Intangibles, productivity, and stock prices *

Baek-Chun Kim[†]

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Abstract

As intangible capital has become important production factor, I estimate firm productivity (TFP^{IC+}) by adding intangible capital together with physical capital. I find that TFP^{IC+} is negatively priced, and subsumes the pricing of productivity (TFP^{IC-}), estimated by omitting intangible capital. I provide the displacement risk channel. First, the investment-specific shock is more negatively related to low TFP^{IC+} firms. Second, the innovation by competitors will more decrease future fundamentals for low TFP^{IC+} firms. Lastly, intangible investment is more costly than physical investment for low TFP^{IC+} firms. Overall, these suggest that high TFP^{IC+} firms provide hedging against displacement risk.

JEL classification: G12,E22, O33, O40, D24

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[†]Baek-Chun Kim, Department of Money and Banking, College of Commerce, National Chengchi University, Commerce Building, Wenshan, Taipei, Taiwan. E-mail: baekchun@nccu.edu.tw.

Intangible capital has been the important share of investment as well as the large share of assets (Hall (2001), Corrado et al. (2005), Corrado et al. (2009), Eisfeldt and Papanikolaou (2013), Crouzet et al. (2022)). Recent studies show that conventional economic proxies such as Tobin's q or productivity weakly performs because they fails to consider the production shift of technology to intangible capital (Peters and Taylor (2017), Belo et al. (2022), Crouzet and Eberly (2021), Eisfeldt et al. (Forthcoming), Crouzet and Eberly (Forthcoming)).[1] This implies that intangible capital is a key in the production side of economy, and cannot be omitted. Crouzet and Eberly (2021) find that missing intangible capital in the production generates mismeasured productivity, and the inclusion of the intangible helps to explain the output growth in the United States over the recent years. Meanwhile, neoclassical theory of investment shows that the real investment return equals stock return, and productivity shock drives the stock return volatility (Cochrane (1991)).[2] Imrohoroglu and Tuzel (2014) empirically estimate firm-level productivity, and show that productivity shocks relate to stock returns as well as firm characteristics. However, they do not include intangible capital in the production function and the estimation of productivity. In this paper, I try to fill this gap by examining the role of intangible capital in productivity from the asset pricing perspective. I first estimate firm-level productivity by including the intangible capital as a key production input with labor and physical capital. I find that the intangible capital adjusted productivity (TFP^{IC+}) explains various asset returns, and subsumes the return predictability of the intangible capital omitted productivity (TFP^{IC-}). Next, I provide the displacement risk,

[1] McGrattan and Prescott (2010) explains the business cycle in 1990s by extending the neoclassical model with intangible investment. Peters and Taylor (2017) propose new Tobin's q by adding intangible capital, and show that it explains both physical and intangible investment better than standard Tobin's q. Belo et al. (2022) examine the determinants of a firm's market value by decomposing it into four different types of capital: labor, physical capital, knowledge capital, and brand capital. They find that two intangible capital (knowledge capital and brand capital) accounts for 40-50% of aggregate market value. Eisfeldt et al. (Forthcoming) improve the pricing power of value factor of Fama and French (1993) by adding the intangible capital to book value of equity. Crouzet and Eberly (Forthcoming) explains the divergence between rising returns and lowering investment with the technology shift toward intangibles, rising rents, and their interaction.

[2] Investment-based asset pricing models link real investment returns to stock returns (Cochrane (1991), Berk et al. (1999), Zhang (2005), and Liu et al. (2009)) from producers' first-order conditions, e.g., firms' optimal investment decisions. This reveals that the investment or the profitability factors capture corporate decisions to the productivity shock, so these indirectly measure the fundamental risk sources (Hou et al. (2015) and Hou et al. (2021)).

driven by the investment-specific shock, as the pricing channel of productivity. That is, firms with different productivity heterogeneously respond to the investment-specific shock, and firms with higher productivity provide hedging against the displacement risk.

To motivate the empirical work, I analyze how the omission of intangible capital affects productivity in the simple production economy, following Crouzet and Eberly (2021).[3] Omitting intangible capital generates the mismeasurement of productivity in two ways. First, the value-added is underestimated because the intangible investment is considered as expense. This mistakenly inflates the labor share. However, increasing the labor share is inconsistent with the literature (Elsby et al. (2013), Karabarbounis and Neiman (2014), Barkai (2020)).[4] Second, the omitted intangble capital directly mismeasures total capital. Productivity might be over- or under- estimated depending on the difference between physical and intangible capitals, and their shares on value-added. Since the difference varies in cross-section and time-series, and capital shares change over time, missing intangible capital results in mismeasured productivity.

Empirically, I use firm-level data to estimate the firm-level total factor productivity (TF-P) by closely following Olley and Pakes (1996) and Imrohoroglu and Tuzel (2014). While the previous researches assume two production factors, labor and physical capital, I add the organizational capital as intangible capital. The organizational capital is considered intangible capital in the literature (Lev and Radhakrishnan (2005), Eisfeldt and Papanikolaou (2013), Eisfeldt and Papanikolaou (2014), and Peters and Taylor (2017)). I use the perpetual inventory method to estimate the organizational capital using sales, general, and administrative expense, and estimate total factor productivity, denoting the intangible capital adjusted productivity (TFP^{IC+}). From the production function, the labor share (β_L), physical capital share (β_K), and intangible capital share (β_{OC}) are 0.54, 0.34, and 0.12, respectively. The

[3] Crouzet and Eberly (2021) show that the omission of intangibles make the mismeasured productivity in three ways: the mismeasured output, mismeasured labor share, and mismeasured total capital. Here, I consider the mismeasured output and labor share as the same channel because the labor share is overestimated due to the mismeasured output.

[4] Elsby et al. (2013) find that the labor share has declined in the United States. Karabarbounis and Neiman (2014) document the global decline of the labor share. The explanations are diverse. Acemoglu and Restrepo (2018) show that technology (e.g., automation) reduces the labor shares. Barkai (2020) find that the increasing pure profits offset the decline in the labor share.

intangible capital share over total capital share ($\frac{\beta_{OC}}{\beta_K+\beta_{OC}}$) is 0.26. This is consistent with the intangible share ranging from 0.145 to 0.286 in Crouzet and Eberly (Forthcoming). Also, I examine whether factor shares vary over time. I find that β_L decreases over time. It is 0.61 in 1980s but it decreases to 0.50 in 2010s. β_K increases over time from 0.32 in 1970s to 0.38 in 2000s but it decreases to 0.27 in 2010s. β_{OC} does not vary until 2000s but it dramtically increases to 0.23 in 2010s. The rapid increase of β_{OC} shows the importance of intangible capital in the recent years.

Next, I construct the decile portfolios sorted on TFP^{IC+}. Similar to Imrohoroglu and Tuzel (2014), TFP^{IC+} is related to various firm characteristics. High TFP^{IC+} firms have larger size, lower book-to-market ratio, higher employment growth, higher investment growth, and higher profits than low TFP^{IC+} firms. Also, I estimate the intangible capital omitted productivity (TFP^{IC-}), which omits the intangible capital, and find that high TFP^{IC+} firm has higher TFP^{IC-} as well.

I examine the returns of TFP^{IC+} sorted portfolios, and find that both value-weighted and equal-weighted expected returns decrease over TFP^{IC+}. That is, high TFP^{IC+} firms have lower expected returns than low TFP^{IC+} firms. The zero-cost portfolio (H-L) by taking the long position on the highest TFP^{IC+} sorted portfolio and the short position on the lowest TFP^{IC+} sorted portfolio is significantly negative. The value- (equal-) weighted zero-cost portfolio has the average return of -0.57% (-0.57%) per month with t-statistics of -2.88 (-4.39). Further, the abnormal returns of the zero-cost portfolios are significant across various factor models such as Carhart (1997) four factor model (FF4).

Next, I run Fama-MacBeth two-pass regressions to estimate the price of risk for TFP^{IC+} and its pricing power in the cross-section. I consider the value-weighted zero-cost portfolio as the pricing factor of TFP^{IC+}, and use 25 size and book-to-market sorted portfolios as test assets. First, I find that the price of risk for TFP^{IC+} ($\gamma_{TFP^{IC+}}$) is significantly negative across different pricing factor models. For example, $\gamma_{TFP^{IC+}}$ is -0.56% per month (t=-2.88) when I use FF4 with the pricing factor of TFP^{IC+}. Second, adding $\gamma_{TFP^{IC+}}$ improves the explanatory power. $\gamma_{TFP^{IC+}}$ alone explains 78% of return variations, and it is higher than

R^2 of Fama-French three (FF3) or four-factor (FF4) models (0.59 and 0.67, respectively). Third, it lowers the pricing error (γ_0). While FF3 has γ_0 of 0.06 (t=2.65), adding TFP^{IC+} to FF3 has γ_0 of 0.05 (t=1.77). To avoid the look-ahead bias, I estimate the rolling betas, and have the similar results. I perform extensive robustness checks, and find that the results are robust to alternative measures of intangible capital and pricing factors, to different test assets, and to the firm-level analysis.

I testify whether TFP^{IC+} captures the information of TFP^{IC-}. If TFP^{IC+} is well estimated, then I expect that TFP^{IC+} sorted portfolios capture TFP^{IC-} sorted portfolios. I construct 4-by-4 dependent sorts on TFP^{IC+} and TFP^{IC-}, and find that TFP^{IC-} loses its pricing power after TFP^{IC+} is controlled in both value-weighted and equal-weighted portfolios. However, when I do the analysis in the reverse order, TFP^{IC+} still predicts the expected returns. This confirms that TFP^{IC+} is more informative than TFP^{IC-} in the asset pricing perspective.

Next, I explore the pricing mechanism of TFP^{IC+}. Inclusion of intangible capital allows to estimate the unbiased productivity shock by reflecting the proper production factor share changes as well as individual firms' reponses against the factor share changes. Since the technology shock of intangible capital reflects the investment-specific shock (Eisfeldt and Papanikolaou (2013) and Kogan et al. (2020))[5] and productivity is affected by such shock (Hulten (1992) and Kogan et al. (2017))[6], I hypothesize that the cross-sectional difference of productivity reflects the heterogeneous response to the investment-specific shock. That said, low TFP^{IC+} firms more negatively reponse to the investment-specific shock than high TFP^{IC+} firms. I examine this pricing channel in three ways. First, following Greenwood et al. (1997), Cummins and Violante (2002), Papanikolaou (2011), Knesl (2023), I estimate the exposure of the aggregate investment-specific shock (IST-shock) between high and low TFP^{IC+} firms. I find that low TFP^{IC+} firms have more negative exposure against the

[5]Eisfeldt and Papanikolaou (2013) show that organizational capital captures key talents or technical change embodied in human capital. Kogan et al. (2020) show that the benefit of technological innovation is asymmetric by sharing the similar idea that the rents from innovation heavily accrue to human capital.

[6]Solow (1960), Hulten (1992), Greenwood et al. (1997), Fisher (2006), Kogan et al. (2017) show that the investment-specific shock is the main driver of economic growth as well as productivity growth.

investment-specific shock than high TFP^{IC+} firms. Since the price of risk for IST-shock is negative (Kogan and Papanikolaou (2014)), expected returns decrease over TFP^{IC+} sorted portfolios. Second, following Kogan et al. (2020), I use innovation by competitors from Kogan et al. (2017), and estimate the magnitude of displacement between high and low TFP^{IC+} firms. I show that the innovation shock by competitors hurts future profits and investments of a focal firm, namely creative destruction. More importantly, I find that the effect of creative destruction becomes large when TFP^{IC+} decreases. That is, future fundamentals of low TFP^{IC+} firms decrease against innovation by competitors more than those of high TFP^{IC+} firms. This confirms that high TFP^{IC+} firms provide the hedging effect against the technological innovation. I further find that this displacement effect exists across industry, and is larger when the product market is more competitive.

Lastly, I estimate the investment adjustment cost from the investment-q regressions. Similar to Peters and Taylor (2017), I regress of lagged Tobin's q, TFP^{IC+}, and their interaction term on either physical or intangible investment. Consistent with Peters and Taylor (2017) and Belo et al. (2022), I find that the coefficient of Tobin's q is smaller for intangible investment. This suggests that the adjustment cost for intangible investment is more expensive than that for physical capital. Further, I find that the interaction term is only significantly negative for physical investment. Firms with high TFP^{IC+} have more expensive adjustment cost than firms with low TFP^{IC+}. However, with intangible investment, the interaction term is insignificant. Taking together, high TFP^{IC+} firms have relatively lower adjustment cost of intangible investment over that of physical investment. As a result, high TFP^{IC+} firms has more flexibility on the intangible investment from the investment-specific shock than low TFP^{IC+} firms.

This paper belongs to a growing literature on the implication of intangible capital. Intangible capital has been the important share of investment and the large share of valuation (Hall (2001), Corrado et al. (2005), Corrado et al. (2009), McGrattan and Prescott (2010), Eisfeldt and Papanikolaou (2013)). Recent studies show that intangible capital is key to explain economic growth as well as firm valuation. Eisfeldt and Papanikolaou (2013) show that the organizational capital is intangible asset, and it is priced in the stock market. Peters and Taylor (2017) adjust Tobin's q by adding intangible capital, and find that it explains both physical and intangible investment. Belo et al. (2022) estimate the contribution of different types of capital to firm value, and show that intangible capital (knowledge capital) explains more than 40% of firm value. Ayyagari et al. (2024) similarly adjust return-on-capital (ROC) with the intangible capital, and attribute the divergence on ROC between star firms and non-star firms to the mismeasurement of intangible capital. Abis and Veldkamp (2024) estimate the Cobb-Douglas production factor shares of labor and knowledge capital by focusing on the financial industry, and find that even though the labor share declines due to the rising of artificial intelligence (A.I.), the size of the sector is becoming larger, resulting in the rise of labor employment and salary. Particularly, my work is closely related to Crouzet and Eberly (2021). They analyze the potential bias of omitting intangible capital in production economy, and find that TFP growth is mismeasured, resulting in the downward bias. While the aggregate TFP growth is downward, the individual firms might have both upward and downward bias because they have different responses with respect to the aggregate technology change over time. Therefore, my paper focuses on the role of intangible capital in production economy and the mismeasurement of TFP at firm-level. Also, I evaluate the role of omitted capital in TFP by using various asset returns in financial market.

This paper also adds to the literature on production-based asset pricing literature (e.g., Cochrane (1991), Restoy and Rockinger (1994), Cochrane (1996), Berk et al. (1999), Zhang (2005), and Liu et al. (2009)). Neoclassical theory of investment relates real investment returns to stock returns, and suggests that production risks drives stock return volatilities. Imrohoroglu and Tuzel (2014) show that firm-level productivity varies in both time-series and cross-section, and it relates to firm characteristics as well as stock returns. Meanwhile, Peters and Taylor (2017) and Belo et al. (2022) find that intangible capital plays an important role to explain an investment opportunity and a firm valuation. Based on their results, my work complements Imrohoroglu and Tuzel (2014) by estimating productivity by adding the intangible capital to the traditional production function, and examining the pricing power of it.

Lastly, my paper contributes to productivity and the investment-specific shock. While the productivity is a key driver of economic growth, many studies distinguish between capital-embodied shock and disembodied shock (Solow (1960), Hulten (1992), Greenwood et al. (1997), and Cummins and Violante (2002)). Particularly, Hulten (1992) shows that TFP is composed of both embodied and disembodied shocks, and the embodied shock explains TFP growth. Also, the capital-embodied technology shock affects firm value and asset prices. Papanikolaou (2011) and Kogan and Papanikolaou (2014) show that the capital-embodied technology shock is negatively priced, and value stocks have more negative exposures with respect to the capital-embodied shock than growth stocks. Knesl (2023) also find that firms with more share of displacable labor have more negative exposures to the investment-specific shock. Meanwhile, Kogan et al. (2020) propose the different mechanism of negative price of risk for the investment-specific shock. Using the empirical measures of Kogan et al. (2017), they show that technological innovation by competitors displaces the incumbent capital, resulting in the creative destruction, and find that growth stocks have lower expected returns by providing hedging against the shock. My paper adds to the literature by studying the cross-sectional implications of investment-specific shock in productivity. Specifically, I find that high TFP firms provide lower expected returns because they have lower exposures against investment-specific shock as well as innovation by competitors.

The rest of the paper proceeds as follows. Section 1 describes the motivating theory to analyze how the omitted intangible capital generates the mismeasured productivity. Section 2 describes the data and the procedures used for estimating firm-level total factor productivity. Section 3 presents the asset pricing tests. Section 4 explores the pricing channel of productivity. Finally, Section 5 concludes.

1 A motivating model: Bias from the omitted intangible capital

I describe how the mismeasurement of intangible investment drives the bias of firm productivity based on Crouzet and Eberly (2021)[7]. Consider the true production function: $Y_t = Z_t(K_{1,t}^{1-\eta}K_{2,t}^{\eta})^{\alpha}L_t^{1-\alpha}$ where Y_t, Z_t, $K_{1,t}$, $K_{2,t}$, and L_t are value-added, productivity, physical capital, intangible capital, and labor at time t, respectively. α is the elasticity of output with respect to total capital ($K_t = K_{1,t}^{1-\eta}K_{2,t}^{\eta}$), and η is the Cobb-Doulgas share of intangible capital over total capital. From the production function, log productivity is as follows,

$$logZ_t = logY_t - \alpha(1-\eta)LogK_{1,t} - \alpha\eta LogK_{2,t} - (1-\alpha)LogL_t. \tag{1}$$

The firm chooses the optimal production inputs, $K_{1,t}$, $K_{2,t}$, and L_t, to minimize the total costs of production:

$$\begin{aligned} &\min_{K_{1,t},K_{2,t},L_t} \sum_{n=1}^{2} R_{n,t}K_{n,t} + W_tL_t \\ &s.t. Z_t(K_{1,t}^{1-\eta}K_{2,t}^{\eta})^{\alpha}L_t^{1-\alpha} \geq Y_t \end{aligned} \tag{2}$$

where $R_{n,t}$, and W_t are the user costs of capital ($K_{n,t}$), and the wage, respectively.

