Skilled Labour Risk: US and International Evidence

by

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Abstract

The paper examines whether reliance on workers in the science, technology, engineering, and mathematics (STEM) fields leads to increased equity risk by reducing the operating flexibility of firms. We construct a STEM index using detailed industry-level occupational data and show that firms in more STEM worker-intensive industries are subject to greater operating leverage. These firms also have a higher market beta and earn higher stock returns. Our results hold for the US and several other developed countries. The paper highlights the risk associated with the employment of STEM workers, which must be balanced against their contribution to innovation and growth.

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1 Introduction

Human capital is a crucial source of competitive advantage in business (Zingales, 2000).[1] The human capital of skilled workers is especially valuable, given their ability to perform complex, non-routine tasks that are not amenable to automation (Autor, Levy, & Murnane, 2003). This paper focuses on skilled workers in the science, technology, engineering, and mathematics (STEM) fields, who are the primary contributors to research and innovation (Peri, Shih, & Sparber, 2015). While investment in STEM workers is critical to taking advantage of technological and scientific advances and the related growth opportunities, it may also subject firms to greater risk, a possibility that has received little attention in the literature. In this paper,

[1] Klaus Schwab, the founder of the World Economic Forum (WEF), remarked at the 2013 WEF meeting: "Capital is being superseded by creativity and the ability to innovate – and therefore by human talents – as the most important factors of production. Just as capital replaced manual trades during the process of industrialization, capital is now giving way to human talent. Talentism is the new capitalism." (Beach, 2014).

we fill this gap by examining whether reliance by a firm on STEM workers affects the firm's equity risk.

Prior research shows that employee replacement costs (i.e. hiring costs) generally increase with the skill level of the worker (Blatter, Muehlemann, & Schenker, 2012; Dolfin, 2006; Dube, Freeman, & Reich, 2010; Manning, 2006; Ochoa, 2013; Wilk & Cappelli, 2003). Compared to less-skilled workers, skilled workers also earn higher and more rigid wages (Campbell, 1997; Du Caju, Fuss, & Wintr, 2012). The reluctance of firms to cut the wages of skilled workers, even during an economic downturn, has been associated with a desire to reduce skilled labour turnover, to preserve specific human capital, to avoid sending a negative signal to prospective recruits, and to insure skilled workers against productivity shocks (Campbell & Kamlani, 1997; Franz & Pfeffer, 2006; Lagakos & Ordonez, 2011).

The presence of information asymmetry between workers and employers, coupled with bounded rationality, means that employment contracts are typically incomplete (Klein, 1984). The costs of writing and enforcing contracts are especially high when contracting with skilled workers due to the complex and tacit knowledge embedded in their activities (Toms, 2010a). The literature suggests that incomplete labour contracts often take the form of a fixed-wage contract that does not have explicit performance incentives but gives employees considerable discretion over their work (Fehr & Falk, 1999).[2] To foster long-term commitment and investment in specific human capital, skilled labour contracts are also likely to be longer-term and relational in nature (Rousseau, 1990; Tsui, Pearce, Porter, & Tripoli, 1997).

The tendency for skilled workers to be offered a fixed-wage contract and the reluctance of firms to dismiss or force wage cuts on them jointly suggest greater fixity of labour costs in skilled labour-intensive firms, and so total operating costs become smoother relative to sales. Consequently, residual cash flow becomes more sensitive to systematic shocks and thus riskier, acting as a source of operating leverage (Lev, 1974; Mandelker & Rhee, 1984; Garcia-Feijóo & Jorgensen, 2010).

We expect the effect of labour-related operating leverage to be particularly manifest in firms reliant on STEM workers, due to the pivotal role of STEM workers in innovation and research and development projects. Such projects are idiosyncratic and long-term in nature and are often irreversible (Dixit & Pindyck, 1994; Holmstrom, 1989), making employee retention a critical

[2] The fixed-wage contracts can benefit the firm where the offered wage exceeds the market-clearing level and induces employees to reciprocate through greater work efforts (Fehr, Kirchsteiger, & Riedl, 1993; Hannan, 2005).

pre-condition for project success. Minimising employee turnover rates also helps to sustain team dynamics and the shared vision that determines innovation effectiveness (Pearce & Ensley, 2004), while preventing a loss of trade secrets and other sensitive knowledge to rivals (Li & Li, 2019). The threat to the firm's innovative capacity and competitive advantage, and the difficulty of finding candidates with the right mix of skills, experience and temperament, can make replacing STEM workers prohibitively costly. Therefore, we expect firms that rely on STEM workers to pay high wages that also persist through the business cycle.

Using detailed occupational employment and wage estimates from the US Bureau of Labor Statistic, we construct a STEM index that measures the annual wage share of workers in STEM occupations, as classified by the Occupational Information Network database, for a wide range of industries. A higher index means that a higher percentage of total wage costs in an industry is attributed to STEM relative to non-STEM workers, indicating a greater reliance on STEM workers by that industry and its constituent firms.

We conduct the analysis on a sample of listed US firms from 1997 to 2018. Our main results are twofold: First, operating profits (wage costs) are significantly more (less) sensitive to sales changes for firms in more STEM worker-intensive industries. Second, both CAPM beta and realized returns are positively related to STEM index, after controlling for known risk factors. To ensure generalisability of our results, we repeat the analysis for listed firms in the other Group of Seven (G7) countries and thirteen European countries. We continue to find the same relationships in these alternative samples. Our inferences are unchanged when we estimate the regressions at the industry level or control for additional industry characteristics. We also show that the operating leverage effect becomes stronger when employee retention is more urgent, which further inhibits firms from labour adjustment. Overall, the results support our view that reliance on STEM workers creates operating leverage, particularly through its impact on labour costs, which increases firms' equity risk.

Our paper contributes to the literature that relates labour market frictions to asset pricing and corporate financial decisions.[3] Much of the applied empirical work has focused on labour market institutions such as unions (Chen, Kacperczyk, & Ortiz-Molina, 2011; Chino, 2016; Matsa, 2010; Rosett, 2001) and labour protection laws (Agrawal & Matsa, 2013; Serfling, 2016), and their role in generating labour frictions. By considering firms' reliance on STEM

[3] Related studies have been done at both the firm level (Belo, Lin, & Bazdresch, 2014; Donangelo, Gourio, Kehrig, & Palacios, 2019; Gourio, 2007; Kuehn, Simutin, & Wang, 2017; Toms, 2010b) and the aggregate level (Danthine & Donaldson, 2002; Favilukis & Lin, 2016a, 2016b; Merz & Yashiv, 2007; Uhlig, 2007).

workers, we contribute to a growing stream of this literature that examines heterogeneity in workforce composition as another source of labour frictions (Belo, Li, Lin, & Zhao, 2017; Donangelo, 2014; Ghaly, Dang, & Stathopoulos, 2017; Ochoa, 2013).

In the two studies closest to ours, Ochoa (2013) and Belo et al. (2017) examine the effects of skilled labour intensity on stock returns. Our paper differs in several important respects. First, Ochoa (2013) and Belo et al. (2017) classify skilled workers broadly as workers with a relatively high level of education and experience, while we focus on a specific group of skilled workers who typically engage in research and innovation. Given the significant value-creating potential of these activities (Chauvin & Hirschey, 1993; Simeth & Cincera, 2016), we expect our STEM index to more precisely capture the importance of human capital. Also, given that only a few managerial roles (conventionally treated as high-skilled) are classified as STEM occupations, our STEM index is a more conservative measure of labour skill, with the advantage that our analysis is less susceptible to confounding factors such as managerial rent-seeking or excess bureaucracy. Second, we provide direct empirical evidence of operating leverage as an essential mechanism behind the higher risk of STEM worker-intensive firms. Third, we show that both the risk effect of reliance on STEM workers, and the economic mechanism behind it, hold in a range of developed markets, thus providing broader and more detailed evidence of skilled labour risk.

Our paper is also related to the literature on the value and risk implications of intangible investments such as R&D (Chambers, Jennings, & Thompson, 2002; Chan, Lakonishok, & Sougiannis, 2001; De Andrés-Alonso, Azofra-Palenzuela, & De La Fuente-Herrero, 2006) and patenting activities (Griliches, 1981; Hirshleifer, Hsu, & Li, 2013; Mazzucato & Tancioni, 2012). We depart by focusing instead on the main enablers of such investments, i.e. STEM workers. Crucially, we show that STEM workers constitute a type of risky asset that reduces firms' operating flexibility in a similar way to illiquid physical capital (Ortiz-Molina and Phillips, 2014; Tüzel, 2010).

