Labor Skills and Technology Change: An Asset Pricing Implication

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Preliminary Draft

Abstract

The productivity of skilled labor is subjected to aggregate technology innovation, implying that a firm's usage of skilled labor determines its exposure to the shock. I find that profits are more sensitive to technology shocks in firms depend more on skilled worker. Combined with the positive price of technology risk, high skill firms exhibit higher expected returns than low skill firms. The results highlight the importance of labor characteristics on asset prices.

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1 Introduction

Investment-specific technology shock has known to be an important factor in explaining aggregate productivity and economic growth (Greenwood et al. (1997, 2000), Fisher (2006)). Since positive investment-specific technology shock is associated with relative decline in investment costs, Papanikolaou (2011) and Kogan and Papanikolaou (2013, 2014) show that technology shock is a priced risk factor that explain time-series and cross-sectional return predictability in asset prices.

The advance in technology is also associated with the demand of labor forces. Technology change has been skill-biased in that the productivity of skilled workers has increased more rapidly than that of less skilled workers. Much attention has given to the technological change due to its ability to explain several phenomena in labor market, such as increasing skill premium, rising inequality, and job polarization (Krusell et al. (2000), Acemoglu (2002), Parker and Vissing-Jorgensen (2010), Autor and Dorn (2013)).

In this study, I examine the role of technology shock on asset prices through the labor channel. Following the labor economics literature, I postulate that the firm production depends on two labor groups (skilled and unskilled workers) and two aggregate shocks (productivity and technology shocks). In this setup, technology innovation involves changes in the productivity of skilled labor only. If firms are operated solely by skilled workers, those firms will be totally exposed to technology shock. On the other hand, firms will be totally isolated from the technology change if they are run by unskilled workers. This simple relation between technology shock and labor composition raises rich implications for firm risk profile.

Using the quality-adjusted price of capital goods relative to consumption goods proposed by Greenwood et al. (1997) as proxy for technology innovation, I start by investigating the dynamics of firm profits alongside technology innovation. Through firm-level panel regression, I find that high skill firms tend to have higher profitability when positive shock arrives, compared to low skill firms. The result implies an skill-induced operating leverage effect that amplifies firms' exposure to systematic risk. Therefore, if technology shock carries a negative risk premia as in Papanikolaou (2011), high skill firms should have lower expected returns than low skill firms in the cross-section.

Regarding the price of technology risk, there is a debate on the sign of technology risk premia. Li (2014) and Garlappi and Song (2016) propose a positive risk price of technology shock, as opposed to Papanikolaou (2011) and Kogan and Papanikolaou (2013, 2014).[1] Due to the debate in the literature, I conduct cross-sectional tests to identify the sign of risk price in my sample. First, I calculate individual stock's technology beta, and form portfolios based on it. I also implement Fama-MacBeth cross-sectional regressions with a broad set of test portfolios to directly infer the price of risk. In all, my estimation results indicate a positive technology risk premia at least within my sample.

This suggests that investors demand higher expected stock returns for holding high skill stocks relative to low skill stocks. Consistent with the prediction, I find that high skill firms exhibit higher returns in the cross-section. The average equal-weighted skill spread measured by Fama-French five factor model is 0.75% monthly. However, the same skill spread becomes 0.47% when technology factor is included to obtain alphas, implying that a signification portion of the skill premia is subsumed by technology factor alone. I find similar or even stronger result when Q-factor model (from Hou et al. (2015)) is used. An increasing pattern of technology beta across portfolios further supports the intuition.

This study mostly contributes to recent advances in asset pricing with labor market. In the literature, only few studies highlight the importance of labor skills. Ochoa (2013) shows that high skill firm are risky due to their exposure to volatility shock. Because skilled labor is costly to adjust, investors demand high returns for high skill firms, especially in highly volatile states. In a neoclassical investment-based model framework, Belo et al. (2016) focuses on the negative hiring-return relation in the cross-section, that is steeper for high skill firms. Both studies rely on the costly adjustment nature of skilled labor, where my findings are based on the relation between labor productivity and economic-wide risk fundamentals.

