The Value of Human Capital for Firm Performance:

Roles of Expertise and Teamwork

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ABSTRACT

We study how well human capital predicts firm performance using machine learning. We argue that employee expertise and teamwork, the latter being the collaboration among employees with specialized knowledge, are key contributors to firm-level human capital and firm performance. By analyzing online job postings, we construct a detailed measure of firms' team-based human capital inflow. In out-of-sample tests, our human capital inflow measure predicts two-year-ahead earnings better than other human-capital proxies. Cross-sectionally, team-based human capital predicts future earnings better for firms with complex tasks and effective employee communication. This systematic cross-sectional variation extends to both employee expertise and synergistic teamwork.

Keywords: human capital; teamwork; complementarity; machine learning; XGBoost
JEL classification: J23; J24; M41; M54

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ABSTRACT

We study how well human capital predicts firm performance using machine learning. We argue that employee expertise and teamwork, the latter being the collaboration among employees with specialized knowledge, are key contributors to firm-level human capital and firm performance. By analyzing online job postings, we construct a detailed measure of firms' team-based human capital inflow. In out-of-sample tests, our human capital inflow measure predicts two-year-ahead earnings better than other human-capital proxies. Cross-sectionally, team-based human capital predicts future earnings better for firms with complex tasks and effective employee communication. This systematic cross-sectional variation extends to both employee expertise and synergistic teamwork.

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Our 73,000 team members are the heart and soul of our company, and our “not-so-secret” sauce.

—Whole Foods Market, 2012 letter to stakeholders

Your employees are your best asset. Happy employees make for happy customers.

—Richard Branson, founder and chairman of Virgin Group

I. INTRODUCTION

People are among firms’ long-term investments and expected to yield future benefits. While firms increasingly recognize the critical link between talent and superior performance, human capital resources are accounted for differently than many other assets, largely remaining off balance sheets. Currently, the SEC and FASB are updating guidelines for human capital disclosures, so that firms and investors can better evaluate human capital. We measure the inflow of firm-level human capital resources using online job requirements to create a structured, multidimensional skill vector. We use extreme gradient boosting (XGBoost), a machine learning algorithm that excels in identifying complex interactions among predictors and their nonlinear impacts on firm performance. Our human capital inflow measure predicts about 18.6% of the variance in two-year-ahead earnings in out-of-sample tests, providing a lower bound on human capital’s predictive value for firm performance.

Firms create value by organizing human capital resources efficiently. We conceptualize firm-level human capital as arising from the collaboration of specialized employees with diverse skills. At the individual level, human capital can be viewed as a multidimensional construct, varying in composition of skills even for the same occupation across firms (e.g., Lazear 2009). Individual human capital emerges from the collaboration of employees with diverse skills, creating new collective firm-level human capital through interactive skill combinations (e.g., Ployhart and Moliterno 2011). Therefore, unlike a mere aggregation of individual employees, firm-level human capital encompasses labor-division-induced employee expertise and teamwork-induced employee skill complementarities. Our measure achieves greater predictive performance by incorporating both individual employee expertise and teamwork into the analysis.

We empirically examine the conditions under which the predictive value of our human capital inflow measure is enhanced. On one hand, human capital is recognized as a crucial factor boosting firm performance and productivity (e.g., Zingales 2000). On the other hand, diminishing returns from increased coordination costs in more diverse teams, combined with potential overinvestment due to agency costs or misplaced optimism in certain skills, can offset the productivity boost (e.g., Becker and Murphy 1992). Consistent with the coordination cost theory, we expect that the predictive value of human capital depends on the complexity of a firm's production processes and the efficacy of employee communication. As job tasks become more complex, the cost for individuals to acquire wide-ranging expertise grows, highlighting the value of specialized, collaborative teams. Moreover, the benefit of teamwork hinges on active communication and expertise integration. Our empirical results align with both expectations.

Data limitations pose challenges in assessing human capital's predictive value. SEC filings offer limited comparable data beyond employee counts, inadequately reflecting the nuanced dynamics of firm-level human capital resources. We analyze firm disclosures outside SEC filings, specifically online job postings. Analyzing all required skills offers insight about firm-specific skill demands and lets us track human capital creation over time (e.g., Ege, Kim, and Wang 2023; Gao, Merkley, Pacelli, and Schroeder 2023). We tally the total number sought by a firm annually, count each unique skill and within-individual skill pair to capture employee expertise, and count each across-individual skill pair to capture simple forms of teamwork. We develop a 1,399-variable human capital skill vector for each firm-year, detailing annual recruitment-driven human capital changes. A preliminary analysis shows that over 96% of the variables correlate non-negatively with subsequent firm performance.

Our findings are compelling: the out-of-sample R^2 values of our multidimensional skill vector models range from 8.25% to 24.70% across different test years, significantly outperforming benchmark models using unidimensional proxies like employee count, hiring rates, and turnover. Moreover, including the skill vector improves the performance of the benchmark models by 48.7% on average, underscoring its incremental predictive value and potential causal importance. Finally, we show the sources of improved predictive performance: the average out-of-sample R^2 values of our skill vector increases from 12.97% to 18.63% when teamwork, alongside employee expertise, is incorporated in the measure.

We then examine the conditions under which our skill vector's predictive value is greater. Consistent with our expectations, we find that the skill vector predicts better for firms with high task complexity (i.e., operating in high-tech industries, lower routine task indexes, and higher Tobin's Q ratios). Additionally, the skill vector shows higher predictive value for firms with low communication costs as indicated by strong teamwork cultures, higher emphasis on teamwork skills in job postings, fewer business segments, and fewer geographical locations. These findings collectively indicate that our skill vector predicts future firm performance better when complex tasks prevail and employees communicate efficiently, consistent with the notion that team-based production adds more value in such scenarios.

We extend the accounting research on labor by using firms' nonfinancial disclosure (i.e., skill requirements in job postings) to craft a structured, multidimensional skill vector that measures the inflow of firm-level human capital resources. Aligning with the notion that understanding a phenomenon requires both causal explanation and prediction (e.g., Gow, Larcker, and Zakolyukina 2023), we demonstrate skill vector's superior predictive value over other unidimensional human capital proxies for future firm performance. Moreover, we enhance the understanding of the division and specialization of labor and skill complementarity by showing that incorporating teamwork, measured by skill co-occurrences, beyond employee expertise enhances the predictive value of our human capital resources measure. We also show that skill vector forecasts earnings better particularly in contexts of high task complexity and strong communication practices. These findings inform managerial decisions on human capital investment and management control system design to foster effective teamwork (Brickley, Smith, and Zimmerman 2016). Finally, we contribute to the growing integration of machine learning in accounting and finance research. Our application of machine learning to human capital is novel, particularly in how we interpret and understand its implications through cross-sectional analysis.

II. THEORETICAL DEVELOPMENT

We apply machine learning methods to predict future firm performance using important off-balance-sheet resources, specifically human capital. Previous attempts to quantify human capital have relied on basic metrics like employee count, hiring rates, and turnover (Dechow, Ge, Larson, and Sloan 2011; Gutiérrez, Lourie, Nekrasov, and Shevlin 2020; Li, Lourie, Nekrasov, and Shevlin 2022). These measures, while informative, do not fully capture the complex impact of human capital on firm success. Our approach not only shed more light on the detailed dynamics of human capital but also diverges from the reliance on financial data in earnings prediction literature (e.g., Monahan 2018; Binz, Schipper, and Standridge 2020; Chen, Cho, Dou, and Lev 2022). This exploration is both academically relevant and practically significant. Regulatory updates such as the 2020 SEC amendment to Regulation S-K and the 2023 FASB proposal on expense disaggregation disclosures aim to improve transparency around human capital, recognizing its importance in corporate valuation and performance (Arif, Marshall, Schroeder, and Yohn 2019; Bourveau, Chowdhury, Le, and Rouen 2022; Berger, Choi, and Tomar 2023). Firms are also encouraged to revamp their employee value propositions to address inefficiencies in talent management strategies (Cappelli 2023; Wagner 2024). In this section, we outline the theory and evidence that link human capital to earnings.