The rest of the paper is organized as follows. Section 2 describes the data, variables, and sample selection. Section 3 presents the main results. Sections 4 and 5 provide additional results and robustness checks. Section 6 concludes.

2 Data

2.1 STEM Index

To quantify reliance on STEM workers, we construct a STEM index that measures the annual percentage of total wage costs in an industry due to workers in STEM occupations, as classified by the Occupational Information Network (O*Net) program.[4] A higher index means that a larger share of the industry's annual wage bill is attributed to STEM workers, thereby indicating a greater reliance on STEM workers by that industry and its firms. We focus on the wage, rather than employment, share of STEM workers to account for the fact that the same STEM occupation can be valued differently between industries.[5]

To construct the STEM index, we obtain industry-level occupational employment and wage estimates from the Occupational Employment Statistics program of the US Bureau of Labor Statistics (BLS-OES) from 1997 to 2019.[6] The BLS-OES classified industries by three-digit Standard Industry Code (SIC) prior to 2002, and by four-digit North American Industry Classification Scheme (NAICS) from 2002 onwards. To ensure consistency in the industry classification during our sample period, we convert the STEM index during 1997-2001 to be based on four-digit NAICS.[7] We set the STEM index to missing for miscellaneous or non-

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[4] See https://www.onetonline.org/find/stem. The O*Net program compiles detailed occupational information and is developed under the sponsorship of the US Department of Labor. As of October 2020, it listed a total of 308 STEM occupations defined by eight-digit Standard Occupation Code (SOC). These are grouped into five categories: "Managerial" (e.g. computer and information systems managers), "Postsecondary Teaching" (e.g. mathematical science teachers), "Research, Development, Design, and Practitioners" (e.g. web developers), "Sales" (e.g. solar sales representatives and assessors), and "Technologists and Technicians" (e.g. robotics technicians). To merge with occupation data from the US Bureau of Labor Statistics, we collapse the 308 STEM occupations on the O*Net list into 184 based on the first six digits of SOC codes.

[5] According to the May 2017 edition of the Occupational Employment Statistics surveys, the mean annual wage of computer network architects (SOC Code 15-1143) is $54,040 in the Building Equipment Contractors industry, but $120,550 in the Software Publishers industry. As another example, the mean annual wage of electrical engineers (SOC Code 17-2071) is $76,910 in the Furniture and Related Product Manufacturing industry but $112,730 in the Motion Picture and Video industry.

[6] See https://www.bls.gov/oes/tables.htm. The BLS-OES conducts semi-annual surveys of nonfarm establishments to produce employment and wage estimates for about 800 detailed occupations at the national, state, metropolitan and nonmetropolitan area, and industry level. For this paper, we use industry-level data from the 1997-2019 OES surveys. We choose 1997 as the starting point for data collection because prior to 1997, not all industries were surveyed each year and occupational wage estimates were unavailable. As we use the May edition of OES surveys from 2003 to 2019, we lag the STEM index estimated during that period by one year.

[7] We note that although three-digit SIC code is roughly equivalent to four-digit NAICS code, there remains discrepancy between the two schemes where one SIC industry can correspond to multiple NAICS industries, and vice versa. For instance, SIC 175 (Carpentry and Floor Work) is linked to both NAICS 2381 (Foundation, Structure, and Building Exterior Contractors) and NAICS 2383 (Building Finishing Contractors); NAICS 3141 (Textile Furnishing Mills) is linked to both SIC 227 (Carpets and Rugs) and SIC 571 (Home Furniture and

classifiable industries, i.e. those with a NAICS code ending in "9", because firms in these industries are unlikely to share a common labour force (Donangelo, 2014).

In total, we can estimate the STEM index for 269 four-digit NAICS industries, which cover the whole spectrum of private-sector economic activity. Table 1 shows the 15 most and 15 least STEM worker-intensive industries based on their average STEM index during 1997-2018. We find that industries in the healthcare, information, and professional service sectors are heavily reliant on STEM workers, who account for half or more of the industry's total wage costs. On the other hand, industries in the retail and hospitality sectors rely much less on STEM workers, who account for less than one percent of the industry's total wage expense.

[Insert Table 1 here]

2.2 Sample Selection

Our baseline sample consists of all US non-financial firms with common stock listed on NYSE, AMEX, and NASDAQ between 1997 and 2018. Financial statement data are from Standard and Poor's Compustat annual industrial files. Stock return data are from the CRSP monthly stock files. Firm-year observations that cannot be matched to the BLS-OES data are excluded. We also require firms to have non-missing monthly returns during the fiscal year and non-missing measures of size, market-to-book ratio, leverage, and CAPM beta at the fiscal year-end. Following Pástor & Veronesi (2003), we remove observations with a market value of equity below $10 million and a market-to-book ratio greater than 100 or less than 0.01. The selection process results in a final sample of 46,977 observations during 1997-2018, corresponding to 6,146 firms across 211 four-digit NAICS industries.

To ensure that our inferences can be generalised beyond the US, we repeat the main analysis for two international samples. The first consists of publicly listed firms in the other G7 countries, i.e. Canada, France, Germany, Italy, Japan, and the United Kingdom. The second consists of publicly listed firms in thirteen European countries with a relatively developed capital market: Austria, Belgium, Denmark, Finland, France, Germany, Italy, the Netherlands, Norway, Spain, Sweden, Switzerland, and the United Kingdom (Dutordoir et al., 2014; Haque & Jones, 2020). For the non-US firms, we download accounting data from Compustat Global,

Furnishing Stores). To avoid distorting the data too much, we choose to reclassify the 1997-2001 index estimates rather than the 2002-2018 index estimates.

and construct monthly returns using daily prices and price adjustment factors from Compustat Securities Daily (Belo et al., 2017).[8] After applying the selection criteria for the US sample, we obtain 72,802 observations for the G6 sample, and 35,608 observations for the European sample. Table 2 reports the year and sectoral distribution of firms in the US and international samples.[9]

[Insert Table 2 here]

2.3 Descriptive Statistics

Each year, firms are sorted into three portfolios based on STEM index. For each of the three STEM portfolios, we calculate the means of several firm characteristics which are then averaged during our sample period. Table 3 reports the results based on the US sample (panel A), the G6 sample (panel B), and the European sample (panel C).[10] We observe, first, that the average STEM index is higher across the STEM portfolios in the US sample than in the two international ones, suggesting that the US has a particularly technology-intensive economy compared to its counterparts in the developed world.

The table shows that the average high-STEM firm is smaller and less leveraged than the average low-STEM firm. The lower debt in high-STEM firms is consistent with the idea that these firms may be less financially flexible, which we argue is due to their significant labour commitments, and so are reluctant to take on more debt (Graham & Harvey, 2001). The positive relation between STEM index and both market-to-book and R&D suggests that high-STEM firms have greater growth opportunities. Compared to low-STEM firms, high-STEM firms are less profitable, invest less in fixed assets, and are more focused in their activities.[11] More

[8] For Canadian firms, we obtain monthly stock prices and the price adjustment factors from Compustat Securities Monthly.

[9] We aggregate the firms into 16 sectors by their two-digit NAICS codes: Agriculture, Forestry, Fishing, and Hunting (NAICS 11), Mining (NAICS 21), Utilities (NAICS 22), Construction (NAICS 23), Manufacturing (NAICS 31-33), Wholesale Trade (NAICS 42), Retail Trade (NAICS 44-45), Transportation and Warehousing (NAICS 48-49), Information (NAICS 51), Professional, Scientific, and Technical Services (NAICS 54), Administrative and Support and Waste Management and Remediation Services (NAICS 56), Educational Services (NAICS 61), Health Care and Social Assistance (NAICS 62), Arts, Entertainment, and Recreation (NAICS 71), Accommodation and Food Services (NAICS 72), and Other Services (NAICS 81).

[10] To ensure consistency across our samples, we convert all accounting and financial data of non-US firms into US dollars before constructing the variables used in this study. Monthly and daily exchange rate data are downloaded from the I/B/E/S database.

[11] We obtain segment data for US firms from the Compustat Historical Segments database. The same data is not available for non-US firms.

importantly, market beta is shown to increase across the STEM terciles, suggesting that the stocks of STEM worker-intensive firms are riskier due to higher exposure to systematic risk. We examine this relationship in more detail in the next section.