From the solution of eq.(2), the elasticity of output with respect to labor $(1-\alpha)$ equals the labor cost share,

$$1-\alpha = \frac{W_tL_t}{MC_tY_t} \tag{3}$$

where MC_t is the Lagrangian multiplier as well as marginal cost. Assume that the price of output (P_t) equals the marginal cost (MC_t) in perfect competition, the labor cost share is

[7]Crouzet and Eberly (2021) extensively study the role of intangible capital in productivity. They also consider the effect of mark up and its interaction effect with the omitted intangible capital. My paper focuses on the role of intangible capital and its implications on the asset pricing by leaving out the role of mark up.

equal to the labor income share ($\hat{s}_{L,t}$) as follows,

$$1-\alpha = \frac{W_t L_t}{MC_t Y_t} = \frac{W_t L_t}{P_t Y_t} = \hat{s}_{L,t}. \tag{4}$$

Now, I discuss the two driving sources of mismeasurement if the intangible investment is omitted. First, value-added (Y_t) is mismeasured because the intangible investment is considered the expense. Denote B_t as the intangible investment, and if it is not measured in value-added, the measured value added ($P_t\hat{Y}_t$) is equal to true value-added (P_tY_t) minus intangible investment (B_t),

$$P_t\hat{Y}_t = P_tY_t - B_t. \tag{5}$$

If the intangible investment is omitted, $\frac{P_t\hat{Y}_t}{P_tY_t}$ is less than 1. Therefore, the measured labor share is overestimated,

$$\hat{s}_{L,t} = \frac{W_tL_t}{P_t\hat{Y}_t} = \frac{W_tL_t}{P_tY_t}\frac{1}{b_t} > 1-\alpha \tag{6}$$

where $b_t \equiv \frac{P_t\hat{Y}_t}{P_tY_t}$. This overestimated labor share distorts productivity through eq.(1).

Second, total capital (K_t) is mismeasured. If intangible capital ($K_{2,t}$) is omitted, the production function is $Z_t(K_{1,t})^\alpha L_t^{1-\alpha}$. The mismeasured productivity ($log\hat{Z}_t$) is

$$log\hat{Z}_t = logY_t - \alpha LogK_{1,t} - (1-\alpha)LogL_t. \tag{7}$$

Then, the difference between true productivity, eq.(1), and mismeasured productivity, e-q.(7), is $\alpha\eta(LogK_{1,t} - LogK_{2,t})$. This shows that mismeasured productivity can be over- or underestimated by depending on the difference between physical capital and intangible capital. Also, the magnitude of difference becomes larger when the share of intangible in value-added ($\alpha\eta$) increases. Since the difference between two capital stocks varies in both cross-section and time-series, and the share of intangible capital changes over time, omitting the intangible capital generates the mismeasurement of productivity.

Overall, omitting intangible capital distorts productivity by inflating the labor share and by mismeasuring the capital stock. While Crouzet and Eberly (2021) focus on aggregate productivity, the above results can be easily applied to individual firms in the cross section. Since individual firms have heterogeneous response with respect to production technology by changing their investment policy, correcting the mismeasurement provides more accurate productivity, and it should be priced in the stock market.

2 Estimating intangible capital adjusted productivity

In this section, I describe how to estimate firm-level total factor productivity (TFP) with three production factors; labor, physical capital, and intangible capital by closely following Olley and Pakes (1996) and Imrohoroglu and Tuzel (2014). Next, I examine the production function estimates and firm characteristics of productivity.

2.1 Data and key variables

I use two main datasets to estimate the total factor productivity (TFP): Annual Compustat and CRSP files, by matching Compustat and CRSP. The sample period starts from 1966 to 2020. I include common stocks listed at NYSE/Amex/Nasdaq. I exclude the financial firms and the utility firms (four-digit SIC between 6000 - 6999 or 4900 - 4999). Also, firms with missing or negative book value of equity, stock price less than $1, missing or negative cost of goods sold (COGS), negative selling, general, and administrative expense (XSGA), and missing capital expenditures (CAPX) and gross (net) property, plant, and equipment (PPEGT and PPENT) are deleted. Finally, the sample firms should report their accounting information more than 2 years to avoid the survivorship bias.

To estimate the productivity, I estimate the value-added, labor, physical capital, intangible capital, and investment. Value-added (Y_{it}) equals sales minus material costs, scaled by GDP deflator. Material costs is total expense minus labor expense as well as 30% of selling, general, and administrative expense[8]. Labor (L_{it}) is the number of employees. Physical

[8]Total expense is sales (SALE) minus operating income before depreciation and amortization (OIBDP). Labor expense is the staff expense (XLR). However, only a small number of firms report the staff expense. I replace the missing observations with the interaction of industry average labor expense ratio and total

capital stock (K_{it}) is gross property, plant, and equipment (PPEGT), divided by the capital price deflator. Investment (I_{it}) is capital expenditure (CAPX) minus sale of property, plant, and equipment (SPPE), which I replace the missing SPPE with 0, deflated by current fixed investment price index. Following Eisfeldt and Papanikolaou (2013) and Peters and Taylor (2017), I consider the organizational capital (OC_{it}) as the intangible capital using the perpetual inventory method as follows,

$$OC_{it} = (1 - \delta_{OC})OC_{it-1} + \frac{0.3 * XSGA_{it}}{cpi_t} \tag{8}$$

where cpi_t denotes the consumer price index from BLS. I replace the missing value of XSGA with zero. The literature finds that the part of SG&A is spent on investing the organizational capital (e.g., employee training, IT expenses, and consulting).[9] The initional organizational capital stock (OC_0) equals $\frac{0.3*XSGA_{i1}}{g+\delta_{OC}}$. Following Eisfeldt and Papanikolaou (2013), I choose the growth rate (g) and the depreciation rate (δ_{OC}) to 10% and 15%, respectively.

2.2 Intangible capital adjusted productivity

I extend the productivity estimation of Olley and Pakes (1996) and Imrohoroglu and Tuzel (2014) by adjusting for intangible capital in the production function. Olley and Pakes (1996) address two endougenous issues involving TFP estimation. First, since input factors (labor and physical capital) are contemporaneously correlated, there is a simultaneity bias. They estimate the production function parameters for each input factor separately to address the simultaneity bias. Second, there is a selection bias. A firm's exit or entry decision depends on its productivity. Olley and Pakes (1996) assume that TFP is a function of a firm's survival probability and include that in the TFP estimation. Olley and Pakes (1996) further assume that (1) TFP is a first-order Markov process; (2) physical capital is predetermined after TFP is observed; and (3) investment reflects the information about TFP. Imrohoroglu and Tuzel

expense. See Appendix A for the detail estimation.

[9]Hulten and Hao (2008), Kogan and Papanikolaou (2014), and Peters and Taylor (2017) assume that 30% of SG&A is spent on the investment of organizational capital.

(2014) apply Olley and Pakes (1996) to estimate firm-level TFP[10]. I follow their estimation process by adding intangible capital.[11]

Assume Cobb-Douglas production function:

$$Y_{it} = L_{it}^{\beta_L} K_{it}^{\beta_K} OC_{it}^{\beta_{OC}} Z_{it} \tag{9}$$

where $Y_{it}, Z_{it}, L_{it}, K_{it}$, and OC_{it} are value-added, productivity, labor, physical capital stock, and intangible capital stock of a firm i at time t. Next, I scale the production function by physical capital and take the logarithm at both sides. I scale the production function for two reasons. First, since TFP is the residual term, it is highly correlated with firm size. Second, the scaling avoids estimating physical capital share directly. It mitigates the upward bias in the labor coefficient. Eq.(9) is rewritten as

$$Log\frac{Y_{it}}{K_{it}} = \beta_L Log\frac{L_{it}}{K_{it}} + (\beta_K + \beta_L + \beta_{OC} - 1)LogK_{it} + \beta_{OC} Log\frac{OC_{it}}{K_{it}} + LogZ_{it} \tag{10}$$

Denote $Log\frac{Y_{it}}{K_{it}}$, $Log\frac{L_{it}}{K_{it}}$, $LogK_{it}$, $Log\frac{OC_{it}}{K_{it}}$ and $LogZ_{it}$ as yk_{it}, lk_{it}, k_{it}, ok_{it} and z_{it}. Also, let β_L, $(\beta_K + \beta_L + \beta_{OC} - 1)$, β_{OC} as β_l, β_k, and β_{oc}. Rewrite Eq.(10) as follows:

$$yk_{it} = \beta_l lk_{it} + \beta_k k_{it} + \beta_{oc} ok_{it} + z_{it} \tag{11}$$

I estimate the production factor shares (β_l, β_k, and β_{oc}) using linear regressions[12]. Then, TFP (z_{it}) is $exp(yk_{it} - \widehat{\beta}_l lk_{i,t} - \widehat{\beta}_k k_{it} - \widehat{\beta}_{oc} ok_{i,t})$. I estimate TFP with the 5-year rolling-window to estimate time-varying production technology. I define it as the intangible capital adjusted productivity (TFP^{IC+}). For the comparison, I estimate TFP in the similar manner without intangible capital, and define it as the intangible capital omitted productivity (TFP^{IC-}).

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

[11]Levinsohn and Petrin (2003) provide another approach to estimate productivity. Both Olley and Pakes (1996) and Levinsohn and Petrin (2003) address the endogeneity concern of the correlation between the unobserved productivity and factor inputs. While Olley and Pakes (1996) use investment to proxy for productivity, Levinsohn and Petrin (2003) assume that intermediante inputs (e.g., electricity) reflect productivity. Intermediate inputs might be a good proxy for productivity as well because investment is often lumpy. However, the intermediate inputs are missing in Compustat so we follow Olley and Pakes (1996).

[12]I include year and industry fixed effects to capture the differences of industrial technologies over time.

See Appendix A for more detail about TFP estimation.

2.3 Three-factor productivity estimates and firm characteristics

I first describe intangible capital adjusted productivity (TFP^{IC+}) estimates and production factor shares in Panel A of Table 1. TFP^{IC+} has a mean of 0.05 with a standard deviation of 0.51. It has a large variation in both time-series and cross-section. Next five rows present the summary statistics for factor shares. The production technology (β_L+β_K+β_{OC}) is constant returns-to-scale on average, and rarely change over time. The labor share (β_L) is 0.54 in our sample period. It is lower than the labor share in the neoclassical model literature (e.g., 2/3). Downward labor share is consistent with Crouzet and Eberly (2021) because omitting intangible capital inflates labor share. β_L has decreased monotonically from 1980s (0.61) to 2010s (0.50). The physical capital share (β_K) and the intangible capital share (β_{OC}) are 0.34 and 0.12, respectively. The last row shows the relative importance of intangible capital share over total capital share ($\beta_{OC}/(\beta_K+\beta_{OC})$), and it is 0.26. Crouzet and Eberly (Forthcoming) estimate intangible capital share relative to capital share for non-financial firms, and it varies from 0.145 to 0.286.[13] My estimate is within their estimate range. Turning to capital shares, β_K has increased upto 2000s, and then decreased in 2010s from 0.38 to 0.27. β_{OC} was 0.11 in 1970s but slightly decreased from 1980s to 2000s. However, in 2010s, β_{OC} dramtically increased from 0.09 to 0.23. Overall, the production estimates are well-estimated by reflecting the technology shift toward intangible capital over time.

Next, I examine the relationship between TFP^{IC+} and firm characteristics. I sort firms at every June of year t into 10 portfolios, based on TFP^{IC+} at the end of year t-1, and hold portfolios from July of year t to June of year t+1. I rebalance portfolios every June of year t. Panel B reports the average firm characteristics for TFP^{IC+} sorted portfolios. First, TFP^{IC+} monotonically increases over TFP^{IC+} sorted portfolios. TFP^{IC+} in Low is more than 5 times smaller than that in High. This suggests that TFP^{IC+} varies alot in the

[13] Crouzet and Eberly (Forthcoming) estimate non-financial firms' intangible share of total capital, $K = K_{1,t}^{1-\eta} K_{2,t}^{\eta}$ where $K_{1,t}$ and $K_{2,t}$ are physical and intangiblve capital, respectively. Intangible share (η) increases over time. For example, it is 0.099 from 1947 to 1965. However, it is 0.286 from 2001 to 2017.

cross-section. Second, firms with higher TFP^{IC+} are larger, more growth, and have lower organizational capital stocks. Also, they have higher investment of employment, physical investment and intangible investment, and higher profitability. Overall, the firm characteristics of TFP^{IC+} echoes Imrohoroglu and Tuzel (2014) where they find that productive firms have higher investment and profitability.

3 Empirical results

3.1 Univariate portfolio

Panel A of Table 2 presents the value-weighted portfolio returns of TFP^{IC+} sorted portfolios as well as the zero-cost portfolio (H-L), which takes the long position on the highest TFP^{IC+} sorted portfolio (High) and the short position on the lowest TFP^{IC+} sorted portfolio (Low). I find that TFP^{IC+} predicts expected stock returns. The portfolio returns (R^{ex}) decrease over TFP^{IC+} sorted portfolios. The zero-cost portfolio (H-L) has -0.57% per month with t=-2.88. The abnormal returns of H-L from CAPM, Fama and French (1993) three-factor model (FF3), and Carhart (1997) four-factor model (FF4) (α^{CAPM}, α^{FF3}, and α^{FF4}, repectively) are significantly negative. For example, α^{FF4} of H-L is -0.41% per month with t=-2.18. Panel B shows the equal-weighted returns. Similar to Panel A, the equal-weighted returns decrease over TFP^{IC+}. The excess return of H-L is -0.57% per month (t=-4.39). The same magnitude of H-L in both Panel A and B suggests that TFP^{IC+} is well-estimated regardless of firm size. α^{CAPM}, α^{FF3}, and α^{FF4} are all negatively significant. Panel C reports the factor loadings of value- and equal-weighted H-L from pricing factor models. The factor loadings of size factor (β_{SMB}) and value factor (β_{HML}) are all significantly negative. These results are consistent with Panel B of Table 1 because higher TFP^{IC+} sorted portfolio is larger and more growth.

For comparison, I similarly construct TFP^{IC-} sorted portfolio in Table D1. I find that the value-weighted return of the zero-cost portfolio (H-L) is slightly negative (-0.04% per month) but insignificant (t=-0.23). The equal-weighted return of H-L is significanlty negative (-0.40%

per month) but the magnitude is about 2/3 of TFP^{IC+}. This is the consistent finding from Imrohoroglu and Tuzel (2014) where they show the stronger return predictability in equal-weighted portfolios.[14] Overall, this suggests that TFP^{IC+} possibly reflects better production risk than TFP^{IC-} in stock return.

3.2 Pricing of productivity in the cross-section

I run Fama-MacBeth two-stage regressions to estimate the price of risk for TFP^{IC+}. I consider the zero-cost portfolio (H-L) from TFP^{IC+} sorted portfolios in Table 2 as the pricing factor. I estimate the factor price of risk of TFP^{IC+} using the excess returns of 25 size and book-to-market ratio sorted portfolios from Kenneth French's data library. In the first stage, betas are estimated as the slope coefficients from factor models, e.g., Carhart (1997) four-factor model, as follows,

$$R_{it} = \alpha_i + \beta_{MKTi} MKT_t + \beta_{SMBi} SMB_t + \beta_{HMLi} HML_t + \beta_{UMDi} UMD_t + \beta_{TFP^{IC+}i} TFP_t^{IC+} + \epsilon_{it} \tag{12}$$

I estimate the betas in two ways. First, I use the full sample to estimate betas (the full sample betas) from eq.(12). If the true factor loadings are constant over time, the full sample betas should be priced. Second, to avoid the look-ahead bias, following Ferson and Harvey (1996), I estimate eq.(12) using 60-month rolling windows (rolling betas). The rolling windows start from July 1977. In the second stage, I run the cross-sectional regressions to estimate the prices of risk as follows,

$$R_{it} = \gamma_i + \gamma_{MKT} \widehat{\beta}_{MKTi} + \gamma_{SMB} \widehat{\beta}_{SMB} + \gamma_{HML} \widehat{\beta}_{HML} + \gamma_{UMD} \widehat{\beta}_{UMD} + \gamma_{TFP^{IC+}} \widehat{\beta}_{TFP^{IC+}} + \epsilon_{it} \tag{13}$$

For the full sample betas, I use the same betas every month. For the rolling betas, test asset returns at t are regressed on the rolling betas estimated from t-60 to t-1. Following

[14] Imrohoroglu and Tuzel (2014) find that unconditionally, the value-weighted return is insignificant while the equal-weighted return is significantly negative. However, the value-weighted return spread becomes significantly negative and the magnitude is larger during the contraction period.

Lewellen et al. (2010), I add the pricing factors of tested factor models to test assets in order to restrict the price of risk to be equal to the average factor returns. I adjust t-statistics for the errors-in-variables problem, following Shanken (1992). I report the adjusted R^2 from Jagannathan and Wang (1996). Following Lewellen et al. (2010), I construct a sampling distribution of adjusted R^2. To be specific, I bootstrap the time-series data of returns and factors by sampling with replacement to estimate the adjusted R^2. I repeat these procedures 10,000 times and report the 5^{th} and 95^{th} percentiles of the sampling distribution of the adjusted R^2.