Labor and firm performance

Corporate executives often state that employees are their firms' most crucial assets (Fulmer and Ployhart 2014). This sentiment is echoed by accounting and finance researchers who emphasize the significant role of a firm's labor force in enhancing productivity (Zingales 2000; Call, Campbell, Dhaliwal, and Moon 2017; Agrawal, Hacamo, and Hu 2021). This consensus aligns with the human capital view that employees with specialized skills for specific tasks collectively support a firm's operational objectives, with their human capital forming a crucial resource for the firm's competitive advantage (Barney 1991; Ployhart, Nyberg, Reilly, and Maltarich 2014). Despite its critical role, public disclosure of human capital data remains limited. In U.S. financial reporting, human capital costs are not separately indicated as an expense on an income statement and human capital resources are not recognized as distinct assets on a balance sheet, with disclosures largely limited to employee counts (Dechow et al. 2011).[1]

Likely due to data limitations, early studies on firm-level human capital treat it as unidimensional: the workforce is endowed with more or less of one catch-all "human capital"

[1] Workers, not the firm, own their individual human capital. Firms rent human capital from individuals inside and outside the firm, whether working full-time or part-time (Basu and Waymire 2008), so these individual skills cannot be recognized as separable firm assets on balance sheets today. Before the Civil War, U.S. firms reported slaves as assets on balance sheets (e.g., Flesher and Flesher 1980; Barney and Flesher 1994), but slavery is now illegal. Firms can increase workers' productivity by teaming them with other skilled workers and firm-controlled physical and intellectual capital, and these synergies are part of (unrecognized) internal accounting goodwill.

and the human capital quality determines productivity gain. This quality is deduced from key personnel or entire workforce education backgrounds (Bamber, Jiang, and Wang 2010; Call et al. 2017), work experiences (Bröcheler, Maijoor, and Van Witteloostuijn 2004; Custódio, Ferreira, and Matos 2013), and professional certifications (De Franco and Zhou 2009).

Alternatively, a more recent approach models human capital as a multidimensional construct, comprising various skills used in differing proportions even for the same occupation across firms (Lazear 2009; Lise and Postel-Vinay 2020; Bernard, Ge, Matsumoto, and Toynbee 2021). This approach facilitates a more nuanced analysis of specific human capital dimensions' impacts on productivity. Prior research mostly zooms in and studies one particular function or employee expertise. For example, investments in the tax function enhances firms' tax planning activities (Chen, Cheng, Chow, and Liu 2021; Barrios and Gallemore 2023). Firms' investments in big data and artificial intelligence lead to faster productivity growth (Tambe 2014; Babina, Fedyk, He, and Hodson 2024). Darendeli, Law, and Shen (2022) link firms' investment in green jobs to operational performance and green innovation. One exception is Lee, Mauer, and Xu (2018) who take a more holistic approach and examine firms' occupation composition with data on industry-level occupation composition and firm-level industry concentration. They document that the across-firm occupation-composition relatedness is a key factor in merger and acquisition performance.

Firm-level human capital: Expertise and teamwork

Classical economics (e.g., Smith, 1776) posits that labor division across people in a society is key to economic growth, which is borne out in empirical tests using cross-cultural data (e.g., Basu, Kirk, and Waymire 2009). Here, the division and specialization of work is influenced by the extent of the market. For firms, however, labor division is also influenced by the cost of coordinating specialized employees (Becker and Murphy 1992). As firms grow, these costs escalate, evidenced by principal-agent conflicts, free riding, and communication difficulties (Cohen and Levinthal 1990; Adams, Akyol, and Verwijmeren 2018). Consequently, firms often divide their workforce into smaller, more manageable teams, structuring themselves into multi-level organizations.[2] This approach becomes increasingly important in today's global and technologically advanced economy, where teams emerges as fundamental organizational units (Wuchty, Jones, and Uzzi 2007).

In the past, firms primarily organized by function (U-form) to improve efficiency, grouping similar roles to leverage economies of scale and facilitate communication within functions (Chandler 1962).[3] This approach streamlined management and enhanced skill development within specialized domains. As firms expanded and diversified through the 20th century, they evolved to adopt an additional organizational layer, creating semi-autonomous divisions responsible for distinct business or geographic areas (i.e., M-form) (Chandler 1977).[4] By the early 1990s, the adoption of the M-form structure was nearly universal among large U.S. firms, driven by its ability to decentralize decision-making and enhance flexibility and performance. In this sense, a firm can be viewed as a team of teams (of teams), with employees collaborating within their respective departments, divisions, and the overall organization.

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[2] Following Becker and Murphy (1992), we define a "team" broadly as a group of workers who collaborate to produce goods or services by performing different tasks and functions. "Team" does not imply that team members have identical goals.

[3] At the same time, firms used the scientific management approach to standardize best practices for repetitive tasks in order to smooth the coordination within and between teams (Taylor 1911). The cost is that the within-firm communication can then become rigid due to the high degree of standardization and formalization (Madsen 2011).

[4] Different divisions may experience different profitability, risks, and growth opportunities, so disaggregated data about major divisions can help investors better understand a firm's performance and make more informed judgments. ASC 280 (Segment Reporting) requires firms to disclose disaggregated data about their operating segments in annual reports. Under ASC 280, one major criterion for identifying an operating segment is the availability of discrete financial data. In 2022, FASB issued a proposed Accounting Standards Update to improve and enrich segment disclosures (retrieved from https://fasb.org/Page/ProjectPage?metadata=fasb-SegmentReporting-022820221200).

Labor division and firm structure shape the micro-level dynamics of firm-level human capital. At the individual level, human capital has long been viewed as a stock of various skills that can help achieve economic outcomes in economic and management literature (Coff and Kryscynski 2011; Lise and Postel-Vinay 2020). Extending this notion to the organizational level, we understand firm-level human capital as the combined skills of all employees and contractors working within a company (Ployhart et al. 2014).

This aggregate of talents and expertise within a firm is more than just adding up individual skills. Given the organizational structure as a network of interlinked teams, the interaction among employees—fueled by a progressive division and specialization of labor—nurtures a depth of expertise in various domains (Becker and Murphy 1992). At the same time, this focus on specialization enhances the importance of collaboration. Employees' skills complement one another, collectively pushing the company towards its goals through their interconnected roles (Raveendran, Silvestri, and Gulati 2020). In other words, individual skills can be combined interactively through employee collaboration, resulting in new and collective firm-level human capital (Ployhart and Moliterno 2011; Ethiraj and Garg 2012). Hence, firm-level human capital is not just an accumulation but a dynamic interplay of specialized skills and collaborative synergy.

In this paper, we examine firm-level human capital resources emerged from employee expertise and synergistic teamwork. The classical economic theory highlights the synergy between capital and labor, showing that more physical capital can make labor, particularly skilled labor, more productive.[5] Such complementarity between different factors of production is arguably more critical for human capital (Neffke 2019). Managing human capital thus entails coordinating specialized employees to maximize complementarity and efficiently produce goods

[5] We defer the study on capital-labor synergy to future research, mainly due to data limitations. Our human capital data is measured at the individual level while public data on physical capital is usually measured at the firm level.

and services (Becker and Murphy 1992; Garicano 2000). By integrating complementary technologies and strategic policies, companies can streamline their operations, strategies, and structures to gain competitive advantage (e.g., Milgrom and Roberts 1995).[6]

Expertise, teamwork, and firm performance

Employees enhance firm productivity by addictively pooling their skills and efforts.[7] This notion aligns with previous discussions that highlights the significant role of employee expertise in boosting task-specific productivity. Firms with a diverse pool of talent are well-positioned to support various value chain activities, thereby creating value (Porter 1985).

Moreover, skills contribute to firm productivity not in isolation but through their complementary nature, suggesting that the synergy from different skills makes the collective skill set more valuable than the sum of individual skills. At the individual level, research shows that the complementarity between broad skill categories, such as cognitive and social skills, leads to positive outcomes in the labor market (Deming and Kahn 2018). Skill complementarity among specific skills is also fairly obvious. For instance, roles in graphic design or product branding often require a combination of logo design and illustration skills (Stephany and Teutloff 2024).