[Insert Table 3 here]

3 Main Results

3.1 Reliance on STEM Workers and Operating Leverage

To test our assumption that reliance on STEM workers generates operating leverage by increasing the degree of fixity in labour costs, we estimate the following two regressions:

$$\Delta WAGE_{i,j,t} = \alpha_0 + \alpha_1 \Delta SALES_{i,j,t} + \alpha_2 STEM_{j,t} + \alpha_3 \Delta SALES_{i,j,t} \times STEM_{j,t} + \varepsilon_{i,j,t} \quad (1)$$

$$\Delta PROFIT_{i,j,t} = \beta_0 + \beta_1 \Delta SALES_{i,j,t} + \beta_2 STEM_{j,t} + \beta_3 \Delta SALES_{i,j,t} \times STEM_{j,t} + e_{i,j,t} \quad (2)$$

Where *i*, *j*, and *t* index firm, industry, and year, respectively. Δ denotes the first difference of the natural logarithm, i.e. growth rate. *STEM* is the standardized STEM index. *WAGE* is annual wage costs.[12] *PROFIT* is annual operating income after depreciation. *SALES* is annual sales. ε and e are the error terms. Both equations include year and sector fixed effects to control for unobserved macroeconomic and sectoral shocks. For the international analysis, we additionally include country fixed effects to partial out country-specific factors.

In equation (1), our test of the effects of *STEM* on labour cost fixity centres on the sign of α_3. If, as we hypothesize, an increased reliance on STEM workers constrains the firm's ability to adjust labour costs in response to external demand shocks, as represented by sales changes, the model should yield a negative coefficient for the interaction term, i.e. $\alpha_3<0$. To assess whether STEM employment increases the upward or downward inflexibility, or both, of labour costs, we also estimate equation (1) for firms with a positive change in sales ($\Delta SALES>0$) and firms with a negative change in sales ($\Delta SALES<0$).

[12] For US firms, annual wage costs are represented by Compustat item XLR. As XLR includes both wages and benefits, we multiply XLR by the ratio of wages to total compensation in the firm's three-digit NAICS industry – based on the National Income and Product Accounts (NIPA) data, as available from the US Bureau of Economic Analysis – when Compustat footnote XLR_FN does not show "XB" (which indicates exclusion of benefits from XLR). For non-US firms, wage costs are represented by Compustat Global item XSTFWS, which refers specifically to the wage component of employee compensation. Where XSTFWS is missing, we multiply XLR by the median industry ratio of XSTFWS to XLR during that year in the firm's country.

In equation (2), our test of the effects of STEM on operating leverage centres on the sign of β_3. If, as we hypothesize, increased reliance on STEM workers leads to riskier cash flows that are more sensitive to external demand shocks, the model should yield a positive coefficient for the interaction term, i.e. $\beta_3>0$. As in the wage sensitivity analysis, we repeat the estimation of equation (2) for two subsamples based on whether the firm had a positive or negative sales change in the previous year.

Table 4 reports the estimation results of equation (1) based on the US sample (panel A) and the two international samples (panels B and C). The unconditional effects in the first column indicate the general stickiness of wages, where a given magnitude of change in sales predicts a lower magnitude of change in wages, as reflected by a $\Delta SALES$ coefficient below one. The degree of wage stickiness is more pronounced in the US than in other developed countries: a 10% change in sales is associated with a roughly 4% change in wages for the US firms, while the corresponding figure is 6% for the G6 and European firms. The negative and significant coefficients on the interaction term in the second column suggest that, consistent with our expectations, wages become even less sensitive to sales changes – and thus stickier – as the firm relies more heavily on STEM workers. Specifically, a one-standard-deviation increase in STEM index reduces the base wage sensitivity among US firms (0.440), G6 firms (0.611), and European firms (0.598), by 25.7%, 18.8%, and 15.7%, respectively.

The last two columns in table 4 show the interaction effects for subsamples based on whether the firm's sales increased or decreased during the previous year. In both cases, the coefficient on the interaction term remains negative and mostly significant across different samples. Notably, the results are more pronounced for firms with negative sales changes than for firms with positive sales changes, suggesting that reliance on STEM workers contributes more to downward wage inflexibility (i.e. after a negative demand shock) than to upward wage inflexibility (i.e. after a positive demand shock).

[Insert Table 4 here]

Table 5 reports the estimation results of equation (2) based on the US sample (panel A) and the two international samples (panels B and C). The unconditional effects in the first column suggest that compared to wages, profits react strongly to sales changes, as reflected by a $\Delta SALES$ coefficient above one. The positive and significant coefficients on the interaction term in the second column suggest that, consistent with our expectations, profits become even more sensitive to sales changes – and thus more volatile – as the firm relies more heavily on STEM workers. Specifically, a one-standard-deviation increase in STEM index is associated with an increase in the base profit sensitivity among US firms (1.642), G6 firms (1.641), and European firms (1.360) by 7.1%, 3.9%, and 7.2%, respectively.

The last two columns in table 5 show the interaction effects for subsamples based on whether the firm's sales increased or decreased during the previous year. In both scenarios, the interaction term continues to have a positive and significant coefficient across the alternative samples. As in the wage sensitivity analysis, we find that the moderating effect of STEM index is more pronounced for firms with negative sales changes than for firms with positive sales changes – in this case by a factor of more than 2. The finding suggests that reliance on STEM workers amplifies both the downside risk and upside potential of firms, with the former effect being more dominant.

Taken together, the results in tables 4 and 5 support our view that employment of STEM workers leads to riskier cash flows by reducing the operating flexibility of firms, particularly through its impact on labour costs. The wage stickiness of STEM worker-intensive firms, and the associated increase in their profit sensitivity, is stronger during a negative demand shock than during a positive one. This asymmetry may reflect a higher cost of downsizing and/or pay cuts in periods of contraction, compared to hiring and/or pay rises in periods of growth, especially for firms reliant on STEM workers (Goux, Maurin, & Pauchet, 2001). In the next section, we examine whether the increased operating leverage at STEM worker-intensive firms translates into higher equity risk.

[Insert Table 5 here]

3.2 Reliance on STEM Workers and Equity Risk

To determine whether reliance on STEM workers increases equity risk, we use two complementary approaches. First, we examine the relationship between STEM index and firms' market beta. Second, we examine the relationship between STEM index and firms' future stock returns.

Having established in the previous section that operating leverage increases with firms' reliance on STEM workers, we expect STEM worker-intensive firms to therefore have a greater exposure to systematic risk. To verify this, we estimate the following regression model:

$$BETA_{i,j,t} = \beta_0 + \beta_1 STEM_{j,t} + \beta_2 SIZE_{i,j,t} + \beta_3 FINLEV_{i,j,t} + \beta_4 MB_{i,j,t} + \beta_5 ROA_{i,j,t} + \beta_6 RD_{i,j,t}$$
$$+ \beta_7 RDMISSING_{i,j,t} + \beta_8 CAPEX_{i,j,t} + \beta_9 BSEG_{i,j,t} + \beta_{10} SALEHHI_{i,j,t} + \varepsilon_{i,j,t} \quad (3)$$

Where *i*, *j*, and *t* index firm, industry, and year, respectively. *BETA* is market beta from the CAPM model, estimated using at least 24 and up to 60 months of past returns. *STEM* is the standardized STEM index. *SIZE* is the natural logarithm of market value of equity at the fiscal year-end. *FINLEV* is the ratio of total debt to the sum of total debt and market value of equity. *MB* is the market-to-book value of equity ratio. *ROA* is the ratio of income before extraordinary items to total assets. *RD* is the ratio of R&D expense to total assets, with missing R&D expense set to zero. *RDMISSING* is a dummy variable equal to 1 if the R&D expense is missing, and 0 otherwise. *CAPEX* is capital expenditure less the sale of property, plant, and equipment, divided by total assets. For the US analysis, we also control for firm focus using the natural logarithm of the number of business segments (*BSEG*), and a Herfindahl-Hirschman index of segment sales (*SALEHHI*) (Low, 2009). ε is the error term.

The model includes year, sector, and country fixed effects. To reduce the influence of outliers, all firm-level variables (except *BSEG* and *SALEHHI*) are winsorized at the 0.5% and 99% levels. Standard errors are clustered at the four-digit NAICS industry level to address the concern that residuals may be correlated across firms within the same industry.