This study also adds to the literature on the technology innovation as a risk factor. Christiano and Fisher (2003) first relates technology shock to equity premium at aggregate

[1] According to Garlappi and Song (2016), the sign of technology risk price is sensitive to test assets and sample periods used.

level. Papanikolaou (2011) and Kogan and Papanikolaou (2013, 2014) further document that technology shock drives cross-sectional heterogeneity in asset prices, by linking risk exposure to various firm-level characteristics. The main driver of their results is the negative technology risk premia. On the other hand, Li (2014) propose a unified framework that explain the value and momentum strategies simultaneously, suggesting that positive risk premia of technology shock is essential to explain the observed patterns. Garlappi and Song (2016) further examine the role of technology shock in the value and momentum strategies, and estimate positive risk premia using a broad sample data. Through the labor channel, I find a positive technology risk premia, providing supportive evidence for the arguement of Li (2014) and Garlappi and Song (2016).

2 Hypotheses Development

To develop testable hypotheses, I consider a production technology similar to Autor et al. (2008) where each firm produces a perishable good with two inputs, skilled labor (L^s) and unskilled labor (L^u), and two aggregate shocks, skill-neutral productivity shock (A_t) and skill-biased technology shock (Z_t).

$$Y_{i,t} = A_t\Big[\alpha_i(Z_t L^s_{i,t})^\rho + (1-\alpha_i)(L^u_{i,t})^\rho\Big]^{\frac{1}{\rho}}. \tag{1}$$

α_i represents the skill intensity (share of work activities allocated to skilled labor) of firm i. In this setting, heterogeneity across firms stems from skill intensity parameter, α. For example, if α equals to one, firm operation depends only on skilled workers and hence will be perfectly exposed to the advances in technology. In contrast, firm will be totally isolated from the shock when α equals to zero. This type of production implies that skill-intensive firms should have profits that are more sensitive to the shock. At the same time, the effect of productivity shock is skill-neutral. From this specification, it is natural to reach the first testable hypothesis:

Hypothesis 1: Firms that require more skilled labor have profits that are more sensitive to the technology shock, compared to low skill firms.

If technology innovation systematically affects firm operation, the shock should be regarded as economic-wide risk factor. As such, it is important to examine its asset pricing implication. If technology shock is a risk that carry a negative risk premia as in Papanikolaou (2011), high skill firms should have lower expected stock returns. In contrast, those firms should have higher returns if technology shock is associated with positive risk premia as in Li (2014) and Garlappi and Song (2016). This lead to the second testable hypothesis:

Hypothesis 2: If technology shock carries positive (negative) risk premia, then high skill firms have higher (lower) expected stock returns.

3 Data

3.1 Measure of Labor Skill

The key variable throughout the study is the labor skill of a firm. Since it is not able to obtain workforce details within a firm, I define labor skill measure at industry level each year as the fraction of high skilled workers, following Belo et al. (2016). I first classify skilled labor at occupation level using the Dictionary of Occupational Titles (DOT): Revised Fourth Edition, 1991 from U.S. Department of Labor. DOT includes the information on Specific Vocational Preparation (SVP), which measures the amount of lapsed time required by a typical worker to learn the techniques, acquire the information, and develop the facility needed for average performance in a specific job-worker situation. The value of SVP ranges from 1 to 9, where SVP =1 corresponds to the lowest preparation, and SVP = 9 corresponds to the highest preparation of over 10 years. I define a high skill occupation if its SVP index is equal to or greater than 7 (this corresponds to an occupation that requires over 2 years of preparation), and low skill otherwise.

I then obtain industry level measure of labor skill by calculating the percentage of skilled workers in the industry. The data on the number of workers by occupation in each industry is from the Bureau of Labor Statistics, Occupational Employment Statistics

(OES) program.[2] I map SVP information of each occupation to OES data to obtain the skill intensity across industries.[3]

[Insert Table 1]

In Table 1, I report top 5 and bottom 5 skill industries in 2010. In high skill industries, over half of employees are skilled workers while bottom industries use less than one percent of skilled workers among total number of employees. It is clear that there is a heterogeneity of skill requirement across industries.