Cross-individual collaborations—whether within departments, divisions, or the entire firm—generate additional synergies that enhance performance. Diverse teams, by combining varied skills, achieve greater performance due to the synergistic effects (Fang and Hope 2021). Successful project implementation often necessitates such synergistic collaboration across

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[6] Complementarity within firms goes beyond capital and labor. For example, firms' investment opportunity sets guide the choice of payout policy, capital structure, pay structure and accounting procedure choice (e.g., Myers 1977; Smith and Watts 1992; Skinner 1993; Basu, Ma, and Briscoe-Tran 2022). Interdependence among firm policies creates complementarities that leads to performance gains (e.g., Ichniowski, Shaw, and Prennushi 1997; Aral, Brynjolfsson, and Wu 2012).

[7] Firms can optimize production efficiency by coordinating employee specialization and assigning job roles to employees with comparative advantage (Ricardo 1817; Rivkin and Siggelkow 2003). For simplicity, this paper takes firms' matching between job roles and employee skills as given.

departments. For example, successful innovation commercialization requires complementary assets such as manufacturing, marketing, and after-sales service (Teece 1986). Knowledge sharing within firms, across semi-autonomous divisions, also bolsters firm performance (Seavey, Imhof, and Westfall 2018).[8] Recognizing the productivity gain from skill complementarities, the role of teamwork has grown increasingly vital. For example, Adhvaryu et al. (2023) show that polished employee teamwork skills boosts productivity of Indian garment workers by 13.5%.

However, to achieve net productivity gains at the firm level, the benefits of human capital must surpass total labor costs. Challenges include the higher compensation required for skilled employees and the risks of misinvesting in human capital due to managerial overconfidence or empire-building (Hope and Thomas 2008; Fedyk and Hodson 2023). Moreover, unlike physical assets, the productivity gains from human capital resources hinge on not only the quantity of expertise but also employees' attitudes. Inefficient human capital management reduce morale and productivity (Becker and Gerhart 1996; Edmans 2011). Furthermore, teamwork does not always yield positive synergy. As mentioned, coordination costs rise with team size. For one, high specialization within teams may hinder the development of a shared understanding, impeding communication and collaboration (Cohen and Levinthal 1990; Adams et al. 2018). For the other, moral hazard problems, such as the free rider problem, intensify when it is challenging to attribute team output to individual contributions (Holmstrom 1982).[9]

When teamwork adds more value

Because of coordination costs, the impact of teamwork on productivity is contingent on the

[8] Since each division operates independently in a M-form firm, cross-division complementarity can be limited. In today's volatile, uncertain, complex, and ambiguous (VUCA) world, firms are encouraged to build a well-connected team of teams that shares the same understanding of the mission, builds trust within and between teams, and works well together (McChrystal, Collins, Silverman, and Fussell 2015).
[9] To reduce such shirking, team members can appoint an external monitor (Alchian and Demsetz 1972) or employ peer-to-peer sanctions (Ostrom, Walker, and Gardner 1992; Fehr and Gächter 2000).

context. For instance, sports like baseball rely more on individual efforts, while basketball demands coordinated teamwork for optimal performance (Wolfe et al. 2005). This variation extends to business settings, with some roles requiring less collaboration, such as customer service call centers, and others, like sell-side analyst teams, demanding high levels of teamwork (Fang and Hope 2021). For firms, the value of teamwork is primarily influenced by two factors: task complexity and ease of employee communication (e.g., Ployhart and Moliterno 2011).

As job tasks grow in complexity, the costs of acquiring relevant skills and knowledge also rise. Consequently, complex tasks can make it challenging for an individual to possess broad expertise and proficiency, increasing the returns to specialization (Einstein 1934; Jones 2009; Jones 2021). Heightened specialization naturally necessitates a higher degree of teamwork among employees to ease the aggregation of specialized knowledge (Jones 2009). Therefore, complex tasks require close coordination and temporal synchronization among team members (Thompson 1967; Ployhart and Moliterno 2011).

Effective communication is crucial for valuable teamwork by enabling interdependent work, trust, knowledge sharing, and the integration of expertise (Mesmer-Magnus and DeChurch 2009). A firm's organizational structure that facilitates employee interactions can act as a cohesive force, amplifying employee complementarity (Ployhart and Moliterno 2011). Appropriate management control systems can lower communication costs and shape the value of teamwork by providing more communication channels (Arnold, Hannan, and Tafkov 2018; Arnold, Hannan, and Tafkov 2020), fostering a culture that emphasizes teamwork, trust, and open communication (Guiso, Sapienza, and Zingales 2015; Li, Mai, Shen, and Yan 2021), and prioritizing team building and collaboration tools in the employee training and development

(Adhvaryu et al. 2023).[10]

Task complexity and ease of communication are not independent of each other. Complex tasks demand employee specialization and collaboration. Firms dealing with complex tasks tailor their organizational structures and job allocations to enhance employee specialization and collaboration. While it is empirically challenging to test due to scarce time-series data, the organizational structure and corporate culture will adapt or adjust over time how the tasks are structured in response to environmental changes (Sarta, Durand, and Vergne 2021).

III. MEASURING HUMAN CAPITAL USING JOB POSTINGS

Main data

Our main job posting data come from Burning Glass Technologies (BGT, now known as Lightcast), a leading firm in employment data analytics. This data provides information about online job postings and skills in demand, sourced from over 40,000 online job boards and company websites. By eliminating duplicates and employing proprietary algorithms, BGT refines job postings to include key details like employer information, job titles, locations, and required skills. Recent studies in accounting use BGT job postings data to examine firm labor (e.g., Ham, Hann, Rabier, and Wang 2020; Darendeli, Law, and Shen 2022; Ege, Kim, and Wang 2023; Gao, Merkley, Pacelli, and Schroeder 2023).[11]

Table 1 Panel A presents the sample selection process. Our BGT data contain 233,098,988 job postings issued by 37,017 firm-year observations from 2010 to 2019. We use the crosswalk file provided by BGT to merge the job postings data with financial data from Compustat and

[10] Management control systems can impact teamwork productivity through other interventions such as goal orientation (Gong, Kim, Lee, and Zhu 2013), performance measurement (Brüggen, Feichter, and Williamson 2018; Klein and Speckbacher 2020; Glover and Xue 2023), financial incentives (Chen, Williamson, and Zhou 2012; Kachelmeier, Wang, and Williamson 2019; Glover and Xue 2023), and personnel control (Autrey, Jackson, Klevsky, and Drasgow 2023).

[11] Even though hiring may occur without an official job opening or recruitment process, studies show that most hiring activities over the past decade are traceable through online records (Faberman and Menzio 2018).

employee hiring and turnover rate data from Revelio Lab. We require benchmark variables (i.e., employee count, hiring rate, and turnover) and two-year-ahead *Return on Assets* (ROA_{t+2}) to be non-missing and a minimum of 10 postings per firm-year. The final sample consists of 13,069 firm-year observations.

Table 1 Panels B and C report the number of firm-year observations by year and by Fama-French 12 industry, respectively. In Panel B, the number of observations increases slightly over the years, consistent with BGT gradually expanding its coverage. In Panel C, firm-year observations in our sample closely aligns with the Compustat universe in the industry distribution, predominantly featuring sectors like business equipment, finance, and manufacturing.

Measuring Human Capital Inflow using Skill Vectors

We take a detailed and structured approach to quantify firms' human capital resources by analyzing skill requirements from online job postings. Specifically, we construct the firm-level human capital inflow measure by aggregating job-posting-level skill and skill pair requirements to the firm-year level. To limit the dimensionality of our predictors to a manageable level, we use skill cluster family, the coarsest level of skill requirements coded by BGT using its own proprietary textual analysis algorithm on job descriptions. To mitigate the influence of outliers, we exclude the skills and skill pairs required by less than 2 percent of job postings. This approach assumes that the skills listed in each job posting reflect individual-level employees' skill endowments for the focal firm. Our analysis spans 27 unique skills and on average, each job posting list 7.8 skill requirements.

We focus on skills rather than job titles as the base element of our human capital inflow measure in order to capture the heterogenous and multidimensional nature of firm-level human capital resources, recognizing that the required skill sets can significantly vary across firms even for the same occupation (e.g., Lazear 2009). Moreover, we analyze firms' job postings rather than individuals' resumes to assess a firm's skill requirements for two key reasons. First, these postings reflect the specific skills critical to the firm's operations, offering a more accurate representation of its human capital needs. For example, an accountant's piano playing, while impressive, is irrelevant to business operations and thus should not be included in our measure. Second, job posting timestamps allow for more precise tracking of changes in a firm's skill requirements year over year.