Table 6 reports estimates of the systematic risk regression in equation (3). Consistent with our expectations, the table shows a positive and significant relationship between STEM index and market beta, after controlling for several firm characteristics. The results are relatively pronounced for the US firms, with the increase in market beta associated with a one-standard-deviation increase in STEM index about 1.7 times that for the G6 and European firms. As for the effects of control variables, we find that market beta increases with size, leverage, and R&D intensity, and decreases with growth, profitability, and firm diversification.

[Insert Table 6 here]

Combined with results in the previous section, the results in table 6 support our proposition that an increased reliance on STEM workers, by generating operating leverage, amplifies the firm's systematic risk exposure. As an extension, we consider whether future returns are also higher for firms that rely more heavily on STEM workers. The rationale is that investors, recognising the higher systematic risk of STEM worker-intensive firms, will require a higher return to invest in their stock. To verify this, we estimate the following regression model:

$$RETURN_{i,j,t+1} = \beta_0 + \beta_1 STEM_{j,t} + \beta_2 SIZE_{i,j,t} + \beta_3 FINLEV_{i,j,t} + \beta_4 MB_{i,j,t} + \beta_5 BETA_{i,j,t} + \beta_6 LAGRET_{i,j,t} + \varepsilon_{i,j,t} \quad (4)$$

Where i, j, and t index firm, industry, and year, respectively. *RETURN* is the realized annual return from July in year t+1 to June in year t+2. *STEM*, *SIZE*, *FINLEV*, *MB*, and *BETA* are as previously defined. *LAGRET* is the lagged eleven-month return from July in year t to May in year t+1 (Carhart, 1997). The model includes year, sector, and country fixed effects. As in the systematic risk regression, we winsorize all firm-level variables at the top and bottom 0.5% and cluster robust standard errors at the four-digit NAICS industry level.

Table 7 reports estimates of the return predictability regression in equation (4), which show that firms' reliance on STEM workers has a positive and significant effect on future returns. The results corroborate our earlier findings by indicating that investors demand a higher return on the stocks of STEM worker-intensive firms to compensate for greater systematic risk. The economic magnitude of our results is also significant: all else equal, a one-standard-deviation increase in STEM index leads to an increase in future returns by 1.9% for US firms, and by 1.0% and 1.3% for the G6 and European firms, respectively.

[Insert Table 7 here]

As a robustness check, we rerun both the systematic risk regression and return predictability regression at the industry level, by converting all firm-level variables – *BETA*, *SIZE*, *FINLEV*, *MB*, *ROA*, *RD*, *CAPEX*, *BSEG*, and *SALEHHI* in equation (3), and *RETURN*, *SIZE*, *FINLEV*, *MB*, *BETA*, *LAGRET* in equation (4) – into four-digit NAICS industry averages, in line with the definition of STEM index.[13] Table 8 reports the results of industry-level regressions for the US sample and the two international samples. We find that STEM index continues to have a positive and significant effect on both market beta and realized returns. In particular, the results suggest that a one-standard-deviation increase in STEM index is associated with an increase in industry-level realized returns by between 1.2% and 2.2%.

[13] We exclude *RDMISSING* in the industry-level estimation of equation (4).

[Insert Table 8 here]

Overall, the evidence presented in this section reinforces our conclusion that investment in a highly skilled workforce, especially one centred around STEM workers, create risk for firms. As the significant cost commitment associated with STEM workers inhibits firms from adjusting to the economic conditions, shareholder cash flow is less insulated from systematic (undiversifiable) demand shocks, which implies a higher risk premium on the firm's stock. The findings in table 6 and table 7 are jointly supportive of this inference.

4 Additional Results

This section presents results from several additional tests. First, we examine the relationship between STEM index and a direct measure of labour-related operating leverage for detailed manufacturing industries. Second, we re-estimate the main regressions by controlling for additional industry characteristics. Third, we examine cross-sectional variation in the operating leverage effect by comparing the baseline results across pairs of subsamples formed according to the relative urgency of employee retention.

4.1 A Direct Measure of Labour-Related Operating Leverage

A potential limitation to our wage sensitivity analysis in Section 3.1 is the scarcity of firm-level wage data, as reflected by the reduced sample sizes.[14] To strengthen our inferences while circumventing the data constraints, we turn to the Manufacturing Industry Database of the National Bureau of Economic Research and the Center for Economic Studies (NBER-CES) (Bartelsman & Guay, 1996),[15] which provides detailed production data for the full spectrum of manufacturing industries (classified at the six-digit NAICS level) from 1958 through 2011. Specifically, we construct a direct measure of labour-related operating leverage (*LOPLEV*) as the slope coefficient from a time-series regression in which the natural logarithm of an industry's total payroll costs is regressed on the natural logarithm of its shipment value or its total factor productivity (TFP),[16] using a 10-, 20-, 30-, and 40-year rolling window. A higher

[14] We note, however, that even after imposing the data restrictions, firms in our three alternative samples remain distributed across a wide range of industries.

[15] See https://www.nber.org/research/data/nber-ces-manufacturing-industry-database

[16] For an industry's TFP, we use both the four-factor TFP index ("TFP4") and five-factor TFP index ("TFP5") as reported in the NBER-CES database. The four factors in TFP4 include capital, production worker hours, non-

(lower) value of *LOPLEV* indicates that wage costs in that industry are more (less) responsive to productivity or demand shocks.

To examine whether reliance on STEM workers affects the degree of wage sensitivity, we match the STEM index data with the NBER-CES data and sort the manufacturing industries into five portfolios each year based on their STEM index. For each of the *STEM* quintiles, we calculate the mean value of *LOPLEV*, which is then averaged over the period from 1997 to 2011. Table 9 reports the results of portfolio sorts, which indicate a generally increasing pattern of *LOPLEV* across the *STEM* portfolios. The t-tests for differences in means show that in all specifications, the mean *LOPLEV* is significantly higher for the most STEM worker-intensive manufacturing industries than for the least STEM-worker intensive industries. These findings complement the interaction regression results in table 4 and further indicate that reliance on STEM workers induces operating leverage by increasing the fixity of labour costs.

[Insert Table 9 here]

4.2 Omitted Industry Characteristics

To isolate the effect of STEM index in our regression analysis, we control for several firm-level factors that may affect systematic risk or stock returns. However, it is possible that both STEM index and the dependent variable are correlated with the same industry characteristics, making the observed relationships spurious. To reduce the likelihood of omitted variable bias, we estimate a less parsimonious model by controlling for additional industry characteristics.

Following previous studies (e.g. Chen, Kacperczyk, & Ortiz-Molina, 2012), we address potential industry life-cycle effects by controlling for industry age (*INDAGE*), which is the log age of the oldest firm (based on the first appearance on CRSP) in an industry; the industry capital-to-labour ratio (*INDKL*); the median one-year asset growth rate in an industry (*INDATGR*); the median return-on-assets in an industry (*INDROA*); and industry sales concentration (*INDCONC*).[17] We also control for two industry-level labour variables that have been associated with firms-level stock returns: unionization rate (*UNION*), which is the share of employed workers in an industry covered by a collective bargaining agreement (Chen et al.,

production worker hours, and materials. The five factors in TFP5 include capital, production worker hours, non-production worker hours, energy materials, and non-energy materials (see Becker, Gray, & Marvakov, 2016).

[17] Hou & Robinson (2006) show that firms in more concentrated (i.e. less competitive) industries have lower returns, which they argue is due to the lower innovation risk or distress risk faced by these firms.

2011);[18] and labour mobility (*MOBILE*), which is the relative flexibility of an industry's workers to switch industries (Donangelo, 2014).[19]

Table 10 reports the estimation results of equations (3) and (4) with additional controls. Two findings are of note: First, the positive effects of STEM index remain statistically significant across all columns, indicating the robustness of our main results. Second, our measure of STEM index outperforms other industry-level variables that prior research suggests have implications for the risk and returns of firms. In columns (3) and (6) where all the additional controls are included, the adjusted R-squared increases from 17.5% and 6.8% (in baseline models) to 18.4% and 7.2%, suggesting that the industry characteristics above capture relevant variation in both systematic risk and stock returns, albeit marginally. In sum, the results in table 10 significantly reduce the likelihood that our main results are driven by omitted industry-level factors.