3.2 Measure of Technology Shock

In the empirical analysis, I rely on two measures of technology shocks. The first measure is the price of new equipment relative to consumption proposed by Greenwood et al. (1997, 2000), which is obtained from macroeconomic data. Krusell et al. (2000) interpret this measure as skill-biased technological change and find that it explains most of variation in skill premium. Following Garlappi and Song (2016), I proxy the technology shock as the innovation in quality-adjusted equipment price relative to consumption:

$$Tech_t = -(ln(P_I/P_C)_t - ln(P_I/P_C)_{t-1}), \tag{2}$$

P_I denotes the price of equipment, and P_C is the price deflator for nondurable consumption goods from the National Income and Product Accounts (NIPA) tables.[4]

The second measure of technology shock is from Papanikolaou (2011), which is obtained from financial data. It is the stock return spread between investment and consumption good producers,

$$IMC_t = r_t^I - r_t^C. \tag{3}$$

For the classification between investment and consumption producers, I follow Gomes et al. (2009) which classify industries into investment and consumption sectors based on

[2] Before 1996, the OES provides employment data once in three years. Therefore, I use the same industry data for three consecutive years to ensure continuous coverage of the full set of industries in early years.

[3] From 1991 to 2001, I calculate industry skill at 3-digit SIC level and 4-digit NAICS level onwards.

[4] I thank Ryan Israelsen for sharing the quality-adjusted equipment price series used in Israelsen (2010).

the contribution to the final demand category in National Income and Product Accounts (NIPA).

This specification assumes that firms producing investment goods have different loadings on the technology shock compared to consumption producers, while both firms have same loadings on the productivity shock. The return difference between investment and consumption firms can be an appropriate measure for technology shock, neutralizing the effect of productivity shock. The advantage of this measure is that it can be measured at monthly or even higher frequency, where the price series in (2) is calculated on annual basis.

4 Empirical Findings

4.1 Sample & Summary Statistics

I construct sample from the intersection of CRSP and Compustat database that span from 1991 to 2012. I exclude financial and utility firms due to their regulatory environment. To avoid results driven by microcap firms discussed in Fama and French (2008), I exclude firms in the lowest 20th size quantile for each year. I keep track of following variables. $Size$ is the firm market capitalization; *BM* is the book-to-market ratio; Inv is the capital expenditures (Compustat item CAPX) to the property, plant, and equipment (item PPENT) ratio; *Book. Lev* is the total debt (item DLC+DLTT) to assets (item AT); $Profit$ is the gross profits (item REVT-COGS) to assets as in Novy-Marx (2013); $Cash\ Flow$ is the ratio of income before extraordinary items (item IB) plus depreciation (item DP) to assets; *Labor* $Share$ is the number of employees (item EMP) to assets ratio; *Cash* is the ratio of cash and cash equivalents (item CHE) to assets ratio.

[Insert Table 2]

In Table 2, I report the time-series average of median characteristics for quintile skill portfolios. On average, high skill firms tend to be smaller, and have lower book-to-market ratio than low skill firms. Moreover, high skill firms have low level of financial leverage, while holding more cash. To summarize, labor skill intensity is related to several firm-level characteristics in the cross-section.

The key property of skill composition is that high skill firms have high exposure to the technology shock. As a preliminary investigation, I directly estimate each stock's technology beta using IMC return as a proxy for technology shock. A stock's monthly IMC beta is obtained by regressing stock return on the IMC return (defined in (3)):

$$r_{i,t} = a_{i,t} + \beta_{i,t}^{IMC} + \epsilon_{i,t}, \forall i, t. \tag{4}$$

I use 36 month rolling window and require stocks to have at least 24 observation in the window. β^{IMC1} is stock's IMC beta obtained from (4) and β^{IMC2} is obtained by adding market risk factor to (4). As reported in 2, high skill firms show higher sensitivity to the technology shock than low skill firms. The median IMC beta of high skill portfolio is 1.02 on average where the median beta of low skill portfolio is 0.551. I find a similar increasing pattern for β^{IMC2}. This pattern clearly implies that high skill firms are more exposed to the technology shock.

4.2 Response to Technology Shock

I investigate how firms' profits react in response to the technology shock. To test my first hypothesis, I consider a specification of the form:

$$Profit_{i,j,t+1} = \beta \times Skill_{i,j,t} + \gamma \times Shock_{t+1} + \delta(Skill_{i,j,t} \times Shock_{t+1}) + ctrls_{i,j,t} + \epsilon_{i,j,t+1}. \tag{5}$$

I first regress logarithm of firm profit at year t+1 on lagged skill, technology shock, and skill-shock interaction variable. I also include several controls such as firm fixed effects, year fixed effects, industry-year fixed effects (2 digit SIC level), logarithm of firm assets, Tobin's Q, tangibility, book leverage, capital investment, firm cash holding, and firm age. The standard errors are clustered at the firm and year level.