In constructing our human capital inflow measure, we explore both the additive and interactive effects of individual skills by quantifying *unique skills and skill pairs* required by the firm in a given year. We analyze skill co-occurrences to identify synergies that bolster the firm's human capital, assuming that firms design job postings to reflect not only the individual skills needed but also the potential for these skills to interact in ways that contribute to the firm's collective human capital. This approach aligns with a fundamental rationale rooted in the concept of labor division since Smith (1776), which posits that combining skills at lower levels leads to the creation of synergies at a higher level (see Figure 1). Online Appendix Figure OA1 shows a complete example of our aggregation process in simplified terms.

To capture the expertise portion of firm-level human capital, we start by tallying every skill listed in job postings for firm *i* in year *t*, referred to as the total skill count *(# skills*). We then compile firm *i*'s annual skill requirements by counting the frequency of each unique skill and normalizing these counts by the total skill count.[12] In addition, we treat each job posting as

[12] In counting the skill frequency, we give all the job postings posted by firm *i* in year *t* the same weight and view the aggregation of all the job postings posted by firm *i* in year *t* as a bag of skills. An analogy would be the bag-of-words approach in textual analysis.

representing one employee's skill set and gauge skill complementarity by identifying and aggregating the instances where unique skill pairs (e.g., Python and writing) co-occur within the same posting. This aggregation across all firm *i*'s postings for year *t* is then normalized by the total skill count.[13]

To capture the synergistic teamwork across employees, we count co-occurrences of skill pairs at the department, division, and firm levels in the following ways. First, we measure the complementarity across individuals within the same *department*, defined as a group of individuals working in the same occupation and the same geographic area. We count the co-occurrences of unique skill pairs in two different job postings within the same department, aggregate across all departments to the firm-year level, and scale them by total skill count. We exclude skill pairs previously counted at the individual level to prevent double counting, making our measure sensitive to the diversity of skills within departments. If departmental skill requirements are uniform, fewer unique skill pairs will be noted. The same rule applies to later aggregation of higher-level skill pairs.

Next, we measure the complementarity across departments within the same *division*. Given the limitation of job posting data for delineating business segments, we focus on geographical segments and define geographical division as a group of job postings that share the same metropolitan statistical area (MSA). We then count the co-occurrences of unique skill pairs in two different teams within the same division, aggregate the counts across all segments to the firm-year level, and scale them by total skill count.

Finally, we measure the complementary across divisions within the same *firm* by counting

[13] Skill combinations within a single job posting can be synergistic (Gibbons and Waldman 2004; Lazear 2009). For example, an individual can use multiple complementary skills to fulfill his/her job, such as empirical research and academic writing abilities to publish journal articles.

the co-occurrences of unique skill pairs across two different divisions within the same firm and scaling them by total skill count. Note that under this research design, firms operating in multiple MSAs, such as retailers, would have more non-zero values for the skill pairs at the firm level.

As a result, our measure of firm-level human capital is a multi-dimensional skill vector that captures the hiring demand for human capital for each firm-year observation. As illustrated in Table 2, Panel A, this vector is composed of one variable for the total skill requirement count *(# skills*), 363 unique skill and skill pair counts that reflect the aggregate sum of employee expertise, and 1,371 unique skill pair counts that capture the interplay and complementarity of different skills across employees. Figure 2 displays a heatmap, representing the average of all skills across the Fama French 12 industries. Furthermore, Table 2, Panels B and C, enumerate the top 10 most commonly required skills and skill pairs at each level.

We caveat several gaps between our underlying construct and empirical measure. First, our methodology, constrained by computational limits, only considers skill pair co-occurrences to assess complementarities, potentially underestimating the full scope of synergies firms could achieve from diverse skill combinations.[14] Second, the reliance on job postings might not capture the actual skill makeup within firms accurately, due to selective information disclosure and skill development via on-job training. Third, the lack of data on existing skill compositions and skill outflow due to employee turnover further constrain our ability to capture the true dynamics of firm-level human capital resources. These data limitations hinder our ability to capture a complete picture of firm-level human capital resources, introducing noises to our empirical analysis and potentially reducing the predictive value of our skill vector models. Consequently, our later empirical findings represent a conservative estimate of the predictive value of human

[14] This limitation is partly mitigated by our later use of machine learning models, which account for nonlinearities and interactions among predictors.

capital for future earnings.

IV. PREDICTING FIRM PERFORMANCE USING MACHINE LEARNING METHOD

We evaluate our skill vector by employing machine learning models to examine its ability to predict two-year-ahead operating performance (ROA_{t+2}), jointly testing the importance of human capital and the validity of our measure. Using flows rather than stocks reduces the chances of detecting spurious correlations due to nonstationarity (e.g., Granger and Newbold 1974). Our prediction analysis involves 1,399 variables that may interact nonlinearly and relate to firm performance without clear patterns. Hence, trying to construct an elaborate OLS regression model based on incomplete theory will likely be suboptimal. Thus, we opte for a machine learning approach, which provides greater flexibility and predictive capacity, especially when dealing with large and complex datasets like ours. We emphasize that our analysis does not examine the causal relationship between human capital resources and firm performance. Instead, we focus on the out-of-sample predictive value of human capital to assess whether a casual impact is plausible, adhering to the view that understanding a phenomenon requires both causal explanation and prediction (Bao et al. 2020; Brown, Crowley, and Elliott; Ding et al. 2020; Bertomeu, Cheynel, Floyd, and Pan 2021; Chen et al. 2022; Gow et al. 2023; Chen, Ke, and Zhao 2024).

Extreme Gradient Boosting (XGBoost) method

We employ a state-of-the-art machine learning method, extreme gradient boosting (XGBoost), to assess the predictive performance of our skill vector. XGBoost is a decision-tree-based ensemble machine learning algorithm that uses a gradient boosting framework, introduced by Chen and Guestrin (2016). XGBoost outperforms other machine learning algorithms (e.g., GBRT and LASSO) due to solving regression, classification, and ranking problems better and more quickly (Tantri 2021; Zheng 2021; Li and Zheng 2023).[15]

XGBoost, like other machine learning algorithms, relies on a set of parameters that require optimization to achieve the best predictive performance. This optimization process is not guided by theory but by empirical exploration (i.e., fine tuning). We utilize the grid search method to identify the optimal parameters that produce the best predictive performance across all possible combinations of a specified subset of parameters. For XGBoost, the parameters are categorized into two groups that define a regression tree and manage boosting. Due to computational constraints, we fine-tune three key parameters used in XGBoost, namely the number of trees, the maximum depth of the tree, and the learning rate.[16] Online Appendix Table OA1 Panel A presents the parameter values' grids used in our fine-tuning process.

We fine-tune the parameters using a 4-split time-series cross-validation approach (Anand, Brunner, Ikegwu, and Sougiannis 2019). First, we partition the sample into five folds and vary the training and validation set in each iteration.[17] In the nth iteration, the XGBoost model is trained using the first *n* folds and validated on the $(n+1)^{th}$ fold (see Figure 3). For example, in the 2nd iteration, the training set is the first two folds, and the validation set is the 3rd fold. In this way, we ensure that the validation data is more recent than the training data to avoid look-ahead

[15] XGBoost is an improvement over the basic Gradient Boosting Regression Tree (GBRT) algorithm, as it includes algorithmic enhancements and system optimization features. GBRT uses an ensemble technique termed gradient boosting to combine multiple weak models (i.e., regression trees) to generate a strong model, with weak models being additively generated based on the gradient of the error with respect to the prediction (Friedman, 2001). Specifically, GBRT iteratively trains an ensemble of shallow regression trees, with each iteration using the error residuals of the previous model to fit the next model. The final prediction is a weighted sum of all tree predictions. XGBoost is a scalable and highly accurate implementation of gradient boosting, being built largely for energizing machine learning model performance and computational speed. In contrast to GBRT, XGBoost builds trees in parallel rather than sequentially, resulting in significantly improved computational performance. Moreover, XGBoost uses a depth-first approach as the stopping criterion for tree splitting and prevents overfitting by penalizing more complex models through both LASSO (L1) and Ridge (L2) regularization.

[16] Increasing these parameters' values improves the model fit, but it may lead to overfitting, where the machine learning model explains noise rather than the generalizable underlying relationship in the test sample.