Panel A of Table 3 presents the regression results using full sample betas. I estimate eq.(13) for CAPM, FF3, and FF4 as the benchmark models to evaluate the pricing power of TFP^{IC+}. First, I use TFP^{IC+} pricing factor (TFP^{IC+}) alone. The price of risk for TFP^{IC+} ($\gamma_{TFP^{IC+}}$) is significantly negative. It is -1.07% per month with t=-4.09. TFP^{IC+} pricing factor explains 78% of the cross-sectional variations of asset returns. This is higher than those of CAPM, FF3, and FF4. Second, I estimate the regressions with other pricing factors. I find that $\gamma_{TFP^{IC+}}$ is significantly priced across all factor models. $\gamma_{TFP^{IC+}}$ of FF4+TFP^{IC+} is -0.56% per month (t=-2.88), consistent with the average H-L of TFP^{IC+}. Also, adding TFP^{IC+} improves the model performance. While the intercept (γ_0) from FF3 is 0.06% per month (t=2.65), the intercept (γ_0) from FF3+TFP^{IC+} is 0.05% per month (t=1.77). The adjusted R^2 from FF4 inceases from 0.67 to 0.85 when TFP^{IC+} is added. The distribution of adjusted R^2 further confirms that TFP^{IC+} explains the returns of test assets. Third, to avoid the look-ahead bias, I use the rolling betas in Panel B, and find the similar results. That is, $\gamma_{TFP^{IC+}}$ is significantly negative across all factor models, and improves the explanatory power. Overall, these results provide evidence that TFP^{IC+} contains the production risk on top of other pricing factors, and plays an important role to explain the test assets.

3.3 Robustness checks

3.3.1 Change of model specifications

I provide the robustness results by changing the model specifications. First, I use the alternative measure of the intangible capital by adding knowledge capital (KC) to organizational capital (OC). The knowledge capital is another type of the intangible capital (Peters and Taylor (2017), and Belo et al. (2022)). Following Peters and Taylor (2017), I use the perpetual inventory method to estimate the knowledge capital by using R&D investment (XRD).

$$KC_{it} = (1 - \delta_{KC})KC_{it-1} + \frac{XRD_{it}}{cpi_t} \tag{14}$$

I use the depreciation rate of R&D (δ_{KC}) from Bureau of Economic Analysis (BEA)'s industry-specific R&D depreciation rates.[15] For the growth rate (g_{KC}), I compute the average growth of R&D investments for the same industry lists of R&D depreciation rates from BEA. The initial KC (KC_0) equals $\frac{XRD_{i1}}{g_{KC}+\delta_{KC}}$. I define the intangible capital as the sum of organizational capital and knowledge capital (OC+KC), then I estimate productivity, and construct the pricing factor of intangible capital adjusted productivity (TFP^{IC+}_{OC+KC}) in the similar manner. I estimate Fama-MacBeth regressions in Panel A of Table 4. First, the price of risk for TFP^{IC+}_{OC+KC} is significantly negative across all factor models. $\gamma_{TFP^{IC+}}$ ranges from -1.62% per month to -0.52% per month. Second, adding TFP^{IC+}_{OC+KC} improves the explanatory power. For example, using TFP^{IC+}_{OC+KC} alone explains about 72% of test asset returns, higher than R^2 of FF3 and FF4. Lastly, it also explains the pricing error (γ_0). γ_0 of FF3+TFP^{IC+}_{OC+KC} is insignificant at 5% significance level.

Second, I estimate the pricing factor of TFP^{IC+} by following Fama and French (1993). That said, I reconstruct the pricing factor by independently sorting on firm size and TFP^{IC+} in 2-by-3 portfolios, and construct the zero-cost portfolio, which takes the equal-weighted portfolios of high TFP^{IC+} minus low TFP^{IC+} across firm size in Fama and French (1993).

[15]Peters and Taylor (2017) use the column 3 of Table 4 from Li (2012) for BEA industry-specific R&D depreciation rates. Also, a depreciation rate for other industries is 15%.

The regression results are in Panel B. While the magnitude of price of risk for TFP^{IC+} decreases, it is still significantly negative across all models and increases R^2.

For the completeness, I estimate the regressions using the rolling window betas in Table C1. Consistent with the full sample betas, TFP^{IC+} is negatively priced, and it improves the model performances in terms of the pricing errors as well as R^2.

3.3.2 Alternative test assets

So far, I use the traditional 25 size and book-to-market sorted portfolios to testify the price of risk for TFP^{IC+}. Lewellen et al. (2010) suggest to expand the test assets when some factors explains nearly all of the variations of asset returns. Since the productivity predicts expected stock return, it should be priced in other test assets as well. I use 100 test assets, including 25 size and book-to-market sorted portfolios, 25 size and investment sorted portfolios, 25 size and operating profitability sorted portfolios, and 25 size and momentum sorted portfolios from Kenneth French's data library.

Panel A of Table 5 presents Fama-MacBeth regression results using the full sample betas. First, $\gamma_{TFP^{IC+}}$ is significantly negative over 100 test assets. It ranges from -1.34% per month (t=-4.02) to -0.52% per month (t=-2.59). This suggests that the price of risk for TFP^{IC+} explains various test asset returns. Second, adding TFP^{IC+} enhances the pricing power. For example, FF4 has the intercept (γ_0) of 0.05 (t=1.86) but FF4+TFP^{IC+} has the insignificant γ_0 of 0.03 (t=1.01). Also, R^2 increases from 0.68 of FF4 to 0.76 of FF4+TFP^{IC+}. Third, I use the rolling betas in Panel B, and find the similar results. Overall, I see that the productivity is negatively priced in the variety of test assets.

3.3.3 Cross section of individual stock returns

In previous sections, I analyze the pricing of TFP^{IC+} by estmating the risk premia in the cross section of portfolios. In this subsection, I use individual stock returns to testify whether TFP^{IC+} predicts expected returns. I estimate the firm-level Fama-MacBeth regressions to use the cross sectional variations of individual stock returns, and control for other informations from different variables. Control variables include firm size (Size), book-to-market (BM), past 1-year return (Mom), past 1-month return (Ret_{t-1}), return-on-equity (ROE), labor hiring (HR), physical investment (I/A), operating capital (OA), idiosyncratic volatility (Ivol), and the market beta (β_{MKT}). The variable definitions are described in Appendix B.

Table 6 reports Fama-MacBeth regression results in firm-level. Column (1)-(2) use TFP^{IC+}, and show that it negatively predicts next month expected return. The coefficient of TFP^{IC+} alone is -0.32% per month with t-statistics of -3.38. The difference of average TFP^{IC+} between Low and High from Table 1 is 2.03. If a stock in Low moves to High, the expected return decreases by 0.65% (-0.32*2.03) per month on average. In Column (2), I include control variables, and the coefficients on those control variables are consistent with the prior literature. For example, Size, Ret_{t-1}, HR, and I/A decrease expected returns while BM, Mom, and ROE increase expected returns. TFP^{IC+} still predicts expected return. Column (3)-(4) use TFP^{IC+}_{OC+KC}, and shows the similar results.

Overall, I close this section by concluding that the intangible adjusted productivity is negatively priced. This suggests that TFP^{IC+} captures the production shock by estimating the production function estimates accurately by considering the intangible capital.

3.4 Explaining intangible capital omitted productivity

I estimate the productivity by assuming that a production function has three production factors, labor, physical capital, and intangible capital, and find that the productivity is informative from the asset pricing perspective. In this subsection, I directly compare between intangible capital omitted productivity (TFP^{IC-}) and intangible capital adjusted productivity (TFP^{IC+}). To begin with, I compute the correlation between TFP^{IC-} and TFP^{IC+}, and it is about 0.85. I also see that TFP^{IC-} increases over TFP^{IC+} sorted portfolios in Table 1. This seems that even though TFP^{IC-} is mismeasured, two measures are positively correlated. To evaluate whether TFP^{IC+} is more informative than TFP^{IC-}, I do the horse race test by using double sorts.

First, I sort stocks on TFP^{IC-}, and construct the decile portfolios as well as zero-cost portfolio in Table D1. Similar to Imrohoroglu and Tuzel (2014), I find that the equal-weighted zero-cost portfolio has the significantly negative return while the value-weighted zero-cost portfolio has the insignificant negative return. Also, the equal-weighted zero-cost portfolio has the significant alphas from CAPM, FF3, and FF4. This suggests that the effect of TFP^{IC-} is stronger for smaller firms. In other words, unlike TFP^{IC+}, TFP^{IC-} of larger firms fails to capture the production risk behind the stock return.

Second, to determine whether the information of TFP^{IC+} fully explains TFP^{IC-}, I do the bi-variate sorts. I sort stocks on TFP^{IC+} first, and then sort stocks on TFP^{IC-} in each TFP^{IC+} sorted portfolio. After controlling for TFP^{IC+}, I estimate the average zero-cost portfolio of TFP^{IC-} across TFP^{IC+} sorted portfolio. I use 4-by-4 dependent sorts analysis and presents the results in Panel A of Table 7. First, when I use the value-weighted portfolios, after controlling for TFP^{IC+}, 3 of 4 zero-cost portfolio of TFP^{IC-} are insignificant and even positive. The average zero-cost portfolio of TFP^{IC-} (Avg. TFP^{IC-}) is also 0.11% per month (t=1.03) while the average zero-cost portfolio of TFP^{IC+} (Avg. TFP^{IC+}) is -0.27% per month (t=-2.07). Turning to equal-weighted, I find the stronger results. All the zero-cost portfolios of TFP^{IC-} is insignificant while those of TFP^{IC+} are significantly negative. Also, Avg. TFP^{IC-} is insignificantly priced while Avg. TFP^{IC+} is significantly negative.

Next, I sort the bi-variate portfolios in the reverse order in Panel B. If TFP^{IC-} explains most of information of TFP^{IC+}, Avg. TFP^{IC+} would be insignificant. For the value-weighted portfolio, Avg. TFP^{IC+} is still significantly negative with -0.21% per month (t=-1.99) while Avg. TFP^{IC-} is -0.19% per month (t=-1.34). For the equal-weighted portfolio, both Avg. TFP^{IC+} and Avg. TFP^{IC-} are negatively significant, -0.30% and -0.24%, respectively.

Overall, bi-variate sorts show that while TFP^{IC+} fully explains the return variations of TFP^{IC-}, TFP^{IC-} fails to explain that of TFP^{IC+}. Additionally, untabulated results show that TFP^{IC-} loses its pricing power with other pricing factors in Fama-MacBeth regressions. This infers that TFP^{IC+} is more informative than TFP^{IC-} in terms of return predictability.

4 Inspecting the pricing mechanism

To understand the pricing power of TFP^{IC+}, in this section, I explore the pricing mechanism. Inclusion of intangible capital allows us to estimate true factor shares as well as different types of investment in both time-series and cross-section. Particularly, the technological shock of intangible capital reflects the investment-specific shock (Eisfeldt and Papanikolaou (2013) and Kogan et al. (2020)). The vast literature studies capital-embodied shock, or investment-specific technology shock as the main driver of economic productivity growth.[16] It is apparent that productivity is affected by embodied shock (Hulten (1992) and Kogan et al. (2017)). Therefore, I hypothesize that the cross-sectional difference of productivity captures the heterogeneous response to the investment-specific shock, and the return spread reflects different systematic risk between high and low TFP^{IC+} firms. While the investment-specific shock displaces old capital of low TFP^{IC+} firms, it improves the performance advances in new capital of high TFP^{IC+} firms. This suggests that high TFP^{IC+} firms hedge against the displacement of capital stocks, driven by the investment-specific shock, so it has lower expected return.

4.1 Exposures to investment-specific shock

The investment-specific shock (IST-shock) delivers the negative premium by lowering the aggregate consumption of investors because the positive IST-shock lowers the cost of new capital, and reallocates the resources from consumption goods to investment goods (Papanikolaou (2011), Kogan and Papanikolaou (2013), and Kogan and Papanikolaou (2014)). If a firm's producitivity reflects its response with respect to the investment-specific shock, firms with low TFP^{IC+} have more negative exposure with respect to IST-shock than those with high TFP^{IC+}. In other words, firms with low TFP^{IC+} have higher expected returns.

Empirically, I use the difference between the growth of the price of consumption goods

[16] Domar (1963), Gordon (1990), Hulten (1992), Greenwood et al. (1997), Papanikolaou (2011), and Gourio and Rognlie (2020) discuss the role of investment-specific shock over economic growth, and its relationship with total factor productivity. Kogan and Papanikolaou (2013), Kogan and Papanikolaou (2014), Kogan et al. (2020), and Knesl (2023) examine the asset pricing implications of investment-specific shock.

and the growth of the quality-adjusted relative prices of capital goods for IST-shock by following Cummins and Violante (2002), Israelsen (2010), Kogan and Papanikolaou (2014), and Knesl (2023). I use NIPA price index of non-durable consumption goods to estimate the growth of the price of consumption goods. For the quality-adjusted relative prices of capital goods, I use the data and the adjustment from Cummins and Violante (2002), and extrapolate the adjustment until 2021. Following Knesl (2023), I use the aggregate price of capital goods.[17] Since IST-shock is annual frequency, I annualize value-weighted returns of TFP^{IC+} sorted portfolio at the end of December, and estimate the exposure of IST-shock by regressing annual portfolio returns on IST-shock with other pricing factors in Table 8.

First, Panel A uses only IST-shock, and presents the exposure of IST-shock (β_{IST}). β_{IST} decreases over TFP^{IC+} sorted portfolios. Consistent with the prediction, firms in the lowest TFP^{IC+} sorted portfolio (Low) have the negative and significant β_{IST}, -4.38 (t=-2.54), while firms in the highest TFP^{IC+} sorted portfolio (High) have the negative but insignificant β_{IST}, -1.25 (t=-0.72). The zero-cost portfolio (H-L) has the significantly positive β_{IST}. Since IST-shock is negatively priced (Papanikolaou (2011)), low TFP^{IC+} firms with more negative β_{IST} have higher returns than high TFP^{IC+} firms. This implies that firms with high TFP^{IC+} provide hedging against the displacement from IST-shock. Second, from Panel B-D, I additionally control pricing factors with IST-shock, and find the similar results. For example, β_{IST} from FF3+IST-shock (in Panel C) in Low is still significantly negative, -2.40 (t=-1.97), while that in High is insignificant but positive, 0.56 (t=0.71). The difference is significant. Third, I estimate β_{IST} for TFP^{IC-} sorted portfolios in Table E1 to examine the pricing channel of IST-shock. I find that β_{IST} does not vary across TFP^{IC-} sorted portfolios. For example, in Panel A, β_{IST} for the lowest TFP^{IC-} sorted portfolio (Low) is -3.24 (t=-2.12) and that for the highest TFP^{IC-} sorted portfolio (High) is -1.99 (t=-

[17] I follow the appendix of Knesl (2023) to estimate IST-shock. Specifically, I interpolate the quality adjustement by regressing log price of equipment on time trend (year), log price of equipment from NIPA (ln_Nipa_eq_new), lagged log price of equipment from NIPA (ln_l_Nipa_eq_new), and lagged GDP growth (l_GDPgrowth), using the data from Cummins and Violante (2002). The interpolation period is from 1947 to 2000. Then, I extrapolate the log price of equipment from 2001 to 2021. The extrapolated log price of equipment is estimated using the regression as follows, 45.87819 -0.0236165*year + 1.106731*ln_Nipa_eq_new -0.1055413*ln_l_Nipa_eq_new -0.0019918*l_GDPgrowth. Similar to Knesl (2023), IST-shock has a mean of 4%.

1.27). The difference is not significant, 1.24 (t=1.18). This confirms that why the return predictability of TFP^{IC-} is subsumed by TFP^{IC+} in the bi-variate sorts. Omitting the intangible capital makes TFP^{IC-} less accurate by failing to capture the investment-specific shock.

4.2 Technological innovation and firm displacement

While Papanikolaou (2011) and Kogan and Papanikolaou (2014) show that the positive investment-specific shock provides the negative premium, the empirical evidence is mixed (Garlappi and Song (2017a), Garlappi and Song (2017b), and Knesl (2023)).[18] Kogan et al. (2020) provide the different mechanism of the investment-specific shock. They show that a technological innovation shock is asymmetric, and the benefit of innovation is not equally shared. This shock makes an old capital by competitors to be obsolete and replaced with new capital, resulting in a creative destruction, namely displacement risk. Since the rents from innovation asymmetrically accrue to the orgnaizational capital (Eisfeldt and Papanikolaou (2013)) and TFP^{IC+} captures such innovation shock, I expect that firms with high TFP^{IC+} provide the hedging against innovation by competitors so they have lower expected returns.

Similar to Kogan et al. (2017), I estimate the regresison as follows,

$$\begin{aligned} Y_{i,t+\tau} =& \beta_0 + \beta_{\theta_i}\theta_{i,t} + \beta_{\theta_i * TFP^{IC+}}\theta_{i,t} * TFP^{IC+}_{i,t} + \beta_{\theta_{I\setminus i}}\theta_{I\setminus i,t} + \beta_{\theta_{I\setminus i} * TFP^{IC+}}\theta_{I\setminus i,t} * TFP^{IC+}_{i,t} \\ &+ \beta_{TFP^{IC+}} TFP^{IC+}_{i,t} + cZ_{it} + d_t + d_j + \epsilon_{i,t+\tau} \end{aligned} \tag{15}$$

I estimate $Y_{i,t+\tau}$ as future fundamentals including operation profitability (Cop) in $t+\tau$, Lerner index $t+\tau$, employment growth from t to $t+\tau$ (ΔL), physical capital growth from t to $t+\tau$ (ΔK), and intangible capital growth from t to $t+\tau$ (ΔOC) where τ is from 1

[18]Garlappi and Song (2017b) show that the price of risk for capital-embodied technological innovation can be positive under flexible capital utilization, and under high market power. Garlappi and Song (2017a) empirically find that the risk premia of the investment-specific shock measures are sensitive to the sample period, data frequency, test assets, and model specifications. Knesl (2023) provides the general equilibrium model which generates both positive and negative price of risk depending on worker's future labor productivity.

to 3. $\theta_{i,t}$ is a market value of all innovations of firm i in year t (own innovation). $\theta_{I\backslash i,t}$ is a market value of all innovations by firm i's competitors (innovation by competitors). Z_{it} is the vector of control variables, including logarithmic value of employment, physical capital, and intangible capital and idiosyncratic volatility. I use both 3-digit SIC industry and year fixed effects. I estimate $\theta_{i,t}$ as the ratio of the innovative output of a firm i in year t over its total asset in year t where innovative output of a firm i is the aggregation of the market value of each patent of a firm i in year t. I replace the missing $\theta_{i,t}$ with zeros. Also, I estimate $\theta_{I\backslash i,t}$ as the weighted average of the innovative output of a firm i's competitors in each year t, $\frac{\Sigma_{i\in I\backslash i}\theta_{i,t}}{\Sigma_{i\in I\backslash i}AT_{i,t}}$ where AT_{it} is total asset in year t. The competitors ($I\backslash i$) are defined as any firms in the same 3-digit SIC industry with a firm i in year t. I download the market value of patents from the authors' website[19]. All variables are winsorzied at 1% and 99%, and standard errors are clustered by firm and year.

