172	0.096	0.097
		(%)	5.2^{**}	13.2^{***}	17.6^{***}	4.3^{*}	2.4	2.4
			(2.441)	(2.391)	(2.821)	(2.523)	(1.590)	(2.424)
		Residual	3.777	3.458	3.284	3.811	3.887	3.886
		(%)	94.8^{***}	86.8^{***}	82.4^{***}	95.7^{***}	97.6^{***}	97.6^{***}
			(4.593)	(5.662)	(6.233)	(4.714)	(5.012)	(6.564)

Note: $r_{i,t+1}$ represents future returns. TFP is is total factor productivity measured at fiscal year-end. Natural logarithms of the following variables, measured in millions of yen, are used. CE, RD, PE and AD represent capital, R&D, personnel and advertising expenditure, respectively. SGAexRD is selling, general and administrative expense minus R&D expenditure. SGAexRDPEAD is selling, general and administrative expense minus R&D, personnel and advertising expenditure. Newey-West HAC standard errors appear in parentheses. ***, **, and * indicate significant at the 1%, 5% and 10% levels, respectively.

Table 13 shows the results of the univariate analysis. The stage one regression confirms the a positive relationship between firm productivity and future returns adjusted for firm characteristics. In stage two, all candidate variables have positive estimated coefficients and all but those for capital and R&D are significant. Personnel, advertising, SGAexRD and SGAexRDPEAD correlate positively with future returns when controlling for TFP. Of the significant candidate estimates, personnel is relatively large. The TFP coefficients remain positive and significant in the presence of each candidate variable indicating a strong and robust relationship between TFP and future returns.

The regressions for stage three show positive and statistically significant univariate relationships between each candidate and TFP. Personnel and R&D expenditure are more closely related to TFP than capital, advertising, SGAexRD and SGAexRDPEAD expenditure. The stage four decompositions suggest that personnel and R&D expenditure show the greatest promise in explaining the TFP-future returns relationship, accounting for about 17.6% and 13.2%, respectively. Capital expenditure and advertising explain substantially less of the relationship at 5.2% and 4.3%, while SGAexRD and SGAexRDPEAD

Table 14:
Decomposing TFP for all candidates simultaneously.

Stage	Description		Coefficient		SE	Coefficient		SE
1	$r_{i,t+1}$ on TFP	TFP	3.983***		(1.138)			
			(1)			(2)		
2	$r_{i,t+1}$ on TFP and Candidates	TFP	3.706***		(0.986)	5.299***		(2.143)
		ln(CE)	0.328		(0.593)	0.092		(0.624)
		ln(RD)	0.766		(0.473)	1.053		(0.854)
		ln(PE)				1.578		(1.284)
		ln(AD)				0.204		(0.430)
		ln(SGAexRD)	0.557**		(0.230)			
		ln(SGAexRDPEAD)				0.599		(0.671)
3	TFP on Candidates	ln(CE)	-0.103		(0.019)	-0.183***		(0.023)
		ln(RD)	0.212***		(0.005)	0.067***		(0.015)
		ln(PE)				0.335***		(0.012)
		ln(AD)				0.025***		(0.005)
		ln(SGAexRD)	0.051***		(0.002)			
		ln(SGAexRDPEAD)				0.015		(0.009)
				Explained (%)			Explained (%)	
4	Decompose Stage-1 Coefficient	ln(CE)	-0.264	-6.6**	(3.056)	-0.858	-21.5***	(2.483)
		ln(RD)	0.470	11.8***	(3.172)	0.355	8.9**	(3.532)
		ln(PE)				1.511	37.9***	(8.960)
		ln(AD)				0.037	0.9	(7.553)
		ln(SGAexRD)	0.063	1.6	(2.319)			
		ln(SGAexRDPEAD)				0.024	0.6	(1.091)
		Residual	3.714	93.2***	(15.904)	2.913	73.1***	(13.147)

Note: $r_{i,t+1}$ represents future returns. TFP is is total factor productivity measured at fiscal year-end. Natural logarithms of the following variables, measured in millions of yen, are used. CE, RD, PE and AD represent capital, R&D, personnel and advertising expenditure, respectively. SGAexRD is selling, general and administrative expense minus R&D expenditure. SGAexRDPEAD is selling, general and administrative expense minus R&D, personnel and advertising expenditure. Newey-West HAC standard errors (SE) appear in parentheses. ***, **, and * indicate significant at the 1%, 5% and 10% levels, respectively.

demonstrate little explanatory power individually.