[17] We use the time-series split cross-validation option in scikit-learn machine learning package. Note that the data is split in five folds instead of four, even though our approach is 4-split time series split. This is because we cannot use the first fold as a test fold since there is no training data before the first fold.

bias. Second, in each of the four iterations, we train the model for every possible combination of the above-mentioned parameter values and assess the model performance by calculating the mean squared error on the validation set.[18] Last, the fine-tuning process chooses the optimal parameter combination that maximizes the model's average performance over the four iterations.

Performance evaluation

To test the predictive value of our skill vector, we follow prior studies to divide our sample into training/validation and test samples that maintain the temporal ordering of the full sample. We use a rolling-sample splitting scheme, in which the samples gradually shift forward in time to incorporate more recent data while keeping the total number of time periods fixed. Specifically, we build an XGBoost model using a five-year window of training/validation data and assess the out-of-sample performance using a one-year window of testing data (e.g., 2010-2014 for training/validation and 2015 for testing in the first rolling window). Under this rolling scheme, our test period covers the years from 2015 to 2019 and consists of five testing samples, corresponding to the five rolling windows (see Figure 4). The results of our analysis will comprise a sequence of out-of-sample R^2s, one for each rolling window.

Benchmark selection

To assess the out-of-sample performance of our skill vector, we compare it against three benchmarks. We repeat the above-mentioned process to train the XGBoost models of these benchmarks separately and jointly and evaluate their out-of-sample predictive performance.

The first benchmark is the number of employees, selected for its broad availability from Compustat and its common use as a proxy for human capital (e.g., Dechow et al. 2011). Yet, this

[18] There are 4 iterations in each 4-split time-series cross-validation process to train an XGBoost model. Moreover, we grid search for 10 possibilities of the number of trees, 6 possibilities of the maximum depth of the tree, and 3 possibilities of learning rate. In total, we run the XGBoost algorithm for 720 (=4*10*6*3) times for each training and validation attempt.

metric provides limited insights into the composition and quality of human capital due to its simplistic aggregation. We enhance our comparison with two additional benchmarks: employee hiring and turnover rates, which prior studies have linked to firm performance. Specifically, Gutiérrez et al. (2020) find that changes in the number of job postings are positively associated with changes in future performance, while Li et al. (2022) document a negative association between current employee turnover and future operating performance. We construct both measures based on resume data from Revelio Labs, which includes individuals' demographic data, educational background, and employment history (e.g., start and end dates of a job position, employer name, and job title). We calculate the hiring (turnover) rate as the employee inflows (outflows) scaled by the number of employees of a firm at the beginning of a year.

V. EMPIRICAL RESULTS

Predicting future firm performance

In this section, we apply our trained models based on the training sample to predict future performance in the test period. Table 3 reports the out-of-sample R^2 results of the test sample in each of the five rolling windows. We also use MSE and MAE as two alternative evaluation metrics and report these robustness results in Online Appendix Table OA2. In Table 3 Panel A, the skill vector yields an average out-of-sample R^2 of 18.63% across the test samples, with a range from 8.25% to 24.70%. Notably, the lowest R^2 occurs when we use 2018 skill vector to predict 2020 earnings, suggesting that the disruptions during the COVID year may have adversely impacted the predictive accuracy of our skill vector.[19] One important feature of XGBoost model is to facilitate nonlinear interactions among predictors in forecasting outcome variables (i.e., future earnings in our context). This feature is particularly valuable as it captures

[19] Online Appendix Table OA1 Panel B provides the parameters for the main XGBoost models selected on the training/validation data, which is based on the cross-validation approach mentioned in Section IV.

variations in skill complementarities beyond what our measure construction process can.[20]

To better illustrate the predictive value of our skill vector, we benchmark it against other human capital-related variables in forecasting firm performance. Across all five rolling windows in Figure 5 Panel A, the predictive value of the skill vector surpasses those of other benchmarks. Specifically, Table 3 Panel A shows that the average out-of-sample R^2 is 12.04% for models with the number of employees, 3.14% for models with hiring rate, and 0.24% for models with turnover, all noticeably lower than the average out-of-sample R^2 of 18.63% using our skill vector.[21]

We further assess if our skill vector incrementally enhances the model's predictive value beyond benchmark variables. Table 3 Panel B presents the results on the incremental predictive value of our skill vector over the benchmark variables. Upon integrating the skill vector into the benchmark models, we observe an approximately 46.3% (= 8.03% / 17.34%) increase in the average out-of-sample R^2. Specifically, while the average out-of-sample R^2 with three benchmark variables stands at 17.34%, this figure rises to 25.37% after including the skill vector. This highlights the skill vector's ability to unveil new insights not captured by existing firm-year human-capital proxies. Figure 6 further visually shows the robustness of our results: the R^2 improvement is substantial and consistent across five rolling windows.[22]

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[20] In untabulated analysis with imposing interaction restrictions in the XGBoost model, the average R^2 of our skill vector decrease from 18.63% to 14.67%, highlighting the importance of incorporating skill complementarities in our analysis.

[21] Note that we evaluate the predictive performance after fine tuning the parameters in XGBoost models using the training/validation set. Therefore, the performance evaluation results of our benchmark models cannot be directly compared with the in-sample OLS R^2 reported in the existing published papers.

[22] In untabulated tests, we find consistent empirical evidence for the incremental predictive value of our skill vector over benchmark models when benchmark variables are included individually rather than in combination. We also find consistent results for the incremental predictive value of our skill vector over benchmark models after controlling for concurrent earnings and market capitalization for four out of five rolling windows. The exception occurs in 2018, when using the 2018 skill vector to forecast 2020 earnings, a discrepancy likely attributed to the disruption in earnings caused by COVID.

To increase the interpretability of our human capital models and make transparent the items responsible for predictive performance, we quantify the importance of each predictor within the skill vector using the SHapley Additive exPlanations (SHAP) method.[23] We estimate the predictor importance by averaging the absolute SHAP values across the test data across five rolling windows.[24] Table 4 Panel A presents the top 10 predictors with the highest average absolute SHAP values across all rolling windows.[25] Skills at the individual level also exhibit significant importance in predicting future performance, including “Science and Research”, “Information Technology”, “Industry knowledge”, “Supply Chain and Logistics”, and “Finance”. Furthermore, among these top predictors, various combinations at different levels stand out, including “Analysis” with “Health Care”, “Customer and Client Support” with “Industry Knowledge”, and “Business” with “Maintenance, Repair, and Installation”.

Expertise and teamwork

In this section, we decompose firm-level human capital resources into employee expertise and teamwork. Specifically, we explore how these two components contribute to the predictive value of our skill vector. Separating employee expertise and teamwork is conceptually and empirically challenging. An employee contributes to the collective firm-level human capital by specializing in a specific domain with her skill endowments to fulfill job requirements. The

[23] SHAP uses game theory concepts to allocate a contribution of each feature for a specific prediction, offering a consistent approach to explain the output of any machine learning model.

[24] Permutation importance is an alternative to SHAP values for feature importance interpretations. Based on the decrease in model performance rather than the magnitude of feature attributions, permutation importance of a predictor is computed as the R^2 decrease when that predictor is randomly shuffled (Altmann, Toloşi, Sander, and Lengauer 2010). One major advantage of SHAP values over permutation importance is to better account for the interactions between features because it calculates the marginal contribution of a feature by considering it in all possible combinations with other features. SHAP calculations can be computationally more expensive than permutation importance, especially for complex models or high-dimensional data, because SHAP values require evaluating the model for every possible combination of predictors.

[25] A predictor has one feature importance value for each of the five rolling windows. We compute the correlation of importance values between two consecutive test years. For the four pairs of consecutive test years (2015 vs. 2016, 2016 vs. 2017, 2017 vs. 2018, and 2018 vs. 2019), the correlation coefficients are 0.81, 0.90, 0.84, and 0.81, suggesting that the predictor importance is reasonably stable over time.

interaction and collaboration among employees, reflected in skill complementarities across individuals within departments, divisions, and the entire firm, constitute the teamwork component. Therefore, we categorize expertise component as the unique skills or skill pairs at the individual level, and the cross-individual skill pairs that foster synergy across individuals as the teamwork component.