[Insert Table 10 here]

4.3 Subsample Analyses

The central argument of this paper is that reliance on STEM workers increases the degree of labour cost fixity and thus operating leverage, which exposes the firm to greater systematic risk. If this argument is correct, the positive effects of STEM index on market beta and stock returns should become stronger when the firm is further limited in its ability to adjust labour costs. As a final robustness check, we test this possibility by repeating the main analysis for four pairs of subsamples of US firms based on the urgency of employee retention.

The four partitioning variables are: First, the stock of R&D capital, which is the firm's five-year cumulative R&D expense scaled by total assets (Chan et al., 2001); second, a dummy for whether the firm applied for at least one patent (which was subsequently granted) during the past three years, using the data from Kogan, Papanikolaou, Seru, & Stoffman (2017);[20] third, the degree of labour market competition, defined as one minus a Herfindahl-Hirschman index of employee concentration in the firm's industry;[21] and fourth, a dummy for whether contingent

[18] We obtain unionization rate data for three-digit Census Industry Classification (CIC) – roughly equivalent to four-digit NAICS – industries from the Union Membership and Coverage Database (www.unionstats.com).

[19] Following Donangelo (2014), we estimate labour mobility as the degree of inter-industry concentration of occupations, weighted by their associated wage costs and aggregated by industry, using also the BLS-OES data.

[20] We download the patent data for US firms during 1926-2019 from the website of Professor Noah Stoffman (https://host.kelley.iu.edu/nstoffma/).

[21] Kim & Ouimet (2014) construct a similar measure and use it as proxy for worker bargaining power.

workers represent a significant share of the firm's workforce.[22] We expect firms with higher R&D investment and recent innovation output to put more emphasis on preserving human capital (Wang, He, & Mahoney, 2009). Likewise, firms in industries with a more dispersed workforce – which indicates lower exit costs for workers – and firms with predominantly full-time permanent workers may perceive employee retention as relatively important (Leana & van Buren, 1997). Consequently, these firms may be less willing to engage in layoffs or pay cuts, which further reduces the flexibility of their labour costs.

Table 11 reports the subsample results for the wage and profit sensitivity regressions in Section 3.1. Supporting our conjecture, panel A shows that reliance on STEM workers reduces the responsiveness of wages to sales mainly for research- and innovation-intensive firms, firms in industries whose workforce is more thinly spread, and firms with a less transient workforce, as reflected by a more negative coefficient on the interaction terms. Correspondingly, panel B shows that profit volatility is also exacerbated by reliance on STEM workers, mainly for the above subsamples of firms, as reflected by a more positive coefficient on the interaction terms.

[Insert Table 11 here]

To complete our analysis, we also compare the coefficient estimates of STEM index from the systematic risk and return predictability regressions in Section 3.2 across the four pairs of subsamples. Consistent with the inferences from table 11, the results in table 12 shows that reliance on STEM workers has a more positive effect of market beta and realized returns when employee retention is more urgent for the firm as a result of internal knowledge investment or external labour market conditions.

[Insert Table 12 here]

Taken together, the evidence presented in this section further reinforces operating leverage due to labour as an essential mechanism through which reliance on STEM workers contributes to higher equity risk.

[22] Specifically, the dummy variable is set to 1 if the Compustat employee footnote shows "IE", which indicates that at least 10% of the firm's workforce are part-time or seasonal workers, and 0 otherwise (Hanka, 1998).

5 Conclusion

The transition towards a knowledge economy has intensified the demand for highly skilled workers. STEM workers, in particular, are at the centre of the global competition for talent due to their ability to leverage advanced technology both effectively and productively. While the contribution of STEM workers to high value-added activities such as R&D and innovation is often highlighted, little research has analyzed the risk that investment in STEM workers may create for individual firms.

In this paper, we argue that reliance on STEM workers reduces the operating flexibility of firms by increasing the stickiness of operating costs, particularly their labour component. The operating leverage thus created increases the volatility of cash flow as it becomes more exposed to systematic risk. Our empirical evidence supports the operating leverage effect by showing, first, that wages are stickier for firms in more STEM worker-intensive industries, whose profits also react more strongly to external demand shocks; and second, both market beta and future stock returns are positively related to firms' reliance on STEM workers. These results hold for firms in the US, the other G7 countries, and several European countries.

Our paper highlights increased equity risk as a cost that firms must contend with as they seek to benefit from investment in STEM workers. Besides optimizing the return on intangible investments that involve STEM workers, e.g. by improving organizational design (Dougherty, 2006) or employee welfare schemes (Mao & Weathers, 2019), firms may consider adjusting the balance between the fixed and variable components of employee compensation packages (Allen & Thompson, 2019), using skilled contingent labour (Bidwell, 2009), or reducing debt and other fixed charges, such that flexibility is restored in their operating structure.

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Table 1
The Most and Least STEM Worker-Intensive Industries

Rank	NAICS	Industry Title	STEM
		Most STEM Worker-Intensive industries	
1	6221	General Medical and Surgical Hospitals	71.12
2	6211	Offices of Physicians	69.85
3	6223	Specialty (except Psychiatric and Substance Abuse) Hospitals	68.59
4	5415	Computer Systems Design and Related Services	66.87
5	5112	Software Publishers	63.45
6	3341	Computer and Peripheral Equipment Manufacturing	62.47
7	5417	Scientific Research and Development Services	61.23
8	5413	Architectural, Engineering, and Related Services	58.45
9	6214	Outpatient Care Centers	57.64
10	6222	Psychiatric and Substance Abuse Hospitals	56.94
11	6212	Offices of Dentists	56.57
12	6213	Offices of Other Health Practitioners	56.22
13	6215	Medical and Diagnostic Laboratories	55.09
14	5181	Internet Service Providers and Web Search Portals	50.33
15	5182	Data Processing, Hosting, and Related Services	48.85
		Least STEM Worker-Intensive industries	
1	4855	Charter Bus Industry	0.02
2	7222	Limited-Service Eating Places	0.03
3	7224	Drinking Places (Alcoholic Beverages)	0.03
4	7221	Full-Service Restaurants	0.04
5	4852	Interurban and Rural Bus Transportation	0.10
6	8111	Automotive Repair and Maintenance	0.12
7	7212	Recreational Vehicle Parks and Recreational Camps	0.21
8	4412	Other Motor Vehicle Dealers	0.23
9	4453	Beer, Wine, and Liquor Stores	0.24
10	4411	Automobile Dealers	0.25
11	4481	Clothing Stores	0.27
12	2383	Building Finishing Contractors	0.27
13	4922	Local Messengers and Local Delivery	0.30
14	4533	Used Merchandise Stores	0.33
15	8122	Death Care Services	0.36

This table lists the 15 most and 15 least STEM worker-intensive industries, out of a total of 269 industries, based on their average STEM index during the period 1997-2018. STEM index measures the annual wage share of STEM workers in an industry. Industries are defined by four-digit NAICS codes.

Table 2
Sample Distribution

	US	G6	Europe
Panel A: Year distribution			
1997	2,962	1,766	615
1998	2,990	1,825	668
1999	2,834	2,038	708
2000	2,571	2,482	725
2001	2,493	2,942	1,366
2002	2,492	2,967	1,380
2003	2,508	3,121	1,466
2004	2,475	3,492	1,820
2005	2,360	3,828	2,093
2006	2,279	3,956	2,124
2007	2,067	3,801	2,000
2008	1,899	3,550	1,778
2009	1,923	3,522	1,771
2010	1,880	3,708	1,906
2011	1,786	3,818	1,986
2012	1,741	3,925	2,050
2013	1,747	3,884	2,034
2014	1,714	3,835	1,946
2015	1,638	3,748	1,873
2016	1,603	3,548	1,782
2017	1,458	3,539	1,778
2018	1,557	3,507	1,739
Total	46,977	72,802	35,608
Panel B: Sectoral distribution			
Agriculture	0	36	23
Mining	2,150	4,680	1,306
Utilities	1,936	1,753	1,371
Construction	660	2,776	768
Manufacturing	23,720	33,346	16,063
Wholesale	1,678	5,307	1,466
Retail	2,902	5,236	1,882
Transportation	1,228	2,967	1,542
Information	5,926	6,540	4,391
Professional Services	2,680	5,639	4,195
Administrative Services	1,060	1,202	792
Education	284	356	43
Health	1,140	360	241
Arts and Entertainment	292	659	620
Accommodation and Food Services	1,133	1,655	782
Other Services	188	290	123

The table reports the year and sectoral distribution of sample firms in the US, G7 countries except US (Canada, France, Germany, Italy, Japan, and the United Kingdom), and thirteen European countries (Austria, Belgium, Denmark, Finland, France, Germany, Italy, the Netherlands, Norway, Spain, Sweden, Switzerland, and the United Kingdom). The sample covers the period from 1997 to 2018.