[Insert Table 3]

In Table 3, I report the estimation results. In column (1) where technology shock ($Tech$) is the variable of interest, a one standard deviation increase in technology shock (1.8) corresponds to 0.9% increase in profits on average. Moreover, I find that high skill firms tend to have higher profits, when positive technology shock arrives. In column (2), $Tech$*$Skill$ is estimated as 0.014 at 1% significance level. This implies that given a typical increase in the technology shock, a one standard deviation increase in skill (0.14) leads to a 0.2% more increase in profitability. In column (3) to (4), I further control for productivity shock (TFP) in the specification to examine the robustness of results.[5]

The results suggest that labor skill dependency amplifies firms' exposure to the technology innovation. Firms that require high degree of labor skills have profits that are more volatile than low skill firms, alongside with aggregate fluctuation. This implies that technology innovation is a economic-wide risk factor, operating through firm labor channel.

4.3 Labor Skill and the Cross-section of Stock Returns

4.3.1 Risk Price of Technology Shock

Having found that high skill firms have high exposure to the technology shock, it is important to examine its asset pricing implications. High skill firms should have lower expected returns if technology shock is a risk that carry negative risk premia as in Papanikolaou (2011). However, several recent studies argue the positive risk premia for technology shock (Li (2014), Garlappi and Song (2016)). For this reason, the discussion regarding the sign of technology risk is essential before investigating the link between labor skill and asset prices.

[Insert Table 4]

In Table 4, I first report equal and value-weighted portfolio alphas sorted on β^{IMC}. β^{IMC} is obtained from the equation (4) after controlling for market risk factor. I use 36 month rolling window and require stocks to have at least 24 observation in the window.

[5]The measure of aggregate productivity (TFP, utilization adjusted productivity factor following Basu et al. (2006)) is obtained from Federal Reserve Bank of San Francisco.

The abnormal returns are obtained from either the Fama-French five factor model (Fama and French (2015)) or the Q-factor model suggested by Hou et al. (2015). In all, the results suggest that technology shock carries a positive risk premia for both results. High-minus-low portfolio alphas are all positive and large in terms of magnitude. For example, when returns are value-weighted, the IMC premia is 0.78% monthly when Fama-French five factors are used to obtain alphas.

I also directly estimate the IMC risk premia through two-stage Fama-MacBeth regressions. I consider a broad set of test assets, including ten size, ten book-to-market, ten momentum, ten operating profitability, ten investment, and ten portfolios sorted on labor skills. The usage of profitability and investment portfolios are motivated by Fama and French (2015). I also include ten skill portfolios, since the exposure to the technology shock is closely tied to labor skill dependency.

[Insert Table 5]

For the first-stage beta regressions, following Liu and Zhang (2008), I estimate portfolio betas with three alternative methods: (i) full-sample window, (ii) rolling five-year windows, and (iii) expanding windows. Using estimated portfolio betas, I report risk premia estimates from the second-stage Fama-MacBeth regressions in Table 5. The t-statistics are Newey-West adjusted with sixty month lags. Panel A shows the full-sample window beta results. I find positive and significant IMC estimates in specifications considered. For example, when market risk factor is added to the regression, the IMC risk premia is 0.67% per month with a t-statistic of 2.20. I also find the positive risk premia even after controlling for Fama-French five risk factors.

In Panel B and C, I report the risk premia estimates with alternative first-stage procedures. The results are qualitatively similar albeit weak in terms of significance. In both panels, I find significant IMC risk premia only when all factors are included. Notably, I cannot find any significance for size, book-to-market, and investment factors for all specification considered. In all, I present supporting evidences of positive technology premia as in Li (2014) and Garlappi and Song (2016).

4.3.2 Cross-sectional Analysis

High skill firms are more exposed to technology shock, and hence should have higher expected returns than low skill firms. Using measure of labor skill, I first conduct firm-level Fama-MacBeth regression to test the prediction.

[Insert Table 6]

In Table 6, I report estimation results. The variable of interest is $Skill$, which indicates skill intensity measured at industry-level. I also include several characteristics that are known to predict stock returns such as firm size ($size$), logarithm of book-to-market ratio (BM), past 11 month stock return momentum ($R^E_{12,2}$), past 1 month lagged stock return (R^E_1), capital investment (Inv), labor hiring ($Hire$) as in Belo et al. (2014), operating leverage ($Op.Lev$), and book leverage ($Book.\ Lev$). I find $Skill$ to be positive and significant in most cases. For example, a one standard deviation increase in labor skill is associated with 0.25% increase in monthly returns, when all control variables are added. Clearly, high skill firms have subsequent high returns.