We assess the collective feature importance of these two components within our skill vector. Following prior literature (Bertomeu et al. 2021; Chen et al. 2022), we sum the absolute SHAP values of predictors within each group to assess their cumulative contribution. In Table 4 Panel B, we find that expertise component accounts for 56.2% and teamwork component accounts for 43.9% of the overall importance on average. However, we acknowledge that there is no standardized method for computing grouped feature importance in existing machine learning literature (Au et al. 2021). For example, the summed cumulative importance may overstate the group importance, particularly in the presence of multicollinearity.

Given the limitations of grouped feature importance calculations, we refine our analysis by isolating the expertise component in XGBoost models and restricting additional interactions to exclude any cross-individual skill complementarities. This adjustment allows us to identify the incremental predictive value of teamwork by comparing the out-of-sample R^2 values for skill vectors with and without teamwork components.[26] Table 5 shows the out-of-sample predictive performance of expertise and expertise with teamwork (i.e., our skill vector). The expertise component alone, under interaction restrictions, yields an average out-of-sample R^2 of 12.97%. When we add cross-individual skill pairs and remove interaction restrictions, the expertise

[26] We acknowledge that this approach is not perfect. By including the expertise component and imposing interaction restrictions, we may not fully capture the individual-level skill complementarities using skill pairs.

combined with teamwork achieves an average R^2 of 18.63%. These results suggest a 43.6% (= 5.66% / 12.97%) improvement in the predictive power of our human capital inflow measure upon considering cross-individual skill complementarities. This evidence highlights the importance of considering *both* expertise and teamwork when examining the relationship between human capital and firm performance.

When human capital is more valuable

We next examine whether the predictive performance of our skill vector is contingent upon the levels of task complexity and ease of employee communication. We divide the entire sample into subsamples and construct separate training/validation and test samples for each subsample. We then retrain the models to fine-tune the parameters and evaluate the prediction performance in the out-of-sample tests. Given that the benefits of teamwork are amplified when tasks are complex and when communication among employees is smooth, we expect that the predictive performance of our skill vector increases with task complexity and ease of communication.

Task complexity

For complex job tasks, a significant portion of the knowledge required for production is intangible and resides within individuals, rather than being readily codified and routinized (Freund 2022). It is particularly pronounced in high-tech industries characterized by extensive investments in research and development. Therefore, we use a high-tech industry indicator, routine task index, and Tobin's Q, as three proxies to capture the multifaceted nature of task complexity (Francis, Philbrick, and Schipper 1994; Peters and Taylor 2017; Tuzel and Zhang 2021).

Figure 7 and Online Appendix Table OA3 present the out-of-sample R^2 results for low task complexity and high task complexity subsamples. As shown in yellow lines in Figure 7 Panel A, we find that the out-of-sample R^2 of our skill vector are consistently higher in the high task complexity subsamples across all test years and partitions compared to their low task complexity counterparts. Using the *Routine Task Index* to partition the sample, we find that the average out-of-sample R^2 is 24.03% for the subsample with a low routine task index and 2.78% for the subsample with a high routine task index. Using *Tobin's Q* to partition the sample, we find that the average out-of-sample R^2 is 23.52% for the subsample with high Tobin's Q. Similarly, we find that predictive value of our skill vector is greater in the subsample with firms in high tech industries (26.26% vs 5.18%).

Figure 7 Panel B presents the out-of-sample predictive performance of the expertise component. The doted yellow lines show that the out-of-sample R^2 values of the expertise component are consistently higher in subsamples characterized by high task complexity across all test years and partitions. On average, the expertise component yields an out-of-sample R^2 of 18.78% (1.91%) for subsample with high (low) routine task index, 18.29% (3.37%) for subsample with high (low) Tobin's Q, and 21.44% (2.01%) for firms in high-tech (non-high-tech) industries. These numbers indicate that incremental predictive value of teamwork component is also superior in subsamples characterized by high task complexity, with 5.25% (0.87%) for subsample with high (low) routine task index, 5.23% (1.22%) for subsample with high (low) Tobin's Q, and 4.82% (3.17%) for firms in high-tech (non-high-tech) industries.

Overall, these findings in this section suggest that both employee expertise and teamwork components of our skill vector exhibit stronger predictive value for firms engaged in complex tasks, consistent with the expectation that teamwork contributes more value in such contexts.

Ease of communication

To capture the level of ease of communication within firms, we employ four proxies. First, communication and coordination among employees are more likely to occur in a social environment that fosters such behavior. Therefore, our first two proxies pertain to the social environment: (1) teamwork culture intensity, measured by the frequency of teamwork-related keywords in earnings conference calls (*Teamwork Culture*) (Li et al. 2021); (2) the number of teamwork skills in all job postings required by the focal firm in a given year (*Teamwork Job*). Additionally, firm structures also influence employee collaboration. For instance, firms with multiple business segments or operations at diverse locations often face challenges in integrating employees across segments, impeding collaboration. To capture this aspect, we use an indicator of one business segment (*One Segment*) and the number of MSAs in all job postings by the focal firm in a given year (*# MSA*).

Figure 8 and Online Appendix Table OA4 present the out-of-sample R^2 results for low and high communication-ease subsamples. In Figure 8 Panel A, the out-of-sample R^2 of our skill vector are consistently higher in the high communication-ease subsamples compared to those in the low communication-ease subsample. For example, the average R^2 is 16.13% (3.83%) for the subsample with high (low) teamwork culture and 24.16% (1.41%) for the subsample with more (fewer) teamwork skill requirements. Moreover, the skill vector predicts better for subsamples with only one business segment (20.29% vs. 14.59%) and fewer geographical locations (21.08% vs. 2.94%).

Figure 8 Panel B presents the out-of-sample predictive performance of the expertise component alone. The doted yellow lines show that the out-of-sample R^2 of the expertise component are greater in subsamples characterized by high ease of communication across all test years and partitions. On average, the expertise component yields an out-of-sample R^2 of 13.90% (vs 3.39%) for the subsample with high teamwork culture, 20.92% (vs 0.19%) for the subsample with teamwork skill requirements, 19.33% (vs 0.97%) for the subsample with fewer geographical locations, 12.72% (vs 11.37%) for the subsample with only one business segment. These results show that the incremental predictive power of teamwork component is also superior in subsamples characterized by high ease of communication, with 2.23% (vs 0.44%) for the subsample with high teamwork culture, 3.24% (vs 1.22%) for the subsample with teamwork skill requirements, 1.97% (vs 1.75%) for the subsample with fewer geographical locations, 8.92% (vs 1.87%) for the subsample with only one business segment.

Our findings in this section collectively suggest that both expertise and teamwork components of our skill vector have more predictive value when the firm's social environment and structure foster effective communication among employees.

Task complexity and ease of communication

We next explore whether the predictive performance of the skill vector is contingent upon *both* task complexity and ease of communication.[27] To facilitate this analysis, we employ the principal component method of factor analysis to condense the proxies of each dimension into a single factor. Online Appendix Table OA5 Panel A presents the factor loadings obtained from both factor analyses. In the complexity factor, the loadings are negative for the routine task index and positive for Tobin's Q and the high-tech indicator. Consequently, a higher value of the complexity factor indicates higher task complexity. In the communication factor, the loadings are positive for teamwork culture and teamwork skill requirements and negative for the number of geographical locations and business segments. Thus, a higher value of the communication factor signifies a higher level of ease of communication among employees. Next, we partition the sample based on both factors, creating four subsamples: low-low, low-high, high-low, and high-

[27] In our sample, the task complexity variables show low correlations with the ease of communication variables, aligning with our expectation that task complexity and ease of communication are conceptually distinct constructs.

high. For each subsample, we retrain the models to fine-tune the model parameters and evaluate the out-of-sample predictive performance.[28] We expect that the skill vector will exhibit the best predictive performance in the high-high subsample where firms have high task complexity and high level of ease of communication.

Figure 9 and Online Appendix Table OA5 present the out-of-sample R^2 values for each subsample. Consistent with our expectation, the out-of-sample R^2 values are the highest in the high-high subsamples for all five test years. Figure 9 Panel A shows that the average out-of-sample R^2 is -9.69 % for the low-low subsample, -20.81% for the high-low subsample, 0.32% for the low-high subsample, and 29.7% for the high-high subsample. Similarly, Figure 9 Panel B shows that expertise component performs the best in the high-high subsample (17.10%) and indicates that the incremental predictive value of the teamwork component is the highest in the high-high subsample (12.60%).