Table 3
STEM Index and Firm Characteristics

Panel A: US Sample												
Portfolio	*STEM*	*SIZE*	*ASSET*	*SALE*	*FINLEV*	*MB*	*ROA*	*RD*	*CAPEX*	*BSEG*	*SALEHHI*	*BETA*
1	0.05	6.19	6.44	6.52	0.25	2.59	0.03	0.00	0.06	0.71	0.76	1.07
2	0.27	6.20	6.07	5.49	0.18	3.61	-0.06	0.08	0.05	0.61	0.79	1.22
3	0.55	6.04	5.74	5.46	0.11	3.74	-0.05	0.10	0.04	0.53	0.80	1.48
3-1		-0.15	-0.70***	-1.07***	-0.14***	1.15***	-0.07***	0.09***	-0.02***	-0.18***	0.04***	0.41***
[t]		-0.86	-4.21	-6.91	-14.71	5.75	-7.18	24.80	-4.78	-5.17	3.88	5.08
Panel B: G6 Sample												
Portfolio	*STEM*	*SIZE*	*ASSET*	*SALE*	*FINLEV*	*MB*	*ROA*	*RD*	*CAPEX*	*BSEG*	*SALEHHI*	*BETA*
1	0.03	5.37	6.19	6.23	0.33	1.61	0.02	0.00	0.04	-	-	0.69
2	0.14	5.53	6.28	6.08	0.31	1.57	0.01	0.01	0.05	-	-	0.92
3	0.45	5.29	5.58	5.26	0.20	2.36	-0.01	0.04	0.04	-	-	1.05
3-1	0.43	-0.08	-0.60***	-0.97***	-0.13***	0.75***	-0.03***	0.04***	0.00			0.36***
[t]		-1.08	-9.43	-12.48	-9.31	6.70	-10.88	29.37	0.65			8.70
Panel C: European Sample												
Portfolio	*STEM*	*SIZE*	*ASSET*	*SALE*	*FINLEV*	*MB*	*ROA*	*RD*	*CAPEX*	*BSEG*	*SALEHHI*	*BETA*
1	0.03	5.70	6.28	6.18	0.30	2.08	0.03	0.00	0.05	-	-	0.77
2	0.16	5.83	6.25	6.06	0.26	2.28	0.02	0.02	0.05	-	-	0.84
3	0.50	5.27	5.28	5.03	0.16	3.18	-0.00	0.06	0.04	-	-	0.98
3-1		-0.44***	-1.00***	-1.15***	-0.14***	1.10***	-0.03***	0.06***	-0.02***			0.21***
[t]		-4.69	-10.64	-10.60	-11.58	6.51	-6.48	15.89	-4.27			2.84

This table reports the time-series averages of mean characteristics for three portfolios sorted on the STEM index. *SIZE* is the natural logarithm of market value of equity at the fiscal year-end. *ASSET* is the natural logarithm of total assets. *SALE* is the natural logarithm of net sales. *FINLEV* is the ratio of total debt to the sum of total debt and market value of equity. *MB* is the ratio of market to book value of equity. *ROA* is the ratio of income before extraordinary items to total assets. *RD* is the ratio of R&D expense to total assets. *CAPEX* is the ratio of capital expenditure less the sale of property, plants, and equipment, divided by total assets. *BSEG* is the natural logarithm of the firm's number of business segments. *SALEHHI* is the Herfindahl-Hirschman index of the firm's segment sales. *BETA* is market beta from the CAPM model, estimated using at least 24 and up to 60 months of past return data. All firm-level variables are winsorized at the 0.5% and 99.5% levels. The sample covers the period from 1997 to 2018.

Table 4
Reliance on STEM Workers and Wage Sensitivity

	Dependent Variable: Δ*WAGE*			
	All		Δ*SALE*>0	Δ*SALE*<0
	(1)	(2)	(3)	(4)
Panel A: US Sample				
Δ*SALE*	0.398***	0.440***	0.432***	0.356***
	(7.579)	(9.367)	(7.790)	(6.923)
STEM		0.026***	0.032***	0.004
		(3.475)	(2.909)	(0.354)
Δ*SALE*×*STEM*		-0.113**	-0.135**	-0.139***
		(-2.501)	(-2.343)	(-2.894)
Year FE	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y
Country FE	N	N	N	N
Obs.	2,847	2,847	2,175	671
Adj. R^2	0.324	0.343	0.293	0.240
Panel B: G6 Sample				
Δ*SALE*	0.594***	0.611***	0.583***	0.446***
	(15.804)	(16.389)	(10.983)	(6.505)
STEM		0.012	0.015	-0.001
		(1.524)	(0.839)	(-0.046)
Δ*SALE*×*STEM*		-0.115***	-0.136**	-0.156**
		(-3.101)	(-2.262)	(-2.065)
Year FE	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y
Country FE	Y	Y	Y	Y
Obs.	17,805	17,805	11,183	6,622
Adj. R^2	0.112	0.112	0.116	0.088
Panel C: European Sample				
Δ*SALE*	0.582***	0.598***	0.544***	0.518***
	(20.297)	(20.884)	(13.549)	(9.541)
STEM		0.017***	0.003	0.008
		(2.706)	(0.250)	(0.436)
Δ*SALE*×*STEM*		-0.094***	-0.063	-0.184***
		(-3.300)	(-1.408)	(-3.042)
Year FE	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y
Country FE	Y	Y	Y	Y
Obs.	27,369	27,369	17,120	10,249
Adj. R^2	0.103	0.103	0.106	0.072

The table reports the results of wage sensitivity regression for US firms (panel A), G6 firms (panel B), and European firms (panel C). The dependent variable is the log change in annual wage costs. The independent variables are the log change in annual sales, the standardized STEM index, and their interaction term. Δ*WAGE*, Δ*SALE*, and Δ*SALE*×*STEM* are winsorized at the 0.5% and 99.5% levels. The t-statistics (in parentheses) are calculated based on robust standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Table 5
Reliance on STEM Workers and Profit Sensitivity

	Dependent Variable: Δ*PROFIT*			
	All		Δ*SALE*>0	Δ*SALE*<0
	(1)	(2)	(3)	(4)
Panel A: US Sample				
Δ*SALE*	1.643***	1.642***	1.369***	1.674***
	(58.147)	(57.797)	(42.994)	(18.932)
STEM		-0.024***	-0.003	-0.046***
		(-5.370)	(-0.465)	(-3.361)
Δ*SALE*×*STEM*		0.116***	0.062*	0.186*
		(4.066)	(1.926)	(1.902)
Year FE	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y
Country FE	N	N	N	N
Obs.	32,296	32,296	24,689	7,606
Adj. R^2	0.230	0.231	0.160	0.111
Panel B: G6 Sample				
Δ*SALE*	1.643***	1.641***	1.438***	1.914***
	(75.301)	(75.048)	(51.045)	(32.026)
STEM		-0.005**	0.002	0.003
		(-2.055)	(0.316)	(0.379)
Δ*SALE*×*STEM*		0.064***	0.056**	0.163***
		(3.207)	(1.975)	(2.617)
Year FE	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y
Country FE	Y	Y	Y	Y
Obs.	57,126	57,126	35,420	21,706
Adj. R^2	0.218	0.219	0.141	0.131
Panel C: European Sample				
Δ*SALE*	1.361***	1.360***	1.220***	1.432***
	(47.741)	(47.814)	(32.409)	(19.814)
STEM		-0.003	0.003	0.005
		(-0.788)	(0.425)	(0.489)
Δ*SALE*×*STEM*		0.098***	0.081**	0.234***
		(3.695)	(2.299)	(2.879)
Year FE	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y
Country FE	Y	Y	Y	Y
Obs.	27,229	27,229	17,865	9,364
Adj. R^2	0.184	0.185	0.120	0.099

The table reports the results of profit sensitivity regression for US firms (panel A), G6 firms (panel B), and European firms (panel C). The dependent variable is the log change in annual operating profits. The independent variables are the log change in annual sales, the standardized STEM index, and their interaction term. Δ*PROFIT*, Δ*SALE*, and Δ*SALE*×*STEM* are winsorized at the 0.5% and 99.5% levels. The t-statistics (in parentheses) are calculated based on robust standard errors clustered by firms. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Table 6
Reliance on STEM Workers and Systematic Risk