[Insert Table 7]

I also sort firms according to labor skill and form quintile portfolios. In Table 7, I report value-weighted portfolio alphas sort on labor skill measure. Consistent with Fama-MacBeth results, I confirm the existence of skill premia in the cross-section. For example, high-minus-low five factor alphas are 0.73% monthly.

More importantly, I find that a significant portion of skill premia can be explained by adding technology factor in the specification. When portfolio alphas are obtained by adding IMC returns to Fama-French five factors, I find relatively smaller and less significant high-minus-low alphas (0.46%). The decrease in alpha is more pronounced when Q-factor model is employed. For example, high-minus-low alphas has decreased almost by half to 0.32% monthly, which is statistically insignificant. Finally, I report IMC factor loadings in Table 7 in last row each panel. Regardless of factor model used, there is a increasing pattern of IMC loadings across skill portfolios. Overall, the results show that a significant portion of skill premia is explained by firms' exposure to technology risk, as predicted.

5 Conclusion

This study provides implication of technology innovation for firm behavior and asset prices, through the labor skill channel. Consistent with the intuition, I find that high skill firms have higher profitability when positive technology shock arrives, suggesting that high skill firms are more exposed to the shock.

It is still in debate as to the sign of technology risk factor. Contrary to the findings in Papanikolaou (2011), I find positive price of technology risk. This leads to high skill firms to have higher subsequent returns. Overall, my findings imply that labor skill mix is an important characteristic, that determine exposure to economic-wide shocks.

References

Acemoglu, D. (2002). Technical change, inequality, and the labor market. *Journal of Economic Literature*, 40(1):7–72.

Autor, D. H. and Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the us labor market. *American Economic Review*, 103(5):1553–1597.

Autor, D. H., Katz, L. F., and Kearney, M. S. (2008). Trends in U.S. wage inequality: Revising the revisionists. *Review of Economics and Statistics*, 90(2):300–323.

Basu, S., Fernald, J. G., and Kimball, M. S. (2006). Are technology improvements contractionary? *American Economic Review*, 96(5):1418–1448.

Belo, F., Lin, X., and Bazdresch, S. (2014). Labor hiring, investment, and stock return predictability in the cross section. *Journal of Political Economy*, 122(1):129–177.

Belo, F., Lin, X., Li, J., and Zhao, X. (2016). Labor-force heterogeneity and asset prices: the importance of skilled labor. *Review of Financial Studies*, Forthcoming.

Christiano, L. J. and Fisher, J. D. M. (2003). Stock market and investment goods prices: Implications for macroeconomics. *NBER Working Paper*.

Fama, E. F. and French, K. R. (2008). Dissecting anomalie. *Journal of Finance*, 63(4):1653–1678.

Fama, E. F. and French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1):1–22.

Fisher, J. D. (2006). The dynamic effects of neutral and investment–specific technology shocks. *Journal of Political Economy*, 114(3):413–451.

Garlappi, L. and Song, Z. (2016). Can investment shocks explain value premium and momentum profits? *Management Science*, Forthcoming.

Gomes, J., Kogan, L., and Zhang, L. (2009). Durability of output and expected stock returns. *Journal of Political Economy*, 117(5):941–986.

Greenwood, J., Hercowitz, Z., and Krusell, P. (1997). Long-run implications of investment-specific technological change. *American Economic Review*, 87(3):342–362.

Greenwood, J., Hercowitz, Z., and Krusell, P. (2000). The role of investment-specific technological change in the business cycle. *European Economic Review*, 44(1):91–115.

Hou, K., Xue, C., and Zhang, L. (2015). Digesting anomalies: An investment approach. *Review of Financial Studies*, 28(3):650–705.

Israelsen, R. D. (2010). Investment based valuation and managerial expectations. *Working Paper*.

Kogan, L. and Papanikolaou, D. (2013). Firm characteristics and stock returns: The role of investment–specific shocks. *Review of Financial Studies*, 26(11):2718–2759.

Kogan, L. and Papanikolaou, D. (2014). Growth opportunities, technology shocks, and asset prices. *Journal of Finance*, 69(2):675–718.