The key variable is the interaction term between innovation by competitors and productivity ($\theta_{I\backslash i,t} * TFP^{IC+}_{i,t}$). The coefficient of the the interaction term ($\beta_{\theta_{I\backslash i} * TFP^{IC+}}$) examines whether the effect of innovation by competitors depends on firm productivity. I expect that $\beta_{\theta_{I\backslash i} * TFP^{IC+}}$ is positive. That is, firms with high TFP^{IC+} less hurt from innovation by competitors.

Panel A of Table 9 presents the regression results. First, for the first three columns, I use the operating profitability (Cop)[20]. I find that the effects of own innovation ($\theta_{i,t}$) and innovation by competitors ($\theta_{I\backslash i,t}$) are consistent with the findings from Kogan et al. (2017). The coefficient of $\theta_{i,t}$ is significantly positive over next 3 years while the coefficient of $\theta_{I\backslash i,t}$ is significantly negative over next 3 years. In other words, own innovation increases future profits but innovation by competitors decreases future profits. Second and more importantly, while the interaction term between $\theta_{i,t}$ and TFP^{IC+} is insignificant, the interaction term between $\theta_{I\backslash i,t}$ and TFP^{IC+} is significantly positive over the first 2 years. This is consistent

[19] https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data

[20] Cop is equals to sales (Sales) minus cost of goods sold (Cogs) minus selling, general, and administrative expense (Xsga) minus interest expense (Xint), scaled by total asset (AT). I replace missing interest expense with zeros.

with my prediction. For example, the interaction term against operating profit in the first year is 0.05. Since the average TFP^{IC+} increase by 2.03 from Low to High, the interaction effect is 0.1015 (0.05*2.03). This absorbs the effect of innovation by competitors (-0.11). That said, high TFP^{IC+} hedges against displacement risk. Third, I use different dependent variables. Following Gaspar and Massa (2005), I use Lerner index[21] to estimate the profit margin. Similar to operating profit, the effect of innovation by competitors is significantly negative but the interaction term between $\theta_{I\backslash i,t}$ and TFP^{IC+} is significantly positive. Turning to the investment, I use the employment growth (ΔL), physical capital growth (ΔK), and intangible capital growth (ΔOC). Again, own innovation significantly increases all different types of investment while innovation by competitors significantly decreases them. Also, the interaction term between $\theta_{I\backslash i,t}$ and TFP^{IC+} are significantly positive for ΔK and ΔOC.

Further, I estimate eq.(15) by replacing TFP^{IC+} with TFP^{IC-} in Table E2. I find that the interaction term between $\theta_{I\backslash i,t}$ and TFP^{IC-} is weaker. For example, the effect of interaction term between $\theta_{I\backslash i,t}$ and TFP^{IC-} on operating profit (Cop) is insignificant over next 3 years.

For the robustness, I estimate $\theta_{I\backslash i,t}$ by aggregating innovations not by competitors but by all other firms excluding firm i, and present the results in Panel B. This allows to study whether the displacement exists not only within the same industry but also across different industries. I have the similar finding. The effect of innovation by all other firms hurt future fundamentals but higher TFP^{IC+} offsets the displacement effect. This suggests that TFP^{IC+} captures the cross-sectional hedging response against aggregate technological shock by innovators so high TFP^{IC+} is less riskier than low TFP^{IC+}.

[21]I estimate the Lerner index in two steps. First, I estimate a firm's operating profit margin, which equals sales minus cost (cost of goods sold plus sales, general, and administrative expense), scaled by sales. Second, I subtract the market share-weighted industry average of the profit margin from the profit margin to control for the structural differences across industries.

4.3 Displacement risk over product market competition

Displacement effect becomes larger if industry competition is higher (Hou and Robinson (2006)). To examine the effect of displacment over different market competition, I split the whole observations into two subsamples on the market competition, and estimate eq.(15). Following Hou and Robinson (2006), I estimate the three-year moving average of Herfindahl-Hirshman Index (HHI) by using sales, and divide the whole sample based on the median value of HHI. I define the subsample lower (higher) than the median value of HHI as competitive (concentrated). Examining results from Panel A of Table 10, I see that the innovation by competitors significantly decreases the future profits in competitive product market while it only marginally decreases them in concentrated market. More importantly, the interaction term between $\theta_{I\setminus i,t}$ and TFP^{IC+} is significantly positive only in competitive market. For example, the coefficient of $\theta_{I\setminus i,t} * TFP^{IC+}$ is 0.06 (t=2.45) in competitive market while it is 0.07 (t=1.52) in concentrated market. Turning to Panel B-E, I use other dependent variables. Similarly, the interaction effect on ΔOC is significant only in competitive market in Panel E. The interaction effects on Lerner index and ΔK are significant in both competitive and concentrated market but the magnitude of $\theta_{I\setminus i,t}$ is larger for more competitive industry. Overall, the significant results from competitive product market validate that TFP^{IC+} reflects the displacement risk.

4.4 Comparing adjustment costs: Investment-q relation

In previous subsections, I show that TFP^{IC+} reflects the heterogeneous response with respect to investment-specific shock. Here, I directly estimate the investment adjustment cost of firms with different TFP^{IC+}, and examine how TFP^{IC+} affects the investment decision. Based on the standard Q-theory, Tobin's q is a sufficient statistic of investment and the coefficient of Tobin's q is the reciprocal of the parameter of the quadratic investment adjustment cost function (Hayashi (1982)). Recent studies find that the adjustment cost of intangible investment is more expensive than that of physical investment (Peters and Taylor

(2017), and Belo et al. (2022)). Since firms with high TFP^{IC+} provide hedging against the investment-specific shock (e.g., innovation by competitors), I expect that firms with high TFP^{IC+} have more flexibility on intangible investment by having lower adjustment cost.

I estimate the investment-q relation by regressing various investment on lagged Tobin's q, lagged TFP^{IC+}, and their interaction term with firm and year fixed effects. Following Peters and Taylor (2017), I estimate two Tobin's q measures: Standard q and Total q. Standard q is the firm's market value over physical capital. Total q is the firm's market value over the sum of physical and intangible capital. For physical capital, I use the book value of property, plant, and equipment. For intangible capital, I aggregate both externally purchased intangible capital and internally created intangible capital. Externally purchased intangible capital is the intangible assets from the balance sheet, or 0 if the observation is missing. Internally created intangible capital is the sum of organizational capital and knowledge capital which are estimated using the perpetual inventory method with the selling, general, and administrative expense and R&D investment, respectively. I use four different investment measures. Physical investment is capital expenditure, scaled by either lagged total capital (Physical) or lagged physical capital (CAPEX/PPE). Intangible investment is either the sum of selling, general, and administrative expense and R&D investment (Intangible) or R&D investment alone (R&D), scaled by lagged total capital. I winsorize all variables at 1% and 99%, and standard errors are clustered by firm.

I estimate the investment-q relation in Table 11. Panel A uses standard q. First, in Columns (1)-(4), consistent with the literature, standard q positively predicts the physical investment. Second, when I add lagged TFP^{IC+} and the interation term with standard q, I find that while TFP^{IC+} positively predicts the physical investment, the interaction term negatively predicts the physical investment. The negative coefficient of the interaction term suggests that firms with high TFP^{IC+} have more expensive adjustment cost for physical investment than firms with low TFP^{IC+}. Third, Columns (5)-(8) report the intangible investment-q relation. While standard q is positively associated with intangible investment, the interaction term is insignificant. Taking together, firms with high TFP^{IC+} have higher adjustment cost of physical investment than firms with low TFP^{IC+} while the adjustment cost of intangible investment are indifferent. This implies that firms with high TFP^{IC+} have relatively cheaper intangible investment.[22] Fourth, I use total q in Panel B, and find the similar results. High TFP^{IC+} firms significantly lower cost of intangible investment than low TFP^{IC+} firms. Overall, the adjustment cost of intangible investment is cheaper than that of physical investment. Since adjusting intangible capital in response to economic changes is less costly for high TFP^{IC+}, this suggests that high TFP^{IC+} firms have more flexibility against the investment-specific shock, and displacement risk.

5 Conclusion

Omitting intangible capital distorts firm productivity. In this paper, I estimate total factor productivity by adding intangible capital as the third production factor. I find that adding intangible capital improves the pricing power of firm productivity. TFP^{IC+} predicts the negative expected return in both cross-section and time-series. Also, I estimate the productivity by omitting intangible capital (TFP^{IC-}), and find that the pricing power of TFP^{IC-} is fully subsumed by TFP^{IC+}. This demonstrates that TFP^{IC+} is better productivity proxy than TFP^{IC-} from the asset pricing perspective.

Further, I show that the displacement risk driven by the investment-specific shock as the pricing mechanism of productivity. First, firms with lower TFP^{IC+} have more negative exposure with respect to the investment-specific shock than firms with higher TFP^{IC+}. Second, future fundamentals of firms with lower TFP^{IC+} are more damaged by innovation by competitors than those of firms with higher TFP^{IC+}. These imply that firms with high TFP^{IC+} provide hedging against the displacement risk from investment-specific shock. Lastly, I estimate the adjustment cost in the investment-q regression, and find that firms with high TFP^{IC+} have relatively cheaper adjustment cost of intangible investment. This additionally

[22]Peters and Taylor (2017) show that firms with high intangible intensity (the ratio of intangible capital to total capital) use more intangible capital because these firms have relatively more expensive adjustment cost of physical investment than intangible investment.

confirms that firms with high TFP^{IC+} have more flexibility against the investment-specific shock.

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Table 1. **Descriptive statistics**

Panel A summarizes the intangible capital adjusted productivity (TFP^{IC+}), the productivity growth (ΔTFP^{IC+}), the labor share (β_L), the physical capital share (β_K), the intangible capital share (β_{OC}), the production technology ($\beta_L+\beta_K+\beta_{OC}$), and the ratio of intangible capital share over total capital share($\beta_{OC}/(\beta_K+\beta_{OC})$), including the number of observations (Obs), mean (Mean), standard deviation (Std), and the subsample mean over 1970s to 2010s. Panel B presents the firm characteristics for TFP^{IC+} sorted portfolios. All stocks are sorted into 10 portfolios, based on three-factor productivity (TFP^{IC+}) described in Section 2.2. I sort stocks on TFP^{IC+} at June of t by using TFP^{IC+} in the end of year $t-1$, and hold the portfolios from July of t to June of $t+1$. TFP^{IC-} is the intangible capital omitted productivity. ΔTFP^{IC-} is the growth of TFP^{IC-}. Size is the market capitalization in billion dollars, BM is the book-to-market ratio, OA is the organizational capital, I/A is the physical investment, HR is the labor hiring, I_{OC}/OC is the organizational capital investment, ROE is return-on-equity, and GP is the gross profitability. All definitions of variables are described in Appendix B. The sample period is from July 1972 to June 2021.

Panel A: TFP^{IC+} and production function estimates											
	Obs	Mean	Std	1970s	1980s	1990s	2000s	2010s			
TFP^{IC+}	59,392	0.05	0.51	-0.12	-0.04	0.07	0.10	0.10			
$\beta_L+\beta_K+\beta_{OC}$	59,392	1.00	0.01	0.98	1.00	1.00	1.00	1.00			
β_L	59,392	0.54	0.04	0.55	0.61	0.54	0.53	0.50			
β_K	59,392	0.34	0.07	0.32	0.31	0.38	0.38	0.27			
β_{OC}	59,392	0.12	0.08	0.11	0.08	0.08	0.09	0.23			
$\beta_{OC}/(\beta_K+\beta_{OC})$	59,392	0.26	0.16	0.26	0.21	0.18	0.20	0.47			
Panel B: Characteristics of TFP^{IC+}-sorted portfolios											
	Low	2	3	4	5	6	7	8	9	High	H-L
TFP^{IC+}	0.48	0.68	0.79	0.90	1.00	1.10	1.22	1.38	1.63	2.51	2.03
ΔTFP^{IC+}	-0.15	-0.04	-0.02	0.00	0.01	0.01	0.02	0.04	0.05	0.09	0.24
TFP^{IC-}	0.66	0.90	1.01	1.10	1.17	1.25	1.36	1.53	1.76	2.54	1.88
ΔTFP^{IC-}	-0.16	-0.06	-0.04	-0.02	-0.01	0.00	0.01	0.03	0.04	0.08	0.25
Size (bil)	8.02	12.36	16.66	22.35	34.20	44.16	59.38	69.93	93.72	103.58	95.55
BM	1.05	0.95	0.89	0.84	0.76	0.73	0.70	0.67	0.62	0.62	-0.42
OA	0.09	0.07	0.06	0.05	0.04	0.04	0.04	0.04	0.04	0.04	-0.05
I/A	0.06	0.06	0.06	0.07	0.07	0.06	0.06	0.06	0.07	0.07	0.01
HR	0.07	0.05	0.05	0.05	0.06	0.06	0.07	0.12	0.10	0.14	0.07
I_{OC}/OC	0.03	0.04	0.05	0.06	0.07	0.08	0.09	0.09	0.09	0.10	0.06
ROE	-0.34	-0.05	0.02	0.05	0.00	0.10	0.10	0.10	0.12	0.14	0.48
GP	0.36	0.40	0.42	0.42	0.44	0.44	0.45	0.45	0.45	0.43	0.07

Table 2. **Excess returns for TFP^{IC+} sorted portfolios**

This table presents the portfolio returns for the intangible capital adjusted productivity (TFP^{IC+}) sorted portfolios. All stocks are sorted into 10 portfolios, based on TFP^{IC+}. I sort stocks on TFP^{IC+} at June of t by using TFP^{IC+} in the last fiscal year $t-1$, and hold the portfolios from July of t to June of $t+1$. Panel A reports the value-weighted portfolio returns (R^{ex}) and alphas (α^{CAPM}, α^{FF3}, and α^{FF4}) over TFP^{IC+} sorted portfolios as well as the zero-cost portfolio (H-L). #firms is the average number of firms in each portfolio. Panel B shows the equal-weighted portfolios in the similar manner. Panel C reports the time-series factor-loadings and R^2 of CAPM, Fama and French (1993) three-factor model (FF3), and Carhart (1997) four-factor model (FF4) against the value-wegihted and the equal-weighted zero-cost portfolios (H-L), respectively. Newey-West adjusted t-statistics with six-month lags are in parentheses. All returns are multiplied by 100. The sample period is from July 1972 to June 2021.

Panel A: Value-weighted TFP^{IC+}-sorted portfolios											
	Low	2	3	4	5	6	7	8	9	High	H-L
R^{ex}	1.03	0.75	0.79	0.59	0.71	0.73	0.65	0.75	0.60	0.46	-0.57
	(3.64)	(2.95)	(3.48)	(2.71)	(3.41)	(3.44)	(3.44)	(4.13)	(2.82)	(1.84)	(-2.88)
α^{CAPM}	0.27	0.04	0.10	-0.05	0.08	0.12	0.07	0.17	-0.01	-0.23	-0.50
	(1.73)	(0.37)	(0.89)	(-0.52)	(0.88)	(1.39)	(0.82)	(2.21)	(-0.12)	(-1.82)	(-2.63)
α^{FF3}	0.24	0.01	0.05	-0.08	0.03	0.15	0.07	0.18	0.03	-0.09	-0.33
	(1.57)	(0.08)	(0.43)	(-0.89)	(0.31)	(1.73)	(0.96)	(2.28)	(0.40)	(-0.87)	(-1.80)
α^{FF4}	0.47	0.21	0.22	0.03	0.12	0.19	0.15	0.24	0.12	0.06	-0.41
	(3.03)	(1.74)	(2.05)	(0.34)	(1.47)	(2.19)	(1.98)	(2.81)	(1.39)	(0.53)	(-2.18)
#firms	102	104	105	106	107	107	107	107	107	107	
Panel B: Equal-weighted TFP^{IC+}-sorted portfolios											
	Low	2	3	4	5	6	7	8	9	High	H-L
R^{ex}	1.39	1.22	1.06	1.05	1.08	1.07	0.97	0.95	0.91	0.82	-0.57
	(4.38)	(4.35)	(4.02)	(4.23)	(4.34)	(4.35)	(3.99)	(3.83)	(3.58)	(2.81)	(-4.39)
α^{CAPM}	0.61	0.49	0.32	0.33	0.36	0.36	0.26	0.21	0.15	-0.02	-0.63
	(3.37)	(3.06)	(2.23)	(2.53)	(2.64)	(2.97)	(2.02)	(2.02)	(1.32)	(-0.13)	(-5.01)
α^{FF3}	0.49	0.36	0.17	0.21	0.23	0.25	0.17	0.14	0.10	-0.05	-0.54
	(3.98)	(3.39)	(2.05)	(2.86)	(2.80)	(3.16)	(2.17)	(2.20)	(1.44)	(-0.51)	(-4.27)
α^{FF4}	0.70	0.52	0.34	0.31	0.37	0.39	0.31	0.27	0.23	0.12	-0.58
	(4.95)	(4.79)	(3.73)	(4.11)	(4.62)	(4.88)	(3.69)	(4.03)	(3.13)	(1.12)	(-4.08)
#firms	102	104	105	106	107	107	107	107	107	107	
Panecl C: Factor-loadings of the zero-cost portfolio (H-L)											
	Value-weighted H-L			Equal-weighted H-L							
	CAPM	FF3	FF4	CAPM	FF3	FF4					
β_{MKT}	-0.11	-0.10	-0.07	0.10	0.12	0.13					
	(-2.04)	(-1.96)	(-1.57)	(2.11)	(2.59)	(3.04)					
β_{SMB}		-0.41	-0.40		-0.30	-0.30					
		(-4.60)	(-4.82)		(-5.62)	(-5.90)					
β_{HML}		-0.36	-0.32		-0.17	-0.15					
		(-4.37)	(-4.31)		(-2.36)	(-2.21)					
β_{UMD}			0.10			0.05					
			(1.44)			(0.89)					
R^2	0.01	0.14	0.15	0.02	0.13	0.14					

Table 3. **Cross-sectional regressions: Main results**

This table presents Fama-MacBeth regressions using the excess returns of 25 portfolios sorted by size and book-to-market ratio. Factors include Fama and French (1993) three factors, Carhart (1997) momentum factor, and the pricing factor of intangible capital adjusted productivity (TFP^{IC+}). I consider the zero-cost portfolio of TFP^{IC+} (H-L) in Table 2 as the pricing factor of TFP^{IC+}. The factor betas are computed either over the full sample (full sample betas in Panel A) or in rolling windows (rolling betas in Panel B). All coefficients are multiplied by 100. The t-statistics are in parentheses and adjusted for errors-in-variables, following Shanken (1992). The adjusted R^2 follows Jagannathan and Wang (1996). The 5^{th} and 95^{th} percentiles of the adjusted R^2 distribution from a bootstrap simulation of 10,000 times are reported in brackets. The sample period is July 1972 to June 2021.