	Dependent Variable: *BETA*		
	US	G6	Europe
STEM	0.167***	0.098***	0.097***
	(4.942)	(4.496)	(4.786)
SIZE	0.025**	0.038***	0.057***
	(2.049)	(5.233)	(7.434)
FINLEV	0.151**	0.342***	0.288***
	(2.488)	(10.730)	(7.520)
MB	-0.005***	0.007***	-0.004*
	(-2.860)	(2.659)	(-1.930)
ROA	-0.654***	-0.646***	-0.479***
	(-7.158)	(-9.567)	(-9.718)
RD	0.413**	0.448*	0.439**
	(2.447)	(1.661)	(2.429)
RDMISSING	-0.094**	-0.035*	-0.061***
	(-2.498)	(-1.680)	(-2.680)
CAPEX	0.133	-0.609***	-0.204
	(0.738)	(-4.534)	(-1.382)
BSEG	-0.053*		
	(-1.854)		
SALEHHI	-0.026		
	(-0.403)		
Constant	0.882***	0.812***	0.265**
	(7.930)	(10.548)	(2.568)
Year FE	Y	Y	Y
Sector FE	Y	Y	Y
Country FE	N	Y	Y
Obs.	46,977	72,802	35,608
Adj. R^2	0.175	0.225	0.196

The table reports the results of systematic risk regression for US firms (panel A), G6 firms (panel B), and European firms (panel C). The dependent variable is market beta from the CAPM model, estimated using at least 24 and up to 60 months of past return data. *STEM* is the standardized STEM index. *SIZE* is the natural logarithm of market value of equity at the fiscal year-end. *FINLEV* is the ratio of total debt to the sum of total debt and market value of equity. *MB* is the ratio of market to book value of equity. *ROA* is the ratio of income before extraordinary items to total assets. *RD* is the ratio of R&D expense to total assets. *RDMISSING* is a dummy variable equal to 1 if R&D expense is missing, and 0 otherwise. *CAPEX* is capital expenditure less the sale of property, plants, and equipment, divided by total assets. *BSEG* is the natural logarithm of the firm's number of business segments. *SALEHHI* is the Herfindahl-Hirschman index of the firm's segment sales. All firm-level variables except *BSEG* and *SALEHHI* are winsorized at the 0.5% and 99.5% levels. The t-statistics (in parentheses) are calculated based on robust standard errors clustered at the four-digit NAICS industry level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Table 7
Reliance on STEM Workers and Realized Returns

	Dependent Variable: *RETURN*		
	US	G6	Europe
STEM	0.019***	0.010***	0.013***
	(4.093)	(2.791)	(3.024)
SIZE	-0.013***	-0.008***	-0.000
	(-8.712)	(-6.348)	(-0.066)
FINLEV	0.065***	0.039***	0.027
	(3.605)	(3.596)	(1.454)
MB	-0.001*	-0.007***	-0.004***
	(-1.945)	(-6.494)	(-4.395)
BETA	0.007	-0.012	-0.002
	(1.529)	(-1.546)	(-0.220)
LAGRET	-0.052***	-0.019***	0.029***
	(-7.849)	(-3.672)	(3.762)
Constant	0.170***	-0.122***	0.076*
	(7.535)	(-4.963)	(1.925)
Year FE	Y	Y	Y
Sector FE	Y	Y	Y
Country FE	N	Y	Y
Obs.	41,551	67,951	32,039
Adj. R^2	0.068	0.097	0.147

The table reports the results of return predictability regression for US firms (panel A), G6 firms (panel B), and European firms (panel C). The dependent variable is the realized annual return estimated from July in year t+1 to June in year t+2. *STEM* is the standardized STEM index. *SIZE* is the natural logarithm of market value of equity at the fiscal year-end. *FINLEV* is the ratio of total debt to the sum of total debt and market value of equity. *MB* is the ratio of market-to-book value of equity. *BETA* is market beta from the CAPM model, estimated using at least 24 and up to 60 months of past return data. *LAGRET* is the lagged 11-month return from July in year t to May in year t+1. All firm-level variables are winsorized at the 0.5% and 99.5% levels. The t-statistics (in parentheses) are calculated based on robust standard errors clustered at the four-digit NAICS industry level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Table 8
Industry-Level Regressions

	Dependent Variable: *INDBETA*				Dependent Variable: *INDRETURN*		
	US	G6	Europe		US	G6	Europe
STEM	0.050*	0.060***	0.063***	*STEM*	0.022***	0.012***	0.020**
	(1.832)	(4.009)	(3.201)		(4.200)	(2.632)	(2.093)
INDSIZE	0.043**	0.055***	0.066***	*INDSIZE*	-0.010**	-0.006***	0.002
	(2.132)	(7.093)	(7.829)		(-2.080)	(-2.812)	(0.329)
INDFINLEV	0.237**	0.292***	0.319***	*INDFINLEV*	0.145***	0.028	0.080*
	(1.994)	(6.153)	(5.682)		(3.407)	(1.603)	(1.871)
INDMB	-0.015**	-0.000	-0.006	*INDMB*	0.001	-0.004*	-0.006**
	(-2.094)	(-0.002)	(-1.406)		(0.462)	(-1.922)	(-2.192)
INDROA	-1.438***	-0.803***	-0.644***	*INDBETA*	-0.007	-0.004	-0.008
	(-5.600)	(-6.413)	(-4.784)		(-0.573)	(-0.443)	(-0.177)
INDRD	1.458	1.600**	1.537**	*INDLAGRET*	0.011	0.024**	0.050**
	(1.445)	(2.434)	(2.272)		(0.529)	(2.018)	(2.566)
INDCAPEX	-0.045	-0.655***	-0.096				
	(-0.104)	(-2.971)	(-0.395)				
INDBSEG	-0.092						
	(-1.052)						
INDSALEHHI	-0.150						
	(-0.678)						
Constant	0.783***	0.637***	0.181*	Constant	0.095***	-0.031	0.081
	(3.002)	(9.518)	(1.797)		(3.085)	(-1.013)	(0.916)
Year FE	Y	Y	Y	Year FE	Y	Y	Y
Sector FE	Y	Y	Y	Sector FE	Y	Y	Y
Country FE	N	Y	Y	Country FE	N	Y	Y
Obs.	3,901	13,553	14,429	Obs.	3,737	12,925	13,434
Adj. R^2	0.285	0.231	0.224	Adj. R^2	0.183	0.160	0.123

The table reports the results of systematic risk regression in table 6 and return predictability regression in table 7, estimated at the industry level. All firm-level variables (*BETA*, *RETURN*, *SIZE*, *FINLEV*, *MB*, *ROA*, *RD*, *CAPEX*, *BSEG*, *SALEHHI*, and *LAGRET*) are averaged over firms in each four-digit NAICS industry in a given year. The t-statistics (in parentheses) are calculated based on robust standard errors clustered at the four-digit NAICS industry level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Table 9
Reliance on STEM Workers and Labour-Related Operating Leverage

STEM Portfolio	1	2	3	4	5	5 – 1	[t]
			10-year rolling window				
LOPLEV_SHIP	0.768	0.682	0.625	0.607	0.603	-0.164***	-8.037
LOPLEV _TFP4	1.133	0.941	0.984	0.636	0.419	-0.714***	-8.103
LOPLEV _TFP5	1.131	0.941	0.982	0.634	0.419	-0.711***	-8.019
			20-year rolling window				
LOPLEV_SHIP	0.818	0.748	0.692	0.656	0.669	-0.149***	-7.509
LOPLEV _TFP4	1.486	1.184	1.415	0.892	0.466	-1.020***	-13.898
LOPLEV _TFP5	1.482	1.182	1.414	0.892	0.466	-1.016***	-13.948
			30-year rolling window				
LOPLEV_SHIP	0.837	0.811	0.768	0.733	0.736	-0.101***	-6.022
LOPLEV _TFP4	1.804	1.535	1.344	1.002	0.664	-1.140***	-9.064
LOPLEV _TFP5	1.798	1.527	1.341	1.000	0.658	-1.139***	-9.098
			40-year rolling window				
LOPLEV_SHIP	0.831	0.822	0.814	0.792	0.772	-0.059***	-6.791
LOPLEV _TFP4	2.109	1.923	1.575	1.131	0.931	-1.178***	-6.612
LOPLEV _TFP5	2.108	1.918	1.576	1.138	0.933	-1.175***	-6.503