Krusell, P., Ohanian, L. E., Ríos-Rull, J.-V., and Violante, G. L. (2000). Capital-skill complementarity and inequality: A macroeconomic analysis. *Econometrica*, 68(5):1029–1053.

Li, J. (2014). Explaining momentum and value simultaneously. *Management Science*, Forthcoming.

Liu, L. X. and Zhang, L. (2008). Momentum profits, factor pricing, and macroeconomic risk. *Review of Financial Studies*, 21(6):2417–2448.

Novy-Marx, R. (2013). The other side of value: The gross profitability premium. *Journal of Financial Economics*, 108(1):1–28.

Ochoa, M. J. (2013). Volatility, labor heterogeneity and asset prices. *Working Paper*.

Papanikolaou, D. (2011). Investment shocks and asset prices. *Journal of Political Economy*, 119(4):639–685.

Parker, J. A. and Vissing-Jorgensen, A. (2010). The increase in income cyclicality of high-income households and its relation to the rise in top income shares. *Brookings Papers on Economic Activity*, 41(2):1–70.

Table 1: Industry Skill Rankings in 2010

This table presents the top 5 and bottom 5 industries sorted on labor skill measure in 2010. Industry-level labor skill measure is calculated as the proportion of skilled workers in each industry. The number of skilled workers are from the number of workers in occupations that have a Specific Vocational Preparation (SVP) value greater or equal to 7. Labor skill measure is defined at 4-digit NAICS level.

Year	*NAICS*	*Skill*	*Description*
2010	5112	65.7%	Software Publishers
2010	5232	61.0%	Securities and Commodity Exchanges
2010	3341	60.0%	Computer and Peripheral Equipment Manufacturing
2010	5417	58.4%	Scientific Research and Development Services
2010	5415	58.2%	Computer Systems Design and Related Services
⋮	⋮	⋮	⋮
2010	8121	0.9%	Personal Care Services
2010	4854	0.8%	School and Employee Bus Transportation
2010	4852	0.8%	Interurban and Rural Bus Transportation
2010	7221	0.7%	Full-Service Restaurants
2010	7222	0.5%	Limited-Service Eating Places

Table 2: Skill Portfolio Characteristics

This table reports time-series averages of median portfolio characteristics of the quintile portfolios sorted on the labor skill measure. Based on information available at the end of the previous years, in June of each year, I sort stocks into five portfolios using the skill measure. $Skill$ is the labor skill measure; $Size$ is the log market value of equity; BM is the book-to-market ratio; Inv is the capital expenditures to property, plant, and equipment ratio; $Leverage$ is the total debt to assets; $Profit$ is the gross profitability following Novy-Marx (2013); $Cash\ Flow$ is the earnings before extraordinary items plus depreciation to assets; $Labor\ Share$ is the number of employees divided by assets; $Cash$ is the ratio of cash and cash equivalent to assets. β^{IMC1} is the stock's IMC beta obtained from the equation 3. β^{IMC2} and β^{MKT2} are the stock's IMC beta and market beta obtained by adding market risk factor to the equation 3. To estimate betas, I use 36 month rolling window and require stocks to have at least 24 observation in the window. The sample period is from 1991 through 2012.

	L	2	3	4	H
$Skill$	0.037	0.102	0.172	0.261	0.417
$Size$	5.335	5.381	5.208	5.131	4.972
BM	0.624	0.595	0.523	0.433	0.448
Inv	0.054	0.040	0.036	0.037	0.036
$Book.\ Lev$	0.230	0.229	0.182	0.097	0.065
$Profit$	0.401	0.333	0.278	0.292	0.365
$Cash\ Flow$	0.089	0.078	0.059	0.047	0.055
$Labor\ Share$	0.011	0.006	0.004	0.004	0.005
$Cash$	0.055	0.062	0.093	0.248	0.239
β^{IMC1}	0.551	0.686	0.778	1.016	1.020
β^{IMC2}	0.068	0.168	0.320	0.503	0.508
β^{MKT}	0.956	0.982	0.947	1.050	1.041