Table 14 provides the results of the multivariate analysis, showing the marginal contribution of the included candidate variables in explaining the TFP-future returns relationship. We specify two multivariate models. Model (1) includes capital, R&D and SGAexRD expenditure. Since personnel and advertising are included in SGAexRD we exclude the former from model (1). Model (2) contains capital, R&D, personnel, advertising and SGAexRDPEAD while SGAexRD is excluded. The stage one regression is identical to that in Table 13 for both models. In stage two, one regression is run for each model. The TFP coefficient is positive and again remains highly significant in in the presence of the candidate variables specified for each model. This suggests that TFP represents a robust risk factor even when controlling for firm size. All candidate coefficient estimates are positive for both models. Given that we suspect the candidates explain at least part of the strong relationship between TFP and future returns rather than future returns directly, we do not necessarily expect the candidate estimates to be significant in stage two. Furthermore, CE, RD and PE are correlated, as are AD and SGAexRDPEAD, thus the candidate coefficient estimates may appear insignificant due to multicollinearity.

The stage three regressions reveal positive relationships between all candidate variables and TFP except for capital expenditure in both models. The coefficient on capital expenditure is negative but not significant in model (1) while it is negative and significant in model (2). Controlling for the other candidates, capital expenditure has the wrong sign to be a risk behind the high TFP premium. Both remaining candidate coefficient estimates are significant in model (1) with R&D having the strongest relationship with TFP. In model (2), all estimates except that for SGAexRDPEAD are significant. Personnel expenditure has the closest relationship with TFP in model (2).

The stage four decomposition shows that model (2) does a superior job of explaining the predictive relationship between TFP and future returns. Ignoring the negative effect of capital expenditure, intangibles expenditure explains about half of the TPF-return relationship.[10] Personnel expenditure has by far the greatest marginal explanatory power at over 37%, followed by R&D with almost 9%. Advertising and SGAexRDPEAD expenditure contribute very little marginal explanatory power. In model (1), R&D has the greatest explanatory power at about 12%, while the contribution of SGAexRD is minor.

Overall, the results from the univariate and multivariate analyses demonstrate that risks related to personnel and R&D expenditure explain a substantial portion of the premium on high TFP stocks. R&D expenditure reflects firms' investment in innovation. Personnel expenditure is related to investment in human and organizational capital as explained in Section 3. However, given that we can only measure investment in human and organizational capital through personnel expenditure, we are unable to differentiate their relative importance. Although investment in R&D, human and organizational capital may enhance firm productivity and facilitate the growth of revenues, it is risky for shareholders. Innovation stemming from R&D may expose the firm to new systematic risks, while related expected future cash flows may be over-discounted by investors. Key employees may seek to appropriate a portion of the cash flows resulting from investment in human and organizational capital investment at the expense of shareholders.

[10]In both models (1) and (2), capital expenditure has a positive although not significant relationship with future returns in stage two but a negative relationship with TFP in stage three. Stage three shows that the variable's marginal contribution to explaining the relationship is negligible and negative negative in models (1) and (2), respectively. Accordingly, capital expenditure does not explain the predictive power of TFP for future returns.

5. Robustness

As a robustness check, we examine whether the premium for high TFP stocks may be explained by mispricing due to limits-to-arbitrage put forth by Shleifer and Vishny (1997). The limits-to-arbitrage hypothesis argues that arbitrage is risky, costly, and limited. If the TFP effect is due to mispricing, it should be more pronounced for stocks that are difficult to arbitrage than for stocks that are easy to arbitrage. Following Lam and Wei (2011), we consider four aspects of limits-to-arbitrage: arbitrage risk, information uncertainty, shareholder sophistication and potential transaction costs. We measure arbitrage risk as idiosyncratic stock return volatility (IVOL), the standard deviation of the 12-monthly error term from a Fama-French three factor model of monthly 36-month stock and TOPIX returns. Information uncertainty is measured by cash flow volatility (OPVOL), defined as the standard deviation of operating income divided by stock market capitalization. Shareholder sophistication is proxied using the percentage of each firm's stock held by domestic institutional (INST) and foreign (FRGN) investors. Potential transaction costs are measured using Amihud's (2002) ILLIQ.