This table reports the time-series averages of mean labour-related operating leverage for five portfolios of detailed manufacturing industries sorted on STEM index. The last two columns show the t-test results of mean differences between extreme portfolios. Labour-related operating leverage is defined as the slope coefficient from a time-series regression in which the natural logarithm of total payroll costs are regressed on the natural logarithm of shipment value (*LDOL_SHIP*) or total factor productivity (*LDOL_TFP4* or *LDOL_TFP5*) over a 10-year, 20-year, 30-year, or 40-year rolling window. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Table 10
Additional Control Variables

	Dependent Variable: *BETA*			Dependent Variable: *RETURN*		
	(1)	(2)	(3)	(4)	(5)	(6)
STEM	0.171***	0.180***	0.174***	0.020***	0.021***	0.016**
	(5.197)	(5.354)	(5.088)	(4.056)	(3.497)	(2.311)
INDAGE	-0.094*	-0.094*	-0.092*	0.012	0.008	0.009
	(-1.893)	(-1.925)	(-1.766)	(1.232)	(0.896)	(0.936)
INDKL	0.038	0.036	0.036	-0.033*	-0.035*	-0.033*
	(0.785)	(0.773)	(0.778)	(-1.804)	(-1.756)	(-1.655)
INDATGR		-0.523***	-0.495***		-0.330***	-0.321***
		(-2.910)	(-2.810)		(-3.046)	(-2.814)
INDROA		0.248	0.263		-0.080***	-0.089***
		(1.225)	(1.129)		(-3.301)	(-3.318)
INDCONC			-0.130			-0.017
			(-0.714)			(-0.560)
UNION			-0.003			-0.001
			(-1.200)			(-1.404)
MOBILE			0.013			0.003*
			(1.169)			(1.789)
Constant	1.272***	1.302***	1.201***	0.119**	0.166***	0.151***
	(5.114)	(5.411)	(5.335)	(2.474)	(3.309)	(2.968)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y	Y	Y
Obs.	46,977	46,977	45,848	41,551	41,551	40,549
Adj. R^2	0.177	0.180	0.184	0.069	0.071	0.072

The table reports the US results of systematic risk regression in table 6 and return predictability regression in table 7, controlling for additional industry characteristics. These include the log age of the oldest firm in the industry (*INDAGE*), the industry median capital-to-labour ratio (*INDKL*), the industry median asset growth rate (*INDATGR*), the industry median return on assets (*INDROA*), the Herfindahl-Hirschman index of industry sales concentration (*INDCONC*), the percentage of unionized workers in the industry (*UNION*), and the degree of mobility of an industry's workforce (*MOBILE*). All industry-level variables are defined at the four-digit NAICS industry level except *UNION*, which is defined at the three-digit CIC industry level. All regressions include year and sector fixed effects. The t-statistics (in parentheses) are calculated based on robust standard errors clustered at the four-digit NAICS industry level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Table 11
Subsample Analysis of Wage and Profit Sensitivity

	R&D Stock		Patent		Labour Competition		Contingent Labour	
	Low	High	No	Yes	Low	High	<10%	≥10%
Panel A: Wage Sensitivity Regression								
	Dependent Variable: Δ*WAGE*							
Δ*SALE*	0.589***	0.317***	0.513***	0.331***	0.557***	0.442***	0.390***	0.692***
	(10.050)	(4.999)	(9.797)	(3.288)	(8.852)	(11.743)	(7.705)	(12.815)
STEM	0.018**	0.034*	0.019**	0.032**	-0.001	0.050***	0.034***	0.009
	(2.333)	(1.847)	(2.556)	(2.248)	(-0.089)	(3.783)	(3.572)	(1.158)
Δ*SALE*×*STEM*	0.044	-0.257***	-0.042	-0.219**	0.099**	-0.322***	-0.181***	-0.024
	(1.065)	(-3.757)	(-0.924)	(-2.084)	(2.099)	(-6.887)	(-3.356)	(-0.684)
Constant	0.092***	0.032	0.097***	0.091***	0.112***	0.056***	0.109***	0.057***
	(4.785)	(0.837)	(5.330)	(2.820)	(4.263)	(3.184)	(5.105)	(3.265)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	2,340	441	2,376	471	1,505	1,342	1,841	1,006
Adj. R^2	0.524	0.114	0.433	0.117	0.522	0.340	0.301	0.583
Panel B: Profit Sensitivity Regression								
	Dependent Variable: *ΔPROFIT*							
Δ*SALE*	1.453***	1.854***	1.536***	1.806***	1.637***	1.603***	1.642***	1.631***
	(34.383)	(39.659)	(45.659)	(33.509)	(40.132)	(38.976)	(51.661)	(27.130)
STEM	-0.001	-0.032***	-0.013**	-0.045***	-0.018***	-0.033***	-0.027***	-0.012
	(-0.117)	(-4.878)	(-2.188)	(-6.165)	(-2.656)	(-4.576)	(-5.244)	(-1.240)
Δ*SALE*×*STEM*	-0.038	0.092**	0.024	0.216***	0.046	0.187***	0.131***	0.067
	(-0.845)	(2.043)	(0.709)	(4.104)	(1.041)	(4.768)	(4.037)	(1.166)
Constant	-0.064***	-0.083*	-0.092***	-0.060	-0.125***	-0.112***	-0.114***	-0.086**
	(-2.613)	(-1.948)	(-3.903)	(-1.457)	(-3.336)	(-4.191)	(-4.109)	(-2.139)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	17,111	14,630	21,361	10,935	16,411	15,885	25,395	6,901
Adj. R^2	0.203	0.260	0.210	0.278	0.225	0.237	0.243	0.184

The table repeats the wage sensitivity regression in table 4, and the profit sensitivity regression in table 5, for US firms divided into four pairs of subsamples. All model variables are as previously defined. The partitioning variables include: first, the stock of R&D capital which is the five-year accumulated R&D expenses; second, an indicator variable for whether the firm applied for a patent during the previous three years; third, the degree of labour market competition, defined as one minus a Herfindahl-Hirschman index of employee concentration in the firm's industry; and fourth, reliance on contingent workers, defined as whether the firm employs at least 10 percent of its workforce on part-time or seasonal contracts. All regressions include year and sector fixed effects. The t-statistics (in parentheses) are calculated based on robust standard errors clustered at the four-digit NAICS industry level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Table 12

Subsample Analysis of Relationship between STEM Index and Equity Risk

	R&D Stock		Patent		Labour Competition		Contingent Labour	
	Low	High	No	Yes	Low	High	<10%	≥10%
Panel A: Systematic Risk Regression								
	Dependent Variable: *BETA*							
STEM	0.062*	0.201***	0.116***	0.247***	0.125***	0.225***	0.188***	0.063
	(1.951)	(3.662)	(4.772)	(3.773)	(3.469)	(2.978)	(5.438)	(1.396)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	22,936	22,922	29,901	17,076	24,311	22,666	37,505	9,472
Adj. R^2	0.182	0.154	0.170	0.181	0.139	0.218	0.198	0.095
Panel B: Return Predictability Regression								
	Dependent Variable: *RETURN*							
STEM	0.004	0.017**	0.016***	0.019**	0.023***	0.032***	0.018***	0.018***
	(0.519)	(2.310)	(2.719)	(2.367)	(3.765)	(3.144)	(3.729)	(2.812)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	20,280	20,253	25,228	16,323	21,418	20,133	33,133	8,418
Adj. R^2	0.085	0.086	0.065	0.099	0.074	0.084	0.072	0.060

The table repeats the systematic risk regression in table 6, and the return predictability regression in table 7, for US firms divided into four pairs of subsamples. All model variables are as previously defined. The partitioning variables include: first, the stock of R&D capital which is the five-year accumulated R&D expenses; second, an indicator variable for whether the firm applied for a patent during the previous three years; third, the degree of labour market competition, defined as one minus a Herfindahl-Hirschman index of employee concentration in the firm's industry; and fourth, reliance on contingent workers, defined as whether the firm employs at least 10 percent of its workforce on part-time or seasonal contracts. Coefficients on the control variables are omitted for brevity. All regressions include year and sector fixed effects. The t-statistics (in parentheses) are calculated based on robust standard errors clustered at the four-digit NAICS industry level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.