Table 3: Response of Profit to Aggregate Shocks

This table shows the response of firm profit to technology shock for firms in different skill industry. The dependent variable is the gross profitability following Novy-Marx (2013). To proxy for technology shock ($Tech$), I use the innovation in quality-adjusted equipment price relative to consumption. TFP is the aggregate productivity shock following Basu et al. (2006). $Skill$ is the labor skill measure. The controls used in the specification are logarithm of firm assets, Tobin's Q, tangibility, book leverage, capital investment, firm cash holding, and firm age. Tobin's Q is define as the ratio of market value of assets (market value of equity, plus total debt, plus preferred stocks, minus deferred taxes and investment tax credit) to book assets. Tangibility is the ratio of plant, property and equipment to assets. Book leverage is defined as the ratio of total debt to assets. Capital investment is the capital expenditures to property, plant, and equipment ratio. Firm cash holding is the ratio of cash and cash equivalents to assets. Firm age is the number of years the firms appears on the data. The sample period is from 1991 through 2012. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The numbers in parentheses are t-statistics clustered at the firm and year level.

	(1)	(2)	(3)	(4)
$Tech$	0.005**		0.004**	
	(2.24)		(2.18)	
$Tech$*$Skill$		0.014***		0.016**
		(5.59)		(2.15)
TFP			-0.002	
			(-0.96)	
TFP*$Skill$				0.007
				(0.39)
$Skill$		-0.118		-0.135
		(-1.26)		(-1.16)
Control	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	N	Y	N	Y
Ind*Year FE	Y	Y	Y	Y
Obs	51,592	51,592	51,592	51,592
R^2	78.1%	78.1%	78.1%	78.1%

Table 4: Quintile IMC Beta Portfolio

This table provides average monthly alphas for quintile portfolios sorted on the IMC beta. The IMC beta is obtained by adding market risk factor to the equation 3. To estimate beta, I use 36 month rolling window and require stocks to have at least 24 observation in the window. I report equal-weighted alphas (Panel A) and value-weighted alphas (Panel B). Alphas are estimated either from the Fama-French five factor model (Five factors α) or from the Q-factor model (HXZ α). The sample period is from 1991 through 2012. *, **, and *** for the High-Low portfolio alphas denote statistical significance at the 10%, 5%, and 1% levels, respectively. The numbers in parentheses are t-statistics based on White (1980) robust standard errors.

	L	2	3	4	H	High-Low
	Panel A: Equal-Weighted Returns					
Five factors α	0.17	0.13	0.28	0.52	0.70	0.52**
	(1.08)	(1.05)	(2.08)	(2.40)	(2.17)	(2.04)
HXZ α	0.32	0.26	0.43	0.79	1.07	0.75**
	(1.78)	(1.68)	(2.68)	(3.20)	(3.08)	(2.52)
	Panel B: Value-Weighted Returns					
Five factors α	-0.08	-0.13	0.12	0.32	0.70	0.78**
	(-0.83)	(-1.43)	(0.86)	(1.87)	(2.67)	(2.52)
HXZ α	-0.02	-0.13	0.21	0.51	0.78	0.80**
	(-0.21)	(-1.28)	(1.23)	(2.75)	(2.46)	(2.13)

Table 5: Risk Premia Estimates

This table reports the estimated IMC risk premia from Fama-MacBeth cross-sectional regressions. The test portfolios are: size deciles, book-to-market deciles, momentum deciles, investment deciles, operating profitability deciles, and skill deciles. I consider both a two-factor model (MKT+IMC) and a six-factor model (FF5+IMC). I employ three methods in the first-stage beta estimation: (1) full-sample window (Panel A); (2) rolling window (Panel B); and (3) extending window (Panel C). The rolling window uses a 5-year moving window. The sample period is from 1991 through 2012. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The numbers in parentheses are t-statistics based on Newey-West adjusted with a lag of 5 years.

	γ_0	MKT	IMC	SMB	HML	UMD	RMW	CMA	R^2
Panel A: Full-Sample Window in the First-Stage Regression									
MKT+IMC	1.545***	-1.276**	0.670**						20.7%
	(3.51)	(-2.41)	(2.20)						
FF5+IMC	0.855***	-0.289	1.260***	0.394	0.214	0.641*	0.738**	0.100	50.2%
	(3.82)	(-0.74)	(4.14)	(1.20)	(0.58)	(1.92)	(2.38)	(0.31)	
Panel B: Rolling Windows in the First-Stage Regression									
MKT+IMC	0.961***	-0.592	0.451						20.9%
	(3.42)	(-1.28)	(1.30)						
FF5+IMC	0.670***	0.066	0.559**	0.579	0.131	0.921**	0.243	0.240	47.2%
	(3.45)	(0.15)	(2.13)	(1.13)	(0.38)	(2.21)	(0.44)	(0.65)	
Panel C: Extending Windows in the First-Stage Regression									
MKT+IMC	0.988**	-0.454	0.133						18.8%
	(2.04)	(-0.72)	(0.36)						
FF5+IMC	0.566**	0.256	0.847***	0.583	-0.011	0.778**	0.681*	0.230	46.5%
	(2.47)	(0.88)	(3.15)	(1.36)	(-0.03)	(2.32)	(1.97)	(0.73)	