Overall, these results demonstrate that our skill vector, both the expertise and teamwork components, exhibits superior predictive performance for firms with *both* complex tasks and effective employee communication.

VI. ADDITIONAL ANALYSIS

High vs. low skills

In this section, we conduct additional analysis to assess the heterogeneous performance of our skill vector based on the complexity level of skill requirements across occupations. Specifically, we evaluate the performance of the skill vector constructed using firms' skill

[28] Splitting our sample into four increases the ratio of model complexity (number of parameters and predictors) to sample size, elevating the risk of overfitting. A complex model may fit the small sample data very closely but fail to capture the underlying relationship that is generalizable to out-of-sample data. Consequently, out-of-sample R^2 may become very low or negative, indicating worse predictive performance than a naive model based on the mean response.

requirements in low-skill occupations vs. high-skill occupations. To measure the complexity level of skill requirements, we use the job zone classification by O*NET that classifies each job occupation into five job zone groups based on levels of education, experience, and training necessary to perform the occupation. Occupations with Job Zone 1 assignment need little or no preparation while occupations with Job Zone 5 assignment need extensive preparation. Since jobs with Job Zone 1 assignment need little preparation and are more mechanical, we would expect that skill vector provides less incremental value to improve team performance. In contrast, for jobs with Job Zone 5 assignments, the extensive collaboration between team members will boost team performance by incorporating synergy from different skill combinations.

Figure 10 and Online Appendix Table OA6 report the predictive performance of 5 different versions of skill vectors created using job posting data with each job zone assignment. In Figure 10, we find higher out-of-sample R^2 values for the skill vector featured with high-skill occupations. For example, the average out-of-sample R^2 is 10.81% for the skill vector based on Job Zone 5 data and is much greater than the average out-of-sample R^2 of 0.36% for the skill vector based on Job Zone 1 data. These findings suggest that our skill vector predicts better for high-skill occupations, consistent with the notion that teamwork contributes more value when job tasks are complex.

Data quality variation

We conduct additional analysis based on the variation in the job posting data's effectiveness in reflecting actual human capital inflow. We compare the number of postings from BGT job posting data and the number of new employees from Revelio Lab resume data and use the absolute difference between the two as an inverse measure of data quality at the firm-year level. We assume that a smaller difference indicates a more accurate representation of human capital inflow by our skill vector. After partitioning the sample by the year median, the untabulated tests show that our skill vector exhibits stronger predictive value for future earnings in firms with higher data quality, evidenced by higher R^2 values (23.03% vs. 2.32%). The results suggest the importance of data quality in enhancing the predictive value of our skill vector for future earnings.

VII. CONCLUSION

This study sheds light on the importance of human capital in predicting firm performance. Drawing on classical economic theories that emphasize the division of labor and task specialization, we conjecture that collaboration among employees with specialized knowledge is crucial for developing internal human capital, creating a competitive advantage, and enhancing firm performance. Our study fills a gap in empirical studies by examining team members' skills and their interactions, which have been largely unmodeled due to limited data availability.

By leveraging firms' online job requirements and employing XGBoost models, we implement a novel approach to investigate the role of human capital in firm performance. Our multidimensional skill vector outperforms other unidimensional human-capital proxies (e.g., employee count, hiring rate, and turnover) in predicting firm performance. Furthermore, the skill vector adds considerable incremental explanatory power to these variables indicating that it captures a new dimension of human capital. We find that skill vector has a higher predictive value for firms facing complex tasks and characterized by efficient employee communication, consistent with teamwork contributing more to firm values under these circumstances.

Overall, our findings contribute to theoretical understanding, inform managerial decision-making, and showcase the applicability of machine learning in accounting research. While previous research has focused on top executives and boards of directors or individual functions, this study takes a holistic approach by proposing a new and comprehensive measure of firms' human capital resources based on skill requirements in job postings. Our findings address the growing importance of human capital disclosure for investors and exploit the job posting data to better capture this crucial construct. We also extend the literature on the application of machine learning in accounting literature.

Future research can expand our understanding of human capital in several areas that we do not tackle in this paper due to data and computational limitations. First, a more comprehensive measure that includes the actual composition of a firms' existing workforce skills and real-time employee collaboration would improve the assessment of human capital's predictive value. Second, relaxing our assumptions to incorporate a broader range of factors—such as employee incentives, morale, effort, the differential quality of skills, and learning on the job—would offer a more nuanced view of how human capital contributes to firm performance. Third, investigating the complementarity between human capital and physical capital resources could shed light on optimal resource allocation and synergy creation within firms.

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Appendix: Variable Definition

Variable	Definition
ROA	Return on assets, defined as income before extraordinary items scaled by the average book value of assets [Source: Compustat]
Skill Vector	A vector of the numbers of individual skills and skill pairs in all job postings issued by a firm in a given year as defined in Section III [Source: Burning Glass]
Ln(Employee)	Log of the number of employees of a firm in a given year [Source: Compustat]
Hiring	Ratio of the number of new employees over the number of total employees of a firm in a given year [Source: Revelio Labs]
Turnover	Ratio of the number of departing employees over the number of total employees of a firm in a given year [Source: Revelio Labs]
Routine Task Index	Firm-level average routine task score of all occupations in a firm. We follow Tuzel and Zhang (2021) to construct the routine-task intensity score for each OES occupation as $\mathrm{Ln}(T_{routine})$-$\mathrm{Ln}(T_{Abstrct})$-$\mathrm{Ln}(T_{nonroutine})$. $T_{routine}$, $T_{Abstrct}$, and $T_{nonroutine}$ represent the required skill level for performing routine, abstract, and nonroutine manual tasks in each occupation, respectively. [Source: Burning Glass]
Tobin's Q	Firm value scaled by the sum of physical and intangible capital as defined by Peters and Taylor (2017) [Source: Compustat]
High Tech	An indicator variable equals 1 if a firm's SIC code is in biotechnology (2833-2836 and 8731-8734), computers (3570-3577 and 7370-7374), electronics (3600-3674), and retail (5200-5961) industries as defined by Francis, Philbrick, and Schipper (1994), and 0 otherwise [Source: Compustat]
Teamwork Culture	Weighted-frequency count of teamwork-related words in the Q&A section of earnings calls averaged over a 3-year window as defined by Li et al. (2021)
Teamwork Job	The number of teamwork skills required in all job postings issued by a firm in a given year [Source: Burning Glass]
# MSA	The number of unique recruiting MSAs in all job postings issued by a firm in a given year [Source: Burning Glass]

# Segment	The number of unique SIC 3-digit codes of a firm's disclosed business segments [Source: Compustat]
One Segment	An indicator variable equals 1 if the firm's disclosed business segments share the same SIC 3-digit code, and 0 otherwise [Source: Compustat]

Figure 1: Skills to Firm-level Human Capital

This figure illustrates the additive and interactive properties of human capital resources (HCR) under two different structures.

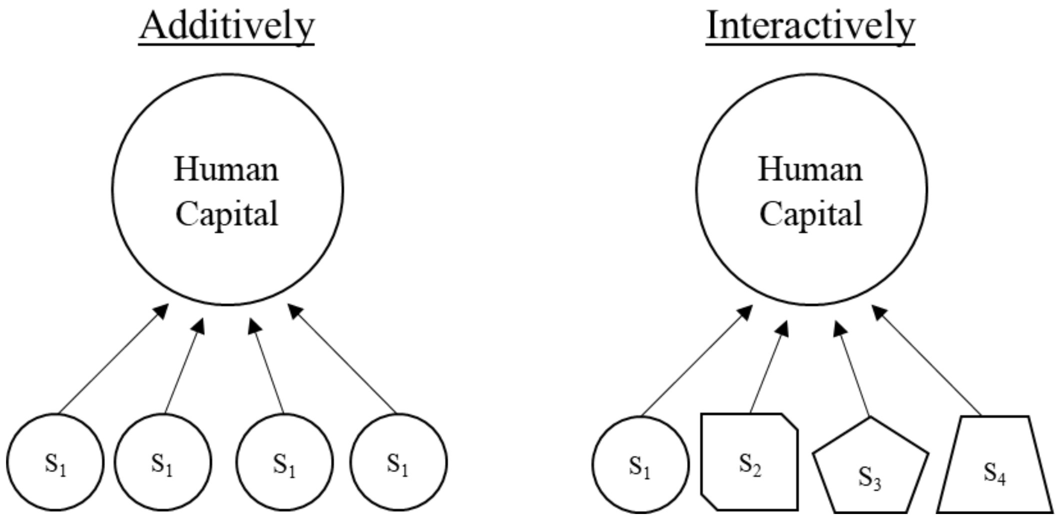


Figure 2: Heatmap of Skills by Fama French 12 Industry

This heatmap shows the average frequency of each individual skill, expressed as a percentage of the total number of skills required by a firm in a given year adjusted by removing the industry average, across the Fama French 12 industries.