We run Fama-MacBeth regressions of TFP on each limits-to-arbitrage variable including sector dummies to focus on the cross-sectional relationships within sector. The results are provided in Table 15. Models (1) to (3) indicate a significant negative relationship between TFP and IVOL, ILLIQ and OPVOL, respectively. Models (4) and (5) show a significant positive relationship between TFP and INST and FRGN, respectively. High TFP firms have relatively low arbitrage risk, information uncertainty and potential transactions costs, and relatively high investor sophistication. We conclude that mispricing does not explain the existence of the TFP premium.[11]

[11] We also investigated whether TFP as a predictor of stock returns may be non-linearly related to arbitrage costs, such as the U-shaped pattern noted in Lam and Wei (2011), and found that it is not.

Table 15:
Fama-MacBeth regressions for TFP on limits-to-arbitrage variables.

	Dependent variable: total factor productivity, $TFP_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
IVOL	-0.006***				
	(0.001)				
ILLIQ		-2.97e-05***			
		(3.26e-06)			
OPVOL			-3.83e-06***		
			(1.67e-07)		
INST				0.006***	
				(0.001)	
FRGN					0.020***
					(0.001)
Constant	2.894***	2.795***	2.949***	2.553***	2.455***
	(0.251)	(0.255)	(0.247)	(0.211)	(0.241)
Observations	11,380	11,390	11,394	11,394	11,394
Adj. R^2	0.025	0.056	0.100	0.026	0.158

Note: The dependent variable for each model is total factor productivity (TFP) measured at fiscal year-end. IVOL is idiosyncratic volatility measured as the standard deviation of the 12-month residual estimated using 36 months of stock and TOPIX returns. Amihud's (2002) ILLIQ is measured as the annual average of the absolute value of monthly stock returns divided by the monthly transaction value. OPVOL is the 10-year standard deviation of operating income divided by the firm's market capitalization. INST is the percentage ownership by institutional investors. FRGN is the percentage of ownership by foreign investors. Sector dummy variables are included. Standard errors appear in parentheses. ***, **, and * indicate significant at the 1%, 5% and 10% levels, respectively.

6. Conclusion

We investigate the relationship between firm-level productivity and future stock returns for Japanese manufacturing firms in the TOPIX over the last 20 years. We find a highly statistically significant and robust positive relationship between TFP and year-ahead returns while controlling for various firm characteristics. The premium for high TFP firms persists after controlling for sector effects and relevant risk factors such as the Fama-French three and five factors. Our finding that more productive firms trade at a significant premium over less productive firms in the year ahead stands in stark contrast to recent similar studies of U.S. stocks.

However, the characteristics of the Japanese manufacturing stocks sorted on productivity in our study are similar to those for U.S. stocks. High (low) TFP Japanese manufacturing firms can be characterized as large growth (small value) firms with high (low) return on equity, asset growth, capital expenditure, R&D expenditure, personnel expenditure and hiring.

We investigate the reason for the premium on high TFP stocks and find that intangibles expenditure relating to R&D and personnel explains a substantial fraction of the return predictability due to TFP. The premium for highly productive firms compensates investors for risks related to innovation and human and organizational capital formation; innovation through R&D and the expansion of economic competencies through investment in human and organizational capital by expenditure on personnel.

The implications of our study are encouraging for Japanese manufacturing firms willing to develop their businesses with substantial intangible expenditure. Investing in R&D and personnel in a way that improves productivity has a substantial positive impact on firms' stock returns. Our results provide a strong incentive for Japanese firms to invest in innovation, human and organizational capital.

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