Table 6: Fama-MacBeth Regression

This table provides the second stage Fama-MacBeth regressions of monthly excess stock returns on the labor skill (*Skill*) along with a set of controls. *Skill* is the labor skill measure; *Size* is log market capitalization; *BM* is the log book-to-market ratio; $R^E_{2,12}$ is the past 12 month stock return skipping the most recent month; R^E_1 is the past 1 month stock return; *Inv* is the capital expenditures to assets ratio; *Hire* is the change in number of employees divided by lagged number of employees; *Op. Lev* is the sum of cost of goods sold and selling, general and administrative expenditures, divided by sales; *Book. Lev* is the total book debt divided by the sum of market value of equity and total book debt. The sample period is from 1991 through 2012. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The numbers in parentheses are t-statistics based on the White (1980) standard errors.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Skill	1.675*	1.562	2.167**	1.640*	1.731*	1.638*	1.821*	1.828**	1.493*	1.767***
	(1.72)	(1.61)	(2.50)	(1.94)	(1.96)	(1.69)	(1.95)	(2.00)	(1.72)	(2.79)
Size		-0.153**								-0.099
		(-2.14)								(-1.64)
BM			0.436***							0.268***
			(5.14)							(3.48)
$R^E_{12,2}$				0.001						0.002
				(0.52)						(0.93)
R^E_1					-0.032***					-0.035***
					(-4.21)					(-5.69)
Inv						-1.388*				-0.313
						(-1.69)				(-0.36)
Hire							-0.848***			-0.617***
							(-6.13)			(-4.95)
Op. Lev								-0.211*		-0.231**
								(-1.66)		(-2.23)
Book. Lev									0.008	-0.037
									(0.19)	(-1.16)
R^2	0.69%	1.60%	1.20%	1.61%	1.51%	0.91%	0.94%	1.30%	0.87%	4.67%
Obs	896,457	896,357	822,589	885,908	896,297	878,889	846,731	803,346	752,126	578,061

Table 7: Quintile Skill Portfolio

This table provides average value-weighted monthly alphas and IMC factor loadings for quintile portfolios sorted on the labor skill. Alphas are estimated either from the Fama-French five factor model (Panel A) or from the Q-factor model (Panel B). For each panel, I also report portfolio alphas and IMC factor loadings, both obtained from adding IMC factor to the original model considered. The sample period is from 1991 through 2012. *, **, and *** for the High-Low portfolio alphas denote statistical significance at the 10%, 5%, and 1% levels, respectively. The numbers in parentheses are t-statistics based on White (1980) robust standard errors.

	L	2	3	4	H	High-Low
Panel A: Fama-French Five Factors						
Five factors α	-0.27	-0.10	-0.18	0.32	0.45	0.73***
	(-2.18)	(-0.97)	(-1.29)	(2.51)	(2.74)	(3.22)
Five+IMC α	-0.19	-0.09	-0.19	0.22	0.27	0.46**
	(-1.57)	(-0.83)	(-1.35)	(1.84)	(1.93)	(2.46)
IMC Loading	-0.22	-0.04	0.03	0.23	0.45	0.67***
	(-4.93)	(-1.05)	(0.44)	(4.52)	(8.92)	(10.45)
Panel B: HXZ Q-Factors						
HXZ α	-0.15	-0.12	-0.08	0.29	0.55	0.70**
	(-0.89)	(-1.05)	(-0.55)	(2.07)	(3.07)	(2.56)
HXZ+IMC α	0.01	-0.06	-0.07	0.14	0.33	0.32
	(0.05)	(-0.51)	(-0.44)	(1.11)	(2.23)	(1.54)
IMC Loading	-0.34	-0.13	-0.03	0.31	0.48	0.81***
	(-7.24)	(-3.39)	(-0.56)	(5.88)	(10.88)	(12.97)