Panel A: Full sample betas														
	TFP^{IC+}		CAPM		CAPM+TFP^{IC+}		FF3		FF3+TFP^{IC+}		FF4		FF4+TFP^{IC+}	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.49	2.92	1.19	2.78	1.04	3.06	0.06	2.65	0.05	1.77	-0.01	-0.34	-0.01	-0.37
γ_{MKT}			-0.38	-0.82	-0.48	-1.16	0.54	2.84	0.53	2.80	0.62	3.27	0.61	3.22
γ_{SMB}							0.19	1.47	0.20	1.52	0.20	1.54	0.21	1.59
γ_{HML}							0.31	2.40	0.31	2.44	0.33	2.60	0.34	2.63
γ_{UMD}											0.67	3.64	0.67	3.65
$\gamma_{TFP^{IC+}}$	-1.07	-4.09			-1.58	-4.15			-0.61	-3.16			-0.56	-2.88
R^2	0.78		0.04		0.86		0.59		0.81		0.67		0.85	
(5^{th}, 95^{th})	(0.38, 0.87)		(-0.04, 0.42)		(0.59, 0.89)		(0.34, 0.77)		(0.60, 0.89)		(0.45, 0.83)		(0.67, 0.91)	
Panel B: Rolling betas														
	TFP^{IC+}		CAPM		CAPM+TFP^{IC+}		FF3		FF3+TFP^{IC+}		FF4		FF4+TFP^{IC+}	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.65	3.35	0.88	3.18	0.67	2.83	0.14	4.64	0.13	3.95	0.15	4.20	0.14	3.96
γ_{MKT}			-0.08	-0.26	0.04	0.12	0.54	2.85	0.56	2.90	0.56	2.94	0.57	2.95
γ_{SMB}							0.19	1.49	0.19	1.48	0.18	1.39	0.18	1.36
γ_{HML}							0.14	1.06	0.14	1.07	0.15	1.13	0.15	1.13
γ_{UMD}											0.37	2.03	0.39	2.15
$\gamma_{TFP^{IC+}}$	-1.24	-4.91			-1.16	-3.96			-0.58	-3.09			-0.61	-3.24
R^2	0.80		0.22		0.76		0.52		0.77		0.56		0.78	
(5^{th}, 95^{th})	(0.37, 0.87)		(-0.12, 0.46)		(0.54, 0.88)		(0.32, 0.78)		(0.59, 0.89)		(0.43, 0.82)		(0.65, 0.91)	

Table 4. **Robustness checks: Model specifications**

This table presents Fama-MacBeth regressions using the excess returns of 25 portfolios sorted by size and book-to-market ratio. Factors include Fama and French (1993) three factors, Carhart (1997) momentum factor, and the pricing factor of intangible capital adjusted productivity (TFP^{IC+}). I consider the zero-cost portfolio of TFP^{IC+} (H-L) as the pricing factor of TFP^{IC+}. Panel A uses the TFP^{IC+} by using alternative intangible capital combining organizational capital (OC) and knowledge capital (KC) (TFP^{IC+}_{OC+KC}). Panel B uses the conventional pricing factor by following Fama and French (1993). The factor betas are computed over the full sample. All coefficients are multiplied by 100. The t-statistics are in parentheses and adjusted for errors-in-variables, following Shanken (1992). The adjusted R^2 follows Jagannathan and Wang (1996). The 5^{th} and 95^{th} percentiles of the adjusted R^2 distribution from a bootstrap simulation of 10,000 times are reported in brackets. The sample period is July 1972 to June 2021.

Panel A: Adding Knowledge capital (TFP^{IC+}_{OC+KC})														
	TFP^{IC+}		CAPM		CAPM+TFP^{IC+}		FF3		FF3+TFP^{IC+}		FF4		FF4+TFP^{IC+}	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.48	3.06	1.19	2.78	1.20	3.29	0.06	2.65	0.05	1.70	-0.01	-0.34	-0.01	-0.51
γ_{MKT}			-0.38	-0.82	-0.63	-1.47	0.54	2.84	0.55	2.86	0.62	3.27	0.62	3.26
γ_{SMB}							0.19	1.47	0.19	1.50	0.20	1.54	0.20	1.57
γ_{HML}							0.31	2.40	0.31	2.45	0.33	2.60	0.34	2.64
γ_{UMD}											0.67	3.64	0.67	3.66
$\gamma_{TFP^{IC+}}$	-0.94	-3.63			-1.62	-4.06			-0.50	-2.63			-0.45	-2.38
R^2	0.72		0.04		0.84		0.59		0.79		0.67		0.83	
(5^{th}, 95^{th})	(0.27, 0.85)		(-0.04, 0.42)		(0.54, 0.88)		(0.34, 0.77)		(0.56, 0.88)		(0.45, 0.83)		(0.63, 0.91)	

Panel B: Constructing the pricing factors following Fama-French

	TFP^{IC+}		CAPM		CAPM+TFP^{IC+}		FF3		FF3+TFP^{IC+}		FF4		FF4+TFP^{IC+}	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	1.08	3.90	1.19	2.78	0.65	2.63	0.06	2.65	0.07	2.88	-0.01	-0.34	0.01	0.41
γ_{MKT}			-0.38	-0.82	-0.03	-0.09	0.54	2.84	0.54	2.81	0.62	3.27	0.61	3.21
γ_{SMB}							0.19	1.47	0.18	1.37	0.20	1.54	0.19	1.45
γ_{HML}							0.31	2.40	0.30	2.39	0.33	2.60	0.33	2.57
γ_{UMD}											0.67	3.64	0.65	3.54
$\gamma_{TFP^{IC+}}$	-0.90	-4.13			-0.80	-3.45			-0.29	-3.73			-0.24	-3.08
R^2	0.65		0.04		0.77		0.59		0.75		0.67		0.80	
(5^{th}, 95^{th})	(0.18, 0.76)		(-0.04, 0.42)		(0.42, 0.82)		(0.34, 0.77)		(0.51, 0.86)		(0.45, 0.83)		(0.60, 0.89)	

Table 5. **Robustness checks: Alternative test assets**

This table presents Fama-MacBeth regressions using the excess returns of 100 portfolios. Test assets include 25 size and book-to-market sorted portfolios, 25 size and investment sorted portfolios, 25 size and operating profitability sorted portfolios, and 25 size and momentum sorted portfolios. Factors include Fama and French (1993) three factors, Carhart (1997) momentum factor, and the pricing factor of intangible capital adjusted productivity (TFP^{IC+}). I consider the zero-cost portfolio of TFP^{IC+} (the highest TFP^{IC+}-sorted portfolio - the lowest TFP^{IC+}-sorted portfolio) in Table 2 as the pricing factor of TFP^{IC+}. The factor betas are computed either over the full sample (full sample betas in Panel A) or in rolling windows (rolling betas in Panel B). All coefficients are multiplied by 100. The t-statistics are in parentheses and adjusted for errors-in-variables, following Shanken (1992). The adjusted R^2 follows Jagannathan and Wang (1996). The 5^{th} and 95^{th} percentiles of the adjusted R^2 distribution from a bootstrap simulation of 10,000 times are reported in brackets. The sample period is July 1972 to June 2021.

Panel A: Full sample betas														
	TFP^{IC+}		CAPM		CAPM+TFP^{IC+}		FF3		FF3+TFP^{IC+}		FF4		FF4+TFP^{IC+}	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.56	3.34	1.28	4.46	1.17	4.91	0.63	5.84	0.50	5.50	0.05	1.86	0.03	1.01
γ_{MKT}			-0.47	-1.32	-0.56	-1.79	0.02	0.09	0.12	0.55	0.59	3.04	0.60	3.13
γ_{SMB}							0.15	1.20	0.18	1.42	0.18	1.40	0.19	1.47
γ_{HML}							0.17	1.26	0.20	1.50	0.42	3.11	0.42	3.16
γ_{UMD}											0.65	3.51	0.65	3.53
$\gamma_{TFP^{IC+}}$	-0.80	-2.57			-1.34	-4.02			-0.69	-3.38			-0.52	-2.59
R^2	0.26		0.09		0.38		0.10		0.25		0.68		0.76	
(5^{th}, 95^{th})	(0.03, 0.47)		(-0.01, 0.34)		(0.13, 0.57)		(0.01, 0.42)		(0.09, 0.53)		(0.51, 0.78)		(0.61, 0.83)	
Panel B: Rolling betas														
	TFP^{IC+}		CAPM		CAPM+TFP^{IC+}		FF3		FF3+TFP^{IC+}		FF4		FF4+TFP^{IC+}	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.63	3.22	0.70	3.13	0.68	3.73	0.50	5.27	0.42	5.57	0.32	6.90	0.28	6.17
γ_{MKT}			0.09	0.33	0.02	0.09	0.22	1.04	0.28	1.47	0.41	2.16	0.44	2.34
γ_{SMB}							0.19	1.52	0.21	1.65	0.20	1.56	0.21	1.63
γ_{HML}							0.05	0.37	0.06	0.46	0.14	1.04	0.14	1.05
γ_{UMD}											0.41	2.23	0.43	2.35
$\gamma_{TFP^{IC+}}$	-1.12	-4.40			-1.04	-4.02			-0.66	-3.12			-0.64	-3.61
R^2	0.31		0.03		0.31		0.13		0.41		0.48		0.63	
(5^{th}, 95^{th})	(0.06, 0.51)		(-0.02, 0.38)		(0.18, 0.58)		(0.04, 0.48)		(0.22, 0.62)		(0.47, 0.76)		(0.58, 0.82)	

Table 6. **Cross-sectional regressions: Individual firm level**

This table presents Fama-MacBeth regressions of individual monthly stock returns on intangible capital adjusted productivity and other variables. Column (1)-(2) use TFP^{IC+}. Column (3)-(4) use TFP^{IC+}_{OC+KC} by using alternative intangible capital combining organizational capital (OC) and knowledge capital (KC). Control variables include log firm size (Size), book-to-market ratio (BM), past 12-months return from $t-2$ to $t-13$ (Mom), past 1-month return (Ret_{t-1}), Return-on-Equity (ROE), labor hiring (HR), physical investment (I/A), organizational capital (OA), idiosyncratic volatility (Ivol), and market beta (β_{MKT}). All control variables are defined in Appendix B. All coefficients are multiplied by 100. Newey-West adjusted t-statistics with six-month lags are in parentheses. I report the average R^2 and the number of observations (N). The sample period is July 1972 to June 2021.

	(1)	(2)	(3)	(4)
TFP^{IC+}	-0.32	-0.16		
	(-3.38)	(-2.15)		
TFP^{IC+}_{OC+KC}			-0.33	-0.14
			(-3.54)	(-1.95)
Size		-0.14		-0.14
		(-3.84)		(-3.75)
BM		0.15		0.16
		(1.97)		(2.02)
Mom		22.36		0.23
		(1.47)		(1.50)
Ret_{t-1}		-4.86		-4.82
		(-8.83)		(-8.83)
ROE		0.15		0.22
		(0.76)		(1.26)
HR		-0.23		-0.27
		(-1.81)		(-1.74)
I/A		-1.22		-12.77
		(-1.84)		(-1.92)
OA		0.32		0.39
		(0.56)		(0.69)
Ivol		-2.34		-2.34
		(-0.52)		(-0.53)
β_{MKT}		-0.02		-0.02
		(-0.13)		(-0.014)
Intercept	1.36	2.64	1.36	2.58
	(4.77)	(4.69)	(4.77)	(4.58)
Average R^2	0.00	0.09	0.00	0.09
N	426,008	425,313	431,550	430,855

Table 7. **Bi-variate sorts: TFP^{IC+} and TFP^{IC-}**

This table presents the bi-variate sorted portfolios for intangible capital adjusted productivity (TFP^{IC+}) and intangible capital omitted productivity (TFP^{IC-}). All stocks are dependently sorted into 16 (4-by-4) portfolios. Panel A reports both value-weighted and equal-weighted returns for each portfolio, sorted on TFP^{IC+} first, and TFP^{IC-} in each TFP^{IC+} sorted portfolio. The zero-cost portfolios (H-L) for TFP^{IC+} and TFP^{IC-} are computed, respectively. Also, the average zero-cost portfolio of TFP^{IC+} (TFP^{IC-}) across TFP^{IC-} (TFP^{IC+}) sorted portfolios is computed in Avg. TFP^{IC+} (Avg. TFP^{IC-}). Panel B shows the similar results of the bi-variate sorts in the reverse order. Newey-West adjusted t-statistics with six-month lags are in parentheses. All returns are multiplied by 100. The sample period is from July 1972 to June 2021.

Panel A: Controlling for TFP^{IC+}

	Value-weighted						Equal-weighted				
	TFP^{IC+}						TFP^{IC+}				
TFP^{IC-}	Low	2	3	High	H-L	TFP^{IC-}	Low	2	3	High	H-L
Low	0.87	0.58	0.80	0.42	-0.44	Low	1.34	0.99	1.00	0.84	-0.50
	(2.71)	(2.11)	(3.65)	(1.75)	(-1.87)		(4.14)	(3.68)	(3.80)	(2.99)	(-3.21)
2	0.83	0.64	0.73	0.56	-0.27	2	1.24	1.08	0.97	0.97	-0.27
	(3.43)	(2.82)	(3.56)	(2.72)	(-1.52)		(4.21)	(4.29)	(3.89)	(3.74)	(-2.15)
3	0.82	0.69	0.73	0.64	-0.17	3	1.27	1.14	0.96	0.91	-0.35
	(3.04)	(3.33)	(3.79)	(2.81)	(-1.02)		(4.26)	(4.70)	(4.16)	(3.38)	(-2.74)
High	0.89	0.81	0.71	0.68	-0.21	High	1.19	1.07	1.06	0.81	-0.38
	(3.97)	(3.83)	(3.40)	(2.58)	(-1.01)		(4.39)	(4.15)	(4.38)	(2.85)	(-2.81)
H-L	0.02	0.23	-0.09	0.26		H-L	-0.14	0.08	0.06	-0.03	
	(0.10)	(1.35)	(-0.55)	(1.35)			(-0.94)	(0.69)	(0.53)	(-0.24)	
Avg. TFP^{IC+}	-0.27	(-2.07)				Avg. TFP^{IC+}	-0.37	(-4.16)			
Avg. TFP^{IC-}	0.11	(1.03)				Avg. TFP^{IC-}	-0.01	(-0.11)			

Panel B: Controlling for TFP^{IC-}

	Value-weighted						Equal-weighted				
	TFP^{IC+}						TFP^{IC+}				
TFP^{IC-}	Low	2	3	High	H-L	TFP^{IC-}	Low	2	3	High	H-L
Low	0.87	0.75	0.91	0.73	-0.14	Low	1.38	1.17	1.11	1.08	-0.30
	(3.99)	(3.99)	(4.99)	(3.99)	(-0.64)		(4.99)	(4.99)	(4.99)	(4.99)	(-1.94)
2	0.90	0.48	0.75	0.72	-0.18	2	1.27	1.01	1.14	1.06	-0.21
	(3.99)	(2.99)	(4.99)	(3.99)	(-0.93)		(4.99)	(4.99)	(5.99)	(4.99)	(-1.59)
3	0.74	0.68	0.64	0.57	-0.17	3	1.17	1.09	0.91	0.94	-0.23
	(3.99)	(3.99)	(3.99)	(3.99)	(-0.94)		(4.99)	(4.99)	(4.99)	(4.99)	(-2.13)
High	0.72	0.68	0.56	0.46	-0.26	High	0.97	0.97	0.83	0.76	-0.21
	(3.99)	(3.99)	(3.99)	(2.99)	(-1.16)		(4.99)	(4.99)	(3.99)	(3.99)	(-1.46)
H-L	-0.15	-0.06	-0.35	-0.27		H-L	-0.41	-0.21	-0.28	-0.32	
	(-0.65)	(-0.35)	(-2.23)	(-1.54)			(-2.55)	(-1.63)	(-2.22)	(-2.42)	
Avg. TFP^{IC-}	-0.19	(-1.34)				Avg. TFP^{IC-}	-0.24	(-2.74)			
Avg. TFP^{IC+}	-0.21	(-1.99)				Avg. TFP^{IC+}	-0.30	(-3.55)			

Table 8. **Exposure of portfolio returns to investment-specific shock (IST-shock)**

This table presents the regression results from annual excess returns on the investment-specific shock (IST-shock) and other pricing factors over value-weighted TFP^{IC+} sorted portfolios. IST-shock is estimated by following Cummins and Violante (2002) using the aggregate quality-adjusted price index. Panel A uses IST-shock alone; Panel B uses the market portfolio of CAPM and IST-shock; Panel C uses three-factors of Fama and French (1993) and IST-shock; Panel D uses four-factors of Carhart (1997) and IST-shock. Newey-West t-statistics with five-year lags are in parentheses. The sample period is from 1972 to 2021.

	Low	2	3	4	5	6	7	8	9	High	H-L
Panel A: IST-shock											
β_{IST}	-4.38	-3.74	-1.85	-1.72	-2.15	-1.69	-2.70	-0.42	-2.57	-1.25	3.13
	(-2.54)	(-3.94)	(-2.16)	(-2.56)	(-2.10)	(-1.85)	(-2.12)	(-0.41)	(-2.33)	(-0.72)	(3.05)
R^2	0.13	0.13	0.04	0.04	0.07	0.04	0.13	0.00	0.09	0.01	0.13
Panel B: CAPM+IST-shock											
β_{IST}	-2.39	-1.92	-0.05	0.01	-0.47	-0.05	-1.18	1.20	-0.90	0.87	3.26
	(-1.89)	(-1.98)	(-0.07)	(0.02)	(-0.91)	(-0.20)	(-1.88)	(3.34)	(-1.59)	(0.99)	(2.89)
β_{MKT}	1.15	1.04	1.04	1.00	0.97	0.95	0.87	0.93	0.96	1.22	0.08
	(6.56)	(8.23)	(7.03)	(13.58)	(22.53)	(15.35)	(19.95)	(15.76)	(16.85)	(15.11)	(0.41)
R^2	0.61	0.72	0.75	0.82	0.85	0.82	0.87	0.90	0.82	0.74	0.14
Panel C: FF3+IST-shock											
β_{IST}	-2.40	-1.87	0.01	0.06	-0.42	-0.17	-1.18	1.20	-0.97	0.56	2.96
	(-1.97)	(-1.93)	(0.01)	(0.07)	(-0.87)	(-0.73)	(-1.79)	(3.44)	(-1.81)	(0.71)	(2.64)
β_{MKT}	1.06	1.04	1.00	0.97	0.97	0.89	0.87	0.93	1.00	1.08	0.02
	(6.67)	(9.56)	(7.20)	(13.68)	(25.01)	(14.61)	(21.04)	(14.35)	(16.46)	(18.60)	(0.15)
β_{SMB}	0.33	0.12	0.26	0.21	0.11	-0.03	0.01	0.01	-0.28	-0.09	-0.41
	(1.49)	(0.62)	(1.41)	(1.60)	(0.77)	(-0.28)	(0.14)	(0.23)	(-2.12)	(-0.83)	(-1.52)
β_{HML}	-0.17	0.04	-0.02	-0.01	0.04	-0.21	-0.01	0.00	0.01	-0.54	-0.37
	(-1.24)	(0.37)	(-0.24)	(-0.16)	(0.48)	(-2.08)	(-0.17)	(-0.07)	(0.11)	(-5.76)	(-2.54)
R^2	0.63	0.72	0.77	0.83	0.85	0.85	0.87	0.90	0.85	0.85	0.27
Panel D: FF4+IST-shock											
β_{IST}	-1.05	-1.18	0.68	0.45	-0.24	-0.08	-1.00	1.23	-0.96	1.22	2.27
	(-1.59)	(-1.15)	(1.09)	(0.47)	(-0.38)	(-0.28)	(-1.48)	(3.30)	(-1.75)	(1.90)	(2.00)
β_{MKT}	0.92	0.97	0.93	0.93	0.95	0.88	0.85	0.93	1.00	1.01	0.10
	(8.44)	(10.20)	(8.13)	(14.72)	(24.20)	(13.18)	(19.45)	(14.32)	(15.15)	(17.62)	(0.71)
β_{SMB}	0.14	0.03	0.17	0.15	0.09	-0.05	-0.01	0.01	-0.28	-0.18	-0.32
	(0.84)	(0.15)	(1.14)	(1.30)	(0.63)	(-0.40)	(-0.16)	(0.16)	(-2.18)	(-1.53)	(-1.34)
β_{HML}	-0.32	-0.04	-0.10	-0.06	0.01	-0.22	-0.03	-0.01	0.01	-0.61	-0.29
	(-2.34)	(-0.40)	(-1.77)	(-0.71)	(0.18)	(-2.17)	(-0.47)	(-0.13)	(0.09)	(-7.21)	(-1.95)
β_{UMD}	-0.67	-0.34	-0.33	-0.19	-0.09	-0.04	-0.09	-0.01	-0.01	-0.33	0.34
	(-2.13)	(-0.34)	(-1.26)	(-0.72)	(0.21)	(-4.32)	(-0.78)	(-0.12)	(0.16)	(-9.11)	(-1.74)
R^2	0.79	0.78	0.84	0.86	0.86	0.86	0.88	0.90	0.85	0.90	0.35

Table 9. **Firms' response to innovation news**

This table presents the regression results from the equation as follows,

$$Y_{i,t+\tau} = \beta_0 + \beta_{\theta_i}\theta_{i,t} + \beta_{\theta_i * TFP^{IC+}}\theta_{i,t} * TFP^{IC+}_{i,t} + \beta_{\theta_{I\setminus i}}\theta_{I\setminus i,t} + \beta_{\theta_{I\setminus i} * TFP^{IC+}}\theta_{I\setminus i,t} * TFP^{IC+}_{i,t} + \beta_{TFP^{IC+}}TFP^{IC+}_{i,t} + cZ_{it} + d_t + d_j + \epsilon_{i,t+\tau} \quad (16)$$

$Y_{i,t+\tau}$ is future fundamentals including operation profitability (Cop), Lerner index, employment growth from t to $t+\tau$ (ΔL), physical capital growth from t to $t+\tau$ (ΔK), and intangible capital growth from t to $t+\tau$ (ΔOC) (τ=1 to 3). $\theta_{i,t}$ is a market value of all innovations of firm i in year t. In Panel A (Panel B), $\theta_{I\setminus i,t}$ is a market value of all innovations by firm i's competitors (all firms except for firm i). TFP^{IC+} is the intangible capital adjusted productivity. Z_{it} is the vector of control variables, including logarithmic value of employment, physical capital, and intangible capital and idiosyncratic volatility. d_t and d_j are time-fixed and industry-fixed effects, respectively. We estimate $\theta_{i,t}$ as the ratio of the innovative output of a firm i in year t over its total asset in year t. We estimate $\theta_{I\setminus i,t}$ as the weighted average of the innovative output of a firm i's competitors (all firms except for firm i) in each year t, $\frac{\Sigma_{i\in I\setminus i}\theta_{i,t}}{\Sigma_{i\in I\setminus i}AT_{i,t}}$ where AT_{it} is total asset in year t. The competitors are defined as any firms in the same 3-digit SIC industry with a firm i in year t. We winsorize all variables at 1% and 99%. Standard errors are clustered by firm and year, t-statistics are reported in parentheses. I report R^2 and the number of observations (N). The sample period is from 1972 to 2021.

Panel A: Using innovation by competitors

	Cop			Lerner index			ΔL			ΔK			ΔOC		
τ	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
θ_{it}	0.09	0.09	0.08	0.00	0.01	0.00	0.09	0.19	0.26	0.15	0.32	0.50	0.03	0.05	0.08
	(3.76)	(3.79)	(3.14)	(0.13)	(0.43)	(0.13)	(2.07)	(2.27)	(2.05)	(3.21)	(2.96)	(2.82)	(1.30)	(1.25)	(1.16)
θ_{it}*TFP^{IC+}	0.00	-0.01	-0.01	0.04	0.03	0.04	0.00	0.01	0.00	-0.02	-0.02	-0.05	0.00	0.01	0.03
	(-0.15)	(-0.56)	(-0.35)	(1.87)	(1.37)	(1.72)	(0.07)	(0.15)	(-0.01)	(-0.76)	(-0.36)	(-0.56)	(0.33)	(0.53)	(0.66)
$\theta_{I\setminus i,t}$	-0.11	-0.10	-0.10	-0.17	-0.16	-0.15	-0.14	-0.24	-0.39	-0.21	-0.43	-0.76	-0.06	-0.11	-0.16
	(-3.13)	(-3.20)	(-2.86)	(-3.77)	(-3.33)	(-2.95)	(-2.81)	(-2.26)	(-2.35)	(-3.81)	(-3.39)	(-3.24)	(-2.63)	(-2.54)	(-2.50)
$\theta_{I\setminus i,t}$*TFP^{IC+}	0.05	0.04	0.04	0.11	0.10	0.09	0.06	0.08	0.14	0.14	0.25	0.46	0.05	0.09	0.12
	(1.86)	(1.89)	(1.55)	(3.26)	(3.18)	(2.60)	(1.27)	(1.14)	(1.26)	(2.92)	(2.51)	(2.51)	(2.47)	(2.24)	(2.08)
TFP^{IC+}	0.03	0.02	0.02	0.03	0.02	0.02	0.04	0.07	0.10	0.05	0.10	0.16	0.02	0.04	0.06
	(12.16)	(9.52)	(8.87)	(11.53)	(9.52)	(8.31)	(8.07)	(7.30)	(6.76)	(7.68)	(7.11)	(7.02)	(15.78)	(15.17)	(15.01)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.23	0.20	0.19	0.26	0.24	0.24	0.09	0.12	0.13	0.14	0.16	0.17	0.67	0.66	0.64
N	41,151	41,151	41,151	41,151	41,151	41,151	41,151	41,151	41,151	41,151	41,151	41,151	41,151	41,151	41,151

Panel B: Using innovation by all other firms

	Cop			Lerner index			ΔL			ΔK			ΔOC		
τ	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
θ_{it}	0.09	0.08	0.07	0.00	0.01	0.00	0.07	0.13	0.17	0.12	0.21	0.31	0.01	0.02	0.03
	(3.38)	(3.32)	(2.48)	(0.17)	(0.47)	(0.02)	(1.55)	(1.75)	(1.39)	(2.38)	(2.16)	(1.94)	(0.74)	(0.62)	(0.51)
θ_{it}*TFP^{IC+}	0.00	-0.01	0.00	0.05	0.04	0.05	0.01	0.03	0.03	0.01	0.04	0.06	0.01	0.02	0.04
	(-0.30)	(-0.47)	(-0.00)	(2.10)	(1.67)	(2.17)	(0.47)	(0.65)	(0.44)	(0.24)	(0.71)	(0.70)	(0.81)	(1.05)	(1.16)
$\theta_{I\setminus i,t}$	-0.31	-0.28	-0.26	-0.57	-0.54	-0.49	-0.24	-0.31	-0.48	-0.39	-0.60	-0.91	-0.02	-0.04	-0.05
	(-3.62)	(-3.85)	(-3.57)	(-5.60)	(-5.24)	(-4.45)	(-2.73)	(-1.67)	(-1.58)	(-3.23)	(-2.30)	(-2.01)	(-0.52)	(-0.44)	(-0.40)
$\theta_{I\setminus i,t}$*TFP^{IC+}	0.16	0.11	0.08	0.27	0.23	0.20	0.12	0.11	0.21	0.21	0.29	0.49	0.08	0.14	0.19
	(2.34)	(1.99)	(1.57)	(3.72)	(3.21)	(2.63)	(1.49)	(0.80)	(1.06)	(2.41)	(1.56)	(1.56)	(1.83)	(1.64)	(1.50)
TFP^{IC+}	0.03	0.02	0.02	0.02	0.02	0.02	0.03	0.07	0.10	0.05	0.10	0.16	0.02	0.04	0.06
	(10.97)	(8.58)	(7.83)	(10.15)	(8.12)	(7.19)	(7.71)	(7.01)	(6.54)	(7.38)	(6.77)	(6.71)	(14.89)	(14.32)	(14.16)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.23	0.20	0.19	0.26	0.24	0.24	0.09	0.12	0.13	0.14	0.16	0.17	0.67	0.66	0.64
N	42,476	42,476	42,476	42,476	42,476	42,476	42,476	42,476	42,476	42,476	42,476	42,476	42,476	42,476	42,476

Table 10. **Firms' response to innovation news: Competitive vs. Concentrated**

This table presents the subsample regression results from the equation as follows,

$$\begin{aligned} Y_{i,t+\tau} =& \beta_0 + \beta_{\theta_i}\theta_{i,t} + \beta_{\theta_i * TFP^{IC+}}\theta_{i,t} * TFP^{IC+}_{i,t} + \beta_{\theta_{I\backslash i}}\theta_{I\backslash i,t} + \beta_{\theta_{I\backslash i} * TFP^{IC+}}\theta_{I\backslash i,t} * TFP^{IC+}_{i,t} + \beta_{TFP^{IC+}}TFP^{IC+}_{i,t} \\ &+ cZ_{it} + d_t + d_j + \epsilon_{i,t+\tau} \end{aligned} \tag{17}$$

I divide the sample on the median value of Herfindal-Hershman index (HHI), and define the subsample lower (higher) than the median value as competitive (concentrated). $Y_{i,t+\tau}$ is future fundamentals including operation profitability (Cop) in Panel A, Lerner index in Panel B, employment growth from t to $t+\tau$ (ΔL) in Panel C, physical capital growth from t to $t+\tau$ (ΔK) in Panel D, and intangible capital growth from t to $t+\tau$ (ΔOC) in Panel E (τ=1 to 3). $\theta_{i,t}$ is a market value of all innovations of firm i in year t. $\theta_{I\backslash i,t}$ is a market value of all innovations by firm i's competitors. TFP^{IC+} is the intangible capital adjusted productivity. Z_{it} is the vector of control variables, including logarithmic value of employment, physical capital, and intangible capital and idiosyncratic volatility. d_t and d_j are time-fixed and industry-fixed effects, respectively. We estimate $\theta_{i,t}$ as the ratio of the innovative output of a firm i in year t over its total asset in year t. We estimate $\theta_{I\backslash i,t}$ as the weighted average of the innovative output of a firm i's competitors in each year t, $\frac{\Sigma_{i\in I\backslash i}\theta_{i,t}}{\Sigma_{i\in I\backslash i}AT_{i,t}}$ where AT_{it} is total asset in year t. The competitors are defined as any firms in the same 3-digit SIC industry with a firm i in year t. We winsorize all variables at 1% and 99%. Standard errors are clustered by firm and year, t-statistics are reported in parentheses. The sample period is from 1972 to 2021.

	Competitive			Concentrated		
τ	1	2	3	1	2	3
Panel A: Cop						
$\theta_{I\backslash i,t}$	-0.16	-0.17	-0.16	-0.09	-0.05	-0.06
	(-3.66)	(-3.99)	(-3.47)	(-1.77)	(-1.10)	(-1.12)
$\theta_{I\backslash i,t}$*TFP^{IC+}	0.06	0.07	0.06	0.07	0.03	0.04
	(2.45)	(2.88)	(2.17)	(1.52)	(0.78)	(0.84)
Panel B: Lerner index						
$\theta_{I\backslash i,t}$	-0.23	-0.24	-0.22	-0.17	-0.14	-0.13
	(-4.83)	(-4.54)	(-3.71)	(-3.28)	(-2.91)	(-2.83)
$\theta_{I\backslash i,t}$*TFP^{IC+}	0.11	0.11	0.10	0.13	0.09	0.09
	(3.87)	(3.95)	(2.87)	(2.93)	(2.45)	(2.21)
Panel C: ΔL						
$\theta_{I\backslash i,t}$	-0.15	-0.31	-0.49	-0.19	-0.27	-0.48
	(-2.79)	(-2.68)	(-2.23)	(-2.00)	(-1.52)	(-2.04)
$\theta_{I\backslash i,t}$*TFP^{IC+}	0.06	0.09	0.15	0.13	0.18	0.37
	(1.28)	(1.44)	(1.25)	(1.26)	(0.99)	(1.60)
Panel D: ΔK						
$\theta_{I\backslash i,t}$	-0.24	-0.56	-0.97	-0.24	-0.38	-0.68
	(-2.86)	(-3.18)	(-2.96)	(-3.30)	(-2.20)	(-2.25)
$\theta_{I\backslash i,t}$*TFP^{IC+}	0.14	0.30	0.54	0.18	0.26	0.47
	(2.43)	(2.51)	(2.47)	(2.46)	(1.45)	(1.56)
Panel E: ΔOC						
$\theta_{I\backslash i,t}$	-0.06	-0.12	-0.18	-0.05	-0.10	-0.15
	(-2.35)	(-2.27)	(-2.22)	(-1.95)	(-1.96)	(-1.94)
$\theta_{I\backslash i,t}$*TFP^{IC+}	0.05	0.09	0.13	0.04	0.08	0.11
	(2.34)	(2.10)	(1.95)	(1.61)	(1.56)	(1.49)

Table 11. **Investment-Q Relation and Productivity**

This table presents the regression results of investment on lagged Tobin's q, lagged intangible capital adjusted productivity (TFP^{IC+}), the interaction between lagged Tobin's q and TFP^{IC+}, and firm and year fixed effects. In Column (1)-(2), physical investment (Physical) is capital expenditure scaled by total capital. In Column (3)-(4), CAPEX/PPE is capital expenditure scaled by physical capital. In Column (5)-(6), intangible investment (Intangible) is research and development (R&D) expenditure plus 0.3*selling, general and administrative expense, scaled by total capital. In Column (7)-(8), R&D is R&D scaled by total capital. Total capital is the sum of physical and intangible capital. Panel A uses standard q, and Panel B uses total q. The numerator for both q variables is the market value of equity plus the book value of debt minus current assets. The denominator for standard q (total q) is physical capital (total capital). I winsorize all variables at 1% and 99%. Standard errors are clustered by firm. t-statistics are reported in parentheses. I report the with-in R^2 and the number of observtions (N). The sample period is from 1972 to 2021.

Panel A: Standard Q								
	Physical		CAPEX/PPE		Intangible		R&D	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Standard Q	0.0020	0.0028	0.0077	0.0088	0.0025	0.0023	0.0012	0.0008
	(15.36)	(10.98)	(22.40)	(13.47)	(18.24)	(10.55)	(11.62)	(4.87)
TFP^{IC+}		0.0134		0.0346		0.0145		0.0050
		(9.67)		(12.71)		(13.72)		(7.06)
Standard Q*TFP^{IC+}		-0.0006		-0.0010		-0.0001		0.0001
		(-4.93)		(-3.12)		(-0.70)		(1.43)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
With-in R^2	0.03	0.04	0.11	0.12	0.10	0.12	0.06	0.07
N	33,028	33,028	33,028	33,028	33,028	33,028	33,028	33,028
Panel B: Total Q								
	Physical		CAPEX/PPE		Intangible		R&D	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total Q	0.0147	0.0205	0.0344	0.0373	0.0128	0.0106	0.0058	0.0033
	(22.23)	(14.64)	(24.52)	(13.51)	(23.11)	(10.84)	(14.19)	(4.56)
TFP^{IC+}		0.0113		0.0334		0.0119		0.0034
		(8.81)		(10.94)		(10.20)		(4.39)
Total Q*TFP^{IC+}		-0.0037		-0.0035		0.0005		0.0011
		(-5.78)		(-2.22)		(0.82)		(2.51)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
With-in R^2	0.10	0.10	0.11	0.13	0.13	0.16	0.07	0.09
N	33,028	33,028	33,028	33,028	33,028	33,028	33,028	33,028

Online Appendices

A TFP estimation

(1) Data

I use two main datasets to estimate the total factor productivity (TFP): Annual Compustat and CRSP files, by matching Compustat and CRSP. The sample period starts from 1966 to 2020. Compustat items used include total assets (AT), gross (net) property, plant, and equipment (PPEGT and PPENT), sales (SALE), operating income before depreciation (OIBDP), depreciation (DP), capital expenditure (CAPX), cost of goods sold (COGS), selling, general, and administrative expense (XSGA), sale of property, plant, and equipment (SPPE), depreciation, depletion and amortization (DPACT), employees (EMP), and staff expense (XLR).

I apply several filters to select the sample firms. I include common stocks listed at NYSE/Amex/Nasdaq. I exclude the financial firms and the utility firms (four-digit SIC between 6000 - 6999 or 4900 - 4999). Also, firms with missing or negative book value of equity, stock price less than $1, missing or negative cost of goods sold (COGS), negative selling, general, and administrative expense (XSGA), and missing capital expenditures (CAPX) and gross (net) property, plant, and equipment (PPEGT and PPENT). Finally, the sample firms should report their accounting information more than 2 years to avoid the survivorship bias.

To calculate real values, I use GDP deflator (NIPA table 1.1.9 line1) and price index for nonresidential private fixed investment(NIPA table 5.3.4 line2).

(2) Input variables

I calculate value-added, employment, physical capital, intangible capital, and investment to estimate TFP.

Value-added (Y_{it}) is $\frac{Sales_{it} - Materials_{it}}{GDP\_deflator}$. Material cost ($Materials_{it}$) is total expenses minus labor expense as well as 0.3*selling, general, and administrative expense. Total expense is sales (SALE) minus operating income before depreciation and amortization (OIBDP). Labor expense is the staff expense (XLR). However, only a small number of firms report the staff expense. I replace the missing observations with the interaction of industry average labor expense ratio and total expense. To be specific, I calculate the labor expense ratio, $\frac{xlr_{it}}{sales_{it}-oibdp_{it}}$, for each firm. Next, in each year I estimate the industry average of the labor expense ratio at 3-digit SIC code level if there are at least 2 firms. Otherwise, I estimate the industry average of the labor expense ratio at 2-digit SIC code level. In the same manner, I estimate the industry average of labor expense ratio at 1-digit. Then, I back out the staff expense by multiplying the industry average labor expense ratio and total expense. To avoid the measurement error, I drop the observations with non-positive total expense, non-positive labor expense ratio, or labor expense ratio higher than 1.

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

Investment (I_{it}) is capital expenditure (CAPX) minus sale of property, plant, and equipment (SPPE), which I replace the missing SPPE with 0, deflated by current fixed investment price index.

Labor (L_{it}) is the number of employees.

Intangible capital stock (OC_{it}) is the organizational capital from Eisfeldt and Papanikolaou (2013) and Peters and Taylor (2017). I estimate the organizational capital (OC_{it}) using the perpetual inventory method as follows,

$$OC_{it} = (1-\delta_{OC})OC_{it-1} + \frac{0.3 * XSGA_{it}}{cpi_t} \tag{18}$$

where cpi_t denotes the consumer price index from BLS. The initional organizational capital stock (OC_0) equals $\frac{0.3*XSGA_{i1}}{g+\delta_{OC}}$. I choose the growth rate (g) and the depreciation rate (δ_{OC})

to 10% and 15%, respectively. I replace the missing value of XSGA with zero. Similar to K_{it}, I take one-year lag for the capital stock to measure the available capital stock at the beginning of the period.

(3) TFP estimation

I follow Olley and Pakes (1996) to estimate the total factor productivity (TFP). Olley and Pakes (1996) provide a robust way to measure production function parameters, solving the simultaneity problem and selection bias. Olley and Pakes (1996) estimate the labor coefficient and the capital coefficient separately to avoid the simultaneity problem. Also, they include the exit probability in TFP estimation process to avoid the selection bias. Imrohoroglu and Tuzel (2014) show how to estimate Olley and Pakes (1996) TFP using annual Compustat and share their codes.[23] I extend Imrohoroglu and Tuzel (2014) to include the intangible capital as additional production factor.

I start from the Cobb-Douglas production technology with three production factors.

$$Y_{it} = Z_{it} L_{it}^{\beta_L} K_{it}^{\beta_K} OC_{it}^{\beta_{OC}} \tag{19}$$

where $Y_{it}, Z_{it}, L_{it}, K_{it}$, and OC_{it} are value-added, productivity, labor, physical capital stock, and intangible capital stock of a firm i at time t. We scale the production function by its physical capital stock for several reasons. First, since TFP is the residual term, it is often highly correlated with the firm size. Second, this avoids estimating the capital coefficient directly. Third, there is an upward bias in labor coefficient without scaling. After being scaled by the capital stock and transformed into logarithmic values, Eq.(19) is rewritten as

$$Log\frac{Y_{it}}{K_{it}} = \beta_L Log\frac{L_{it}}{K_{it}} + (\beta_K + \beta_L + \beta_{OC} - 1)LogK_{it} + \beta_{OC} Log\frac{OC_{it}}{K_{it}} + LogZ_{it} \tag{20}$$

We define $Log\frac{Y_{it}}{K_{it}}$, $Log\frac{L_{it}}{K_{it}}$, $LogK_{it}$, $Log\frac{OC_{it}}{K_{it}}$ and $LogZ_{it}$ as yk_{it}, lk_{it}, k_{it}, ok_{it} and z_{it}. Also,

[23] Available at http://www-bcf.usc.edu/ tuzel/TFPUpload/Programs/

denote β_L, $(\beta_K + \beta_L + \beta_{OC} - 1)$, β_{OC} as β_l, β_k, and β_{oc}. Rewrite Eq.(20) as

$$yk_{it} = \beta_l lk_{it} + \beta_k k_{it} + \beta_{oc} ok_{it} + z_{it} \tag{21}$$

Olley and Pakes (1996) assume a monotonic relationship between the investment and productivity (i.e., investment captures information of productivity). Hence, productivity is a function of investment, i.e., $z_{it} = h(ik_{it})$ and assume that the function $h(ik_{it})$ is 2^{nd}-order polynomials of ik_{it}. I further assume that the productivity is a function of both physical investment as well as intangible investment. Further, since the intangible capital is the funcation of the intangible investment in equation (8), I assume that the productivity is a function of both physical investment as well as intangible capital.

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

$$y_{it} = \beta_l lk_{it} + \beta_k k_{it} + \beta_{oc} ok_{it} + \beta_0 + \beta_{ik} ik_{it} + \beta_{ik^2} ik_{it}^2 + \beta_{oc^2} ok_{it}^2 + \beta_{ikoc} ik_{it} ok_{it} + \eta_t + \eta_j + \epsilon_{it} \tag{22}$$

where $h(ik_{it}) = \beta_0 + \beta_{ik} ik_{it} + \beta_{ik^2} ik_{it}^2 + \beta_{oc} ok_{it} + \beta_{oc^2} ok_{it}^2 + \beta_{ikoc} ik_{it} ok_{it}$. I include year ($\eta_t$)and 4-digit SIC industry fixed (η_j) effect to capture the differences of industrial technologies over time. From this stage, we estimate the labor coefficients, $\widehat{\beta}_l$.

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

$$\begin{aligned} E_t(yk_{i,t+1} - \widehat{\beta}_l lk_{i,t+1} - \eta_t - \eta_j) &= \beta_k k_{i,t+1} + \beta_{oc} ok_{i,t+1} + E_t(z_{i,t+1} | z_{i,t}, survival) \\ &= \beta_k k_{i,t+1} + + \beta_{oc} ok_{i,t+1} + g(z_{it}, \widehat{P}_{survival,t}) \end{aligned} \tag{23}$$

where $\widehat{P}_{survival,t}$ is the probability of a firm survival from t to t+1. The probability is estimated with the Probit regression of a survival indicator variable on the 2nd polynomials in investment and intangible capital. z_{it} is $\beta_0 + \beta_{ik} ik_{it} + \beta_{ik^2} ik_{it}^2 + \beta_{oc} ok_{it} + \beta_{oc^2} ok_{it}^2 + \beta_{ikoc} ik_{it} ok_{it}$. The Function g is the 2nd-order polynomials of the survival probability ($\widehat{P}_{survival,t}$) and lagged TFP (z_{it}). At this step, we estimate the coefficient of physical capital, $\widehat{\beta}_k$, which gives $\widehat{\beta_K}$, and the coefficient of intangible capital, $\widehat{\beta_{oc}}$.

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

$$TFP_{it} = exp(yk_{it} - \widehat{\beta}_l lk_{i,t} - (\beta_K + \widehat{\beta_l + \beta}_{oc} - 1)k_{it} - \widehat{\beta}_{oc} ok_{i,t} - \eta_t - \eta_j) \tag{24}$$

I truncate TFP at 0.5^{th} and 99.5^{th} percentile every year. TFP estimates are available from 1972 to 2020. I estimate TFP with the 5-year rolling-window to estimate production technology changes over time.

Finally, I define total factor productivity as intangible capital adjusted productivity (TFP^{IC+}). Also, I estimate total factor productivity without intangible capital in the above process, and define it as intangible capital omitted productivity (TFP^{IC-}).

B Variable definitions

Variable	
Size	Firm size is the logrithimic value of market capitalization at month t-1.
Size (bil)	Firm size is the dollaor amount of market capitalization in billions at month t-1.
BM	Book-to-market ratio is defined as the ratio of book value of equity for the last fiscal year-end in year t over market capitalization in December of year t. Book value of equity is computed in Fama and French (1993).
OA	Organizational capital over book value of total assets. Organizational capital is estimated by following Eisfeldt and Papanikolaou (2013) and Peters and Taylor (2017), described in Section 2.1.
I/A	Physical investment is the capital expenditure over book value of total assets.
HR	Labor hiring is the growth of employment.
I_{OC}/OC	Organizational investment (I_{OC}) over organizational capital. Organizational investment (I_{OC}) equals 0.3*selling, general, and administrative expense (XSGA), scaled by consumer price index.
ROE	Return-on-equity is net income over book value of equity.
GP	Gross profitability is revenue minus cost of goods sold, scaled by total asset.
Mom	Momentum is the cumulative return from prior twelve-month (from t-2 to t-13) with a one-month gap in month t.
Ret_{t-1}	Reversal is the prior one-month return.
Ivol	Idiosyncratic volatility is computed as the standard deviation of the daily residual return from Fama-French three-factor models every month t.
β_{MKT}	Market beta is a firm's exposure with respect to market portfolio over the last 5 years (60 months) in the market model. Market portfolio is the CRSP value-weighted portfolio from Kenneth French's website.
Standard Q	Following Peters and Taylor (2017), Standard Q is the firm's market value over physical capital. Market value is the market value of outstanding equity (Compustat item prcc_f times csho), plus the book value of debt (Compustat items dltt + dlc), minus the firm's current assets (Compustat item act).
Total Q	Following Peters and Taylor (2017), Total Q is the firm's market value over total capital. Market vaue is same as one from Standard Q. Total capital equals physical capital and intangible capital.
Physical capital	Physical capital is the book value of property, plant, and equipment (Compustat item ppegt).
Intangible capital	Intangible capital equals externally purchased intangible capital plus internally created intangible capital. Externally purchased intangible capital is intangible assets from the balance sheet (Compustat item intan), which equals zero if missing. Internally created capital is the sum of knowledge capital and organizational capital. Knowledge capital is estimated using the perpetual inventory method as follows, $KC_{it} = (1 - \delta_{KC})KC_{it-1} + XRD_{it}$ For the depreciation rate, I use BEA's industry-specific R&D depreication rates. I replace the missing value of R&D expenditure (XRD) with zero. Initial knowledge capital is $\frac{XRD_{i1}}{g+\delta_{KC}}$. I choose the growth rate as the average growth rate across BEA industry.

C Robustness checks: Model specifications in the rolling window

To avoid the look-ahead bias, I use the rolling betas of various alternative pricing factors, and estimate the regression results in Table C1. First, in Panel A, I estimate the intangible capital by adding knowledge capital (KC) to organizational capital (OC), and construct the pricing factor of intangible capital adjusted productivity (TFP^{IC+}_{OC+KC}). Similar to the full-sample betas, the price of risk for TFP^{IC+}_{OC+KC} ($\gamma_{TFP^{IC+}}$) is significant and negative across all factor models. The magnitude is -0.53% per month (t=-2.81) in FF4+TFP^{IC+}. Also, adding TFP^{IC+}_{OC+KC} increases the explanatory power. For example, while FF4 has R^2 of 0.56, FF4+TFP^{IC+} has 0.76. Second, Panel B reports the rolling window betas using Fama-French style TFP pricing factors, and find the similar results. While the magnitude becomes smaller than the original pricing factor, it still significantly negative and improve the model performance. For exmple, CAPM+TFP^{IC+} has the insignificant alphas at 5% significant level. Overall, Table C1 confirms that the main results are robust.

D Pricing of intangible capital omitted productivity (TFP^{IC-})

Panel A of Table D1 presents the value-weighted excess returns and abnormal returns of TFP^{IC-} sorted portfolios as well as the zero-cost portfolio (H-L), which take the long position on the highest TFP^{IC-} sorted portfolio (H) and the short position on the lowest TFP^{IC-} sorted portfolio (L). The expected return does not decrease over TFP^{IC-} sorted portfolios. H-L generates -0.04% per month (t=-0.23). The abnormal returns of H-L also generate insignificant. Turning to Panel B, I compute the equal-weighted returns for TFP^{IC-} sorted portfolios. I see that the expected return decreases over TFP^{IC-}, and H-L generates the significantly negative return. It is -0.40% per month (t=-3.29). Alphas of CAPM, FF3, and FF4 are all significantly negative. This is consistent with the univariate sorts of Imrohoroglu and Tuzel (2014) finding that the effect of TFP^{IC-} is stronger for small sized firms.

E The pricing mechanism of intangible capital omitted productivity (TFP^{IC-})

I examine whether TFP^{IC-} shares the same risk component of TFP^{IC+} by testifying the displacement risk via the investment-specific shock.

First, I annualize value-weighted returns of TFP^{IC-} sorted portfolio at the end of December, and estimate the exposure of IST-shock by regressing annual portfolio returns on IST-shock with other pricing factors in Table E1. Panel A uses only IST-shock, and presents the exposure of IST-shock (β_{IST}). β_{IST} does not decrease over TFP^{IC-} portfolios. The zero-cost portfolio (H-L) has the insignificant β_{IST}. This is consistent with the univariate sorts in Table D1, which shows that H-L has an insignificant return. Second, from Panel B-D, I additionally control pricing factors with IST-shock, and find that β_{IST} are not significantly different across high and low TFP^{IC-}.

Second, I estimate the equation (15) by replacing TFP^{IC+} with TFP^{IC-} in Table E2. First, for the first three columns, I use the operating profitability (Cop). I find that the effects of own innovation ($\theta_{i,t}$) and innovation by competitors ($\theta_{I\backslash i,t}$) are consistent with the findings from Kogan et al. (2017). The coefficient of $\theta_{i,t}$ is significantly positive over next 3 years while the coefficient of $\theta_{I\backslash i,t}$ is significantly negative over next 3 years. That is, own innovation increases future profits but innovation by competitors hurts future profits. Second and more importantly, both the interaction term between $\theta_{i,t}$ and TFP^{IC-} and the interaction term between $\theta_{I\backslash i,t}$ and TFP^{IC-} are insignificant. This suggests that the effect of technological shock on future profit does not vary across TFP^{IC-}. That is, high TFP^{IC-} firms do not provide hedging effect against the innovation shock from competitors. Third, I use the different fundamental variables. I find that labor growth and intangible capital growth have the insignificant interaction effect.

Overall, two test results suggest that while TFP^{IC+} and TFP^{IC-} are highly correlated, TFP^{IC+} reflects the investment-specific shock better than TFP^{IC-}.

Table C1. **Robustness checks: Model specifications**

This table presents Fama-MacBeth regressions using the excess returns of 25 portfolios sorted by size and book-to-market ratio. Factors include Fama and French (1993) three factors, Carhart (1997) momentum factor, and the pricing factor of intangible capital adjusted productivity (TFP^{IC+}). I consider the zero-cost portfolio of TFP^{IC+} (H-L) as the pricing factor of TFP^{IC+}. Panel A uses the TFP^{IC+} by using alternative intangible capital combining organizational capital (OC) and knowledge capital (KC) (TFP^{IC+}_{OC+KC}). Panel B uses the conventional pricing factor by following Fama and French (1993). The factor betas are computed over the rolling window. All coefficients are multiplied by 100. The t-statistics are in parentheses and adjusted for errors-in-variables, following Shanken (1992). The adjusted R^2 follows Jagannathan and Wang (1996). The 5^{th} and 95^{th} percentiles of the adjusted R^2 distribution from a bootstrap simulation of 10,000 times are reported in brackets. The sample period is July 1972 to June 2021.

Panel A: Adding Knowledge capital (TFP^{IC+}_{OC+KC})

	TFP^{IC+}		CAPM		CAPM+TFP^{IC+}		FF3		FF3+TFP^{IC+}		FF4		FF4+TFP^{IC+}	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.59	3.17	0.88	3.18	0.69	3.00	0.14	4.64	0.14	4.10	0.15	4.20	0.15	4.06
γ_{MKT}			-0.08	-0.26	0.00	0.02	0.54	2.85	0.55	2.85	0.56	2.94	0.56	2.9
γ_{SMB}							0.19	1.49	0.19	1.46	0.18	1.39	0.17	1.34
γ_{HML}							0.14	1.06	0.14	1.05	0.15	1.13	0.14	1.1
γ_{UMD}											0.37	2.03	0.38	2.06
$\gamma_{TFP^{IC+}}$	-1.06	-4.22			-1.07	-3.76			-0.50	-2.70			-0.53	-2.81
R^2	0.76		0.22		0.73		0.52		0.74		0.56		0.76	
(5^{th}, 95^{th})	(0.28, 0.85)		(-0.12, 0.46)		(0.48, 0.86)		(0.32, 0.78)		(0.55, 0.89)		(0.43, 0.82)		(0.62, 0.91)	

Panel B: Constructing the pricing factors following Fama-French

	TFP^{IC+}		CAPM		CAPM+TFP^{IC+}		FF3		FF3+TFP^{IC+}		FF4		FF4+TFP^{IC+}	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
γ_0	0.93	4.84	0.88	3.18	0.25	1.78	0.14	4.64	0.13	3.71	0.15	4.20	0.14	3.7
γ_{MKT}			-0.08	-0.26	0.46	1.96	0.54	2.85	0.56	2.89	0.56	2.94	0.58	3
γ_{SMB}							0.19	1.49	0.18	1.44	0.18	1.39	0.17	1.32
γ_{HML}							0.14	1.06	0.13	0.96	0.15	1.13	0.14	1.03
γ_{UMD}											0.37	2.03	0.39	2.11
$\gamma_{TFP^{IC+}}$	-0.36	-2.93			-0.32	-2.45			-0.29	-3.26			-0.31	-3.39
R^2	0.25		0.22		0.62		0.52		0.72		0.56		0.75	
$(5^{th}, 95^{th})$	(0.17, 0.65)		(-0.12, 0.46)		(0.35, 0.78)		(0.32, 0.78)		(0.52, 0.87)		(0.43, 0.82)		(0.60, 0.89)	

Table D1. **Excess returns for TFP^{IC-} sorted portfolios**

This table presents the portfolio returns for the intangible capital omitted productivity (TFP^{IC-}) sorted portfolios. All stocks are sorted into 10 portfolios, based on TFP^{IC-}. I sort stocks on TFP^{IC-} at June of t by using TFP^{IC-} in the last fiscal year $t-1$, and hold the portfolios from July of t to June of $t+1$. Panel A reports the value-weighted portfolio returns (R^{ex}) and alphas (α^{CAPM}, α^{FF3}, and α^{FF4}) over TFP^{IC-} sorted portfolios as well as the zero-cost portfolio (H-L). #firms is the average number of firms in each portfolio. Panel B shows the equal-weighted portfolios in the similar manner. Panel C reports the time-series factor-loadings and R^2 of CAPM, Fama and French (1993) three-factor model (FF3), and Carhart (1997) four-factor model (FF4) against the value-wegihted and the equal-weighted zero-cost portfolios (H-L), respectively. Newey-West adjusted t-statistics with six-month lags are in parentheses. All returns are multiplied by 100. The sample period is from July 1972 to June 2021.

Panel A: Value-weighted TFP^{IC-}-sorted portfolios											
	Low	2	3	4	5	6	7	8	9	High	H-L
R^{ex}	0.76	0.71	0.69	0.67	0.65	0.68	0.58	0.68	0.57	0.72	-0.04
	(2.80)	(2.82)	(2.98)	(3.02)	(3.30)	(3.85)	(3.10)	(3.46)	(2.76)	(2.92)	(-0.23)
α^{CAPM}	0.00	0.00	0.01	0.03	0.03	0.12	-0.02	0.11	-0.04	0.04	0.04
	(0.03)	(-0.04)	(0.13)	(0.32)	(0.36)	(1.27)	(-0.22)	(1.37)	(-0.48)	(0.34)	(0.19)
α^{FF3}	-0.05	-0.10	-0.01	-0.05	0.01	0.12	0.01	0.10	0.00	0.20	0.25
	(-0.35)	(-0.92)	(-0.12)	(-0.53)	(0.17)	(1.32)	(0.13)	(1.46)	(0.04)	(2.00)	(1.44)
α^{FF4}	0.19	0.08	0.13	0.07	0.05	0.18	0.05	0.20	0.14	0.31	0.11
	(1.37)	(0.81)	(1.41)	(0.84)	(0.61)	(2.08)	(0.55)	(3.02)	(1.67)	(3.02)	(0.67)
#firms	102	105	106	106	106	107	107	107	107	107	
Panel B: Equal-weighted TFP^{IC-}-sorted portfolios											
	Low	2	3	4	5	6	7	8	9	High	H-L
R^{ex}	1.27	1.15	1.10	1.03	1.08	1.07	0.93	1.01	0.98	0.87	-0.40
	(4.09)	(4.14)	(4.14)	(4.04)	(4.32)	(4.24)	(3.86)	(4.14)	(3.78)	(3.15)	(-3.29)
α^{CAPM}	0.50	0.41	0.35	0.30	0.38	0.36	0.20	0.28	0.23	0.06	-0.44
	(2.75)	(2.57)	(2.43)	(2.21)	(2.72)	(2.63)	(1.70)	(2.46)	(1.90)	(0.47)	(-3.76)
α^{FF3}	0.37	0.23	0.20	0.15	0.25	0.25	0.10	0.23	0.19	0.06	-0.31
	(3.04)	(2.43)	(2.30)	(2.02)	(3.42)	(2.94)	(1.34)	(2.98)	(2.52)	(0.77)	(-2.93)
α^{FF4}	0.56	0.40	0.35	0.31	0.36	0.41	0.25	0.38	0.32	0.22	-0.34
	(4.15)	(3.91)	(3.78)	(3.72)	(5.09)	(4.60)	(3.37)	(4.83)	(3.97)	(2.43)	(-2.97)
#firms	102	105	106	106	106	107	107	107	107	107	

Panel C: Factor-loadings of the zero-cost portfolio (H-L)						
	Value-weighted H-L			Equal-weighted H-L		
	CAPM	FF3	FF4	CAPM	FF3	FF4
β_{MKT}	-0.13	-0.13	-0.09	0.06	0.07	0.08
	(-2.73)	(-2.81)	(-2.13)	(1.53)	(2.42)	(2.75)
β_{SMB}		-0.44	-0.44		-0.33	-0.33
		(-4.20)	(-4.56)		(-10.04)	(-9.94)
β_{HML}		-0.46	-0.40		-0.27	-0.25
		(-5.27)	(-5.41)		(-6.00)	(-5.28)
β_{UMD}			0.15			0.04
			(2.88)			(1.15)
R^2	0.02	0.20	0.22	0.01	0.23	0.23

Table E1. **Exposure of portfolio returns to investment-specific shock (IST-shock)**

This table presents the regression results from annual excess returns on the investment-specific shock (IST-shock) and other pricing factors over value-weighted TFP^{IC-} sorted portfolios. IST-shock is estimated by following Cummins and Violante (2002) using the aggregate quality-adjusted price index. Panel A uses IST-shock; Panel B uses the market portfolio of CAPM and IST-shock; Panel C uses three-factors of Fama and French (1993) and IST-shock; Panel D uses four-factors of Carhart (1997) and IST-shock. Newey-West t-statistics with five-year lags are in parentheses. The sample period is from 1972 to 2021.

	Low	2	3	4	5	6	7	8	9	High	H-L
Panel A: IST-shock											
β_{IST}	-3.24	-4.56	-2.10	-3.06	-1.03	-0.62	-1.76	-2.72	-1.46	-1.99	1.24
	(-2.12)	(-4.21)	(-2.43)	(-3.70)	(-0.87)	(-0.70)	(-1.32)	(-2.63)	(-1.70)	(-1.27)	(1.18)
R^2	0.09	0.19	0.05	0.12	0.02	0.01	0.05	0.12	0.04	0.04	0.02
Panel B: CAPM+IST-shock											
β_{IST}	-1.35	-2.71	-0.29	-1.29	0.51	0.72	-0.07	-1.10	0.17	0.05	1.40
	(-1.33)	(-4.85)	(-0.48)	(-3.11)	(0.99)	(2.03)	(-0.12)	(-3.24)	(0.45)	(0.06)	(1.23)
β_{MKT}	1.08	1.06	1.04	1.02	0.89	0.77	0.97	0.93	0.94	1.18	0.09
	(8.53)	(9.82)	(8.91)	(19.87)	(21.45)	(8.43)	(12.82)	(14.62)	(20.77)	(11.02)	(0.56)
R^2	0.64	0.78	0.81	0.88	0.90	0.78	0.89	0.88	0.88	0.74	0.03
Panel C: FF3+IST-shock											
β_{IST}	-1.26	-2.53	-0.30	-1.26	0.52	0.74	-0.05	-1.11	0.10	-0.25	1.01
	(-1.19)	(-5.16)	(-0.52)	(-3.43)	(0.98)	(1.98)	(-0.09)	(-3.14)	(0.30)	(-0.32)	(0.86)
β_{MKT}	1.04	1.10	1.03	0.99	0.88	0.76	0.98	0.97	0.98	1.07	0.03
	(10.55)	(13.06)	(9.12)	(21.87)	(23.38)	(8.58)	(12.86)	(16.47)	(29.07)	(11.75)	(0.32)
β_{SMB}	0.35	0.23	0.02	0.16	0.05	0.07	0.02	-0.17	-0.28	-0.22	-0.57
	(2.16)	(1.66)	(0.16)	(1.92)	(0.62)	(0.45)	(0.31)	(-1.85)	(-4.32)	(-1.55)	(-2.33)
β_{HML}	0.00	0.23	-0.03	-0.03	0.00	0.00	0.02	0.06	0.00	-0.46	-0.46
	(-0.01)	(2.04)	(-0.42)	(-0.57)	(-0.07)	(0.01)	(0.30)	(0.82)	(-0.02)	(-5.13)	(-2.63)
R^2	0.66	0.82	0.81	0.89	0.90	0.78	0.89	0.90	0.91	0.83	0.30
Panel D: FF4+IST-shock											
β_{IST}	-0.18	-1.88	0.08	-0.92	0.61	0.84	-0.14	-0.93	0.30	0.37	0.55
	(-0.29)	(-4.09)	(0.14)	(-2.13)	(1.14)	(2.14)	(-0.24)	(-2.37)	(0.82)	(0.59)	(0.48)
β_{MKT}	0.93	1.03	0.99	0.96	0.87	0.75	0.99	0.95	0.96	1.01	0.08
	(14.44)	(15.87)	(10.21)	(27.39)	(21.97)	(8.18)	(13.14)	(15.01)	(31.36)	(10.92)	(0.79)
β_{SMB}	0.20	0.14	-0.03	0.11	0.03	0.06	0.03	-0.19	-0.31	-0.31	-0.51
	(1.15)	(1.24)	(-0.21)	(1.43)	(0.48)	(0.36)	(0.48)	(-2.22)	(-4.74)	(-2.13)	(-2.04)
β_{HML}	-0.13	0.15	-0.08	-0.07	-0.01	-0.01	0.03	0.04	-0.02	-0.53	-0.40
	(-0.65)	(1.26)	(-1.01)	(-1.43)	(-0.24)	(-0.12)	(0.45)	(0.52)	(-0.71)	(-6.58)	(-2.14)
β_{UMD}	-0.53	-0.32	-0.19	-0.17	-0.05	-0.05	0.04	-0.09	-0.10	-0.31	0.23
	(-0.70)	(1.93)	(-1.50)	(-1.10)	(-0.64)	(-0.22)	(0.64)	(0.51)	(-0.63)	(-8.57)	(-2.31)
R^2	0.79	0.87	0.83	0.91	0.90	0.78	0.89	0.90	0.92	0.88	0.35

Table E2. **Firms' response to innovation news**

This table presents the regression results from the equation as follows,

$$Y_{i,t+\tau} = \beta_0 + \beta_{\theta_i}\theta_{i,t} + \beta_{\theta_i * TFP^{IC-}}\theta_{i,t} * TFP^{IC-}_{i,t} + \beta_{\theta_{I\setminus i}}\theta_{I\setminus i,t} + \beta_{\theta_{I\setminus i} * TFP^{IC-}}\theta_{I\setminus i,t} * TFP^{IC-}_{i,t} + \beta_{TFP^{IC-}} TFP^{IC-}_{i,t} + cZ_{it} + d_t + d_j + \epsilon_{i,t+\tau} \quad (25)$$

$Y_{i,t+\tau}$ is future fundamentals including operation profitability (Cop), Lerner index, employment growth from t to $t+\tau$ (ΔL), physical capital growth from t to $t+\tau$ (ΔK), and intangible capital growth from t to $t+\tau$ (ΔOC) (τ=1 to 3). $\theta_{i,t}$ is a market value of all innovations of firm i in year t. In Panel A (B), $\theta_{I\setminus i,t}$ is a market value of all innovations by firm i's competitors (all firms except for firm i). TFP^{IC-} is the intangible capital omitted productivity. Z_{it} is the vector of control variables, including logarithmic value of employment, physical capital, and intangible capital and idiosyncratic volatility. d_t and d_j are time-fixed and industry-fixed effects, respectively. We estimate $\theta_{i,t}$ as the ratio of the innovative output of a firm i in year t over its total asset in year t. We estimate $\theta_{I\setminus i,t}$ as the weighted average of the innovative output of a firm i's competitors (all firms except for firm i) in each year t, $\frac{\Sigma_{i\in I\setminus i}\theta_{i,t}}{\Sigma_{i\in I\setminus i}AT_{i,t}}$ where AT_{it} is total asset in year t. The competitors are defined as any firms in the same 3-digit SIC industry with a firm i in year t. We winsorize all variables at 1% and 99%. Standard errors are clustered by firm and year, t-statistics are reported in parentheses. I report R^2 and the number of observations (N). The sample period is from 1972 to 2021.

	Cop			Lerner index			ΔL			ΔK			ΔOC		
τ	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
θ_{it}	0.11	0.11	0.10	0.02	0.03	0.03	0.09	0.19	0.27	0.15	0.30	0.46	0.04	0.07	0.11
	(4.54)	(4.45)	(3.77)	(0.59)	(0.91)	(0.80)	(2.34)	(2.51)	(2.24)	(3.41)	(3.11)	(2.95)	(1.65)	(1.64)	(1.59)
θ_{it}*TFP^{IC-}	-0.01	-0.02	-0.02	0.02	0.02	0.02	0.00	-0.01	-0.01	-0.02	-0.02	-0.04	0.00	0.00	0.00
	(-1.51)	(-1.66)	(-1.50)	(1.63)	(0.91)	(1.02)	(-0.23)	(-0.19)	(-0.25)	(-1.00)	(-0.51)	(-0.61)	(-0.28)	(-0.13)	(0.03)
$\theta_{I\setminus i,t}$	-0.10	-0.10	-0.10	-0.16	-0.15	-0.16	-0.12	-0.20	-0.31	-0.19	-0.36	-0.62	-0.03	-0.07	-0.11
	(-2.51)	(-2.71)	(-2.58)	(-3.20)	(-2.96)	(-2.77)	(-2.52)	(-1.96)	(-1.93)	(-3.92)	(-3.30)	(-3.06)	(-1.58)	(-1.70)	(-1.76)
$\theta_{I\setminus i,t}$*TFP^{IC-}	0.04	0.03	0.03	0.09	0.08	0.08	0.04	0.04	0.07	0.11	0.17	0.30	0.02	0.04	0.06
	(1.36)	(1.47)	(1.44)	(2.53)	(2.57)	(2.32)	(1.04)	(0.75)	(0.77)	(2.90)	(2.33)	(2.26)	(1.53)	(1.48)	(1.41)
TFP^{IC-}	0.03	0.02	0.02	0.02	0.02	0.02	0.04	0.07	0.11	0.05	0.11	0.17	0.02	0.04	0.06
	(14.18)	(12.17)	(10.42)	(13.55)	(10.65)	(8.40)	(9.91)	(8.77)	(7.96)	(10.74)	(10.29)	(9.99)	(16.58)	(16.60)	(16.84)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.23	0.20	0.19	0.26	0.24	0.23	0.09	0.12	0.13	0.14	0.17	0.18	0.67	0.65	0.64
N	40,977	40,977	40,977	40,977	40,977	40,977	40,977	40,977	40,977	40,977	40,977	40,977	40,977	40,977	40,977

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