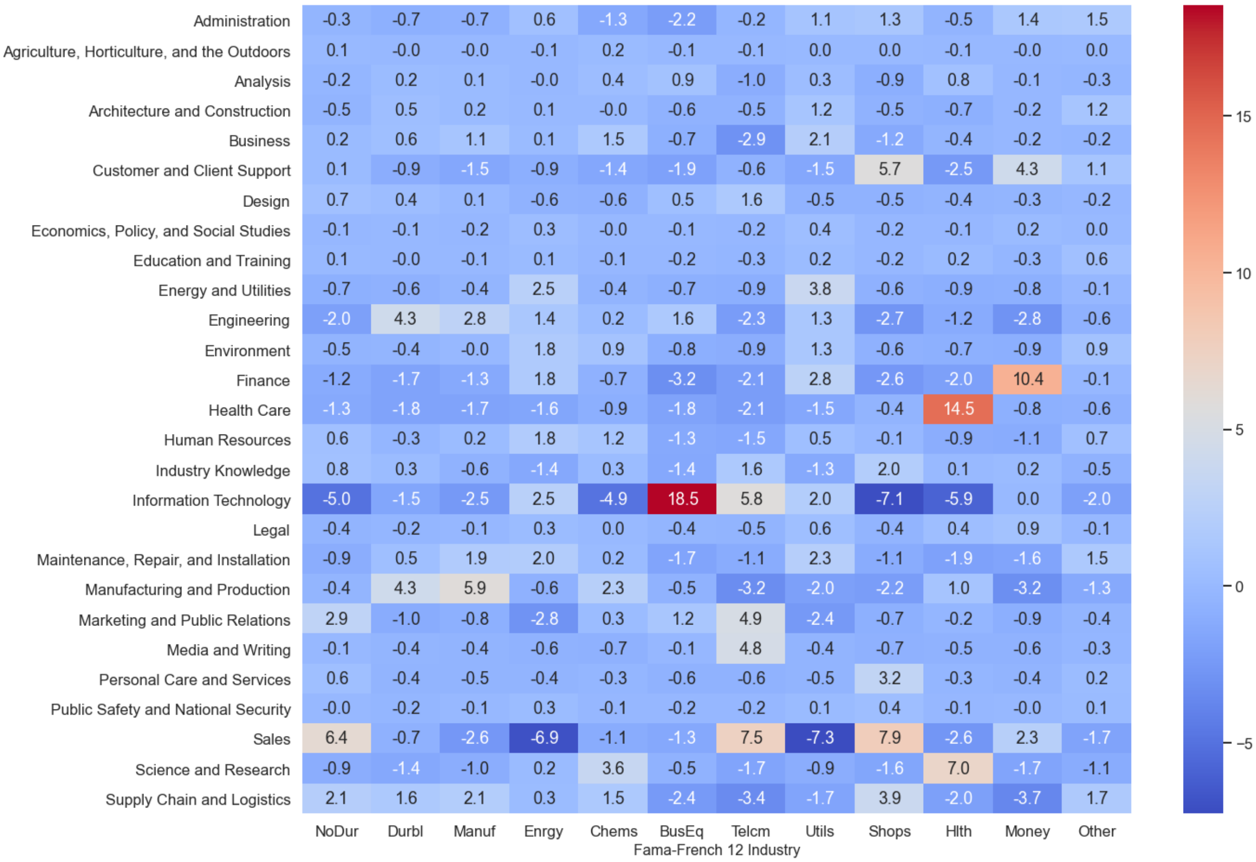


Figure 3: Illustration of Time Series Split Cross-Validation Approach

This figure presents our split cross-validation approach for our test. We cross validate our sample 4 times. In the first iteration, we use 20% of the sample as the training set and the next 20% of the sample as the testing set. In the second iteration, we use 40% of the sample as the training set and the next 20% of the sample as the testing set. In the third iteration, we use 60% of the sample as the training set and the next 20% of the sample as the testing set. In the fourth iteration, we use 80% of the sample as the training set and the next 20% of the sample as the testing set.

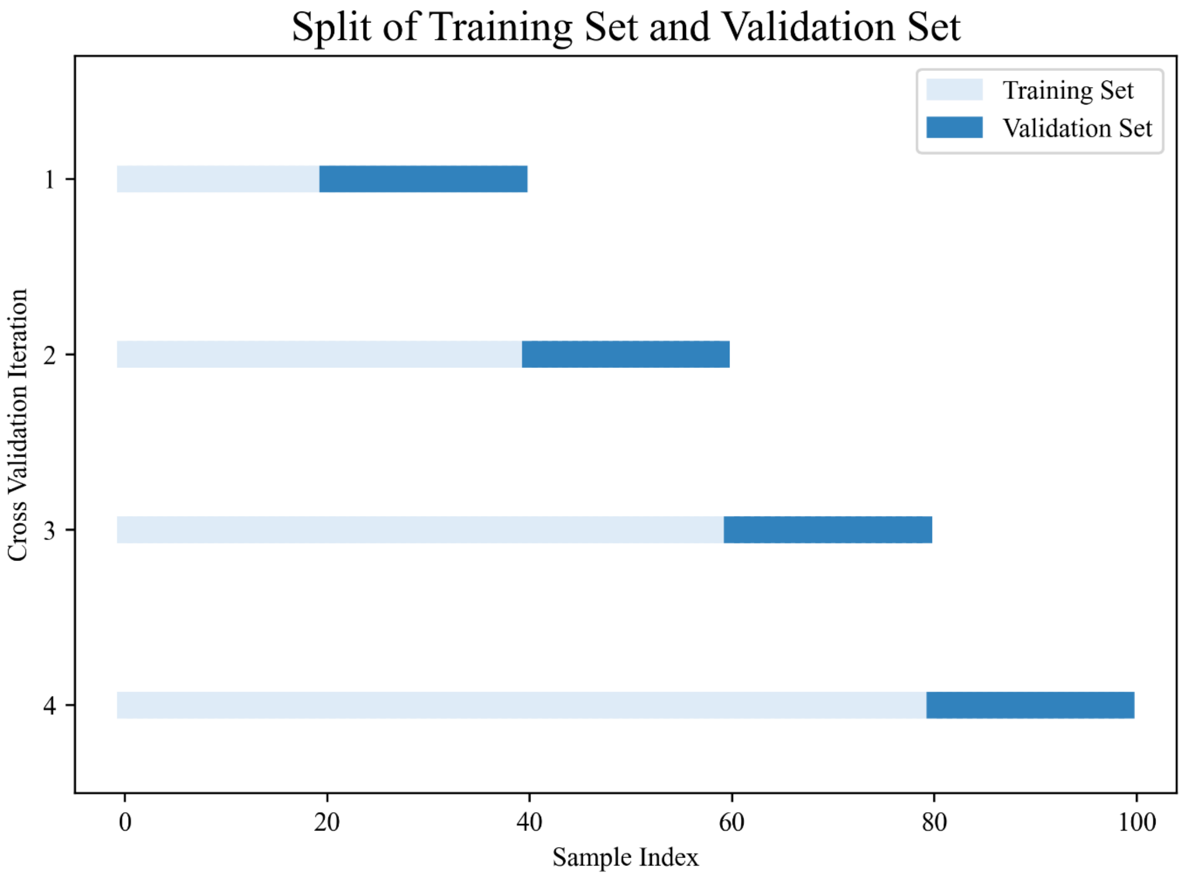


Figure 4: Illustration of the Rolling Scheme

This figure presents the rolling scheme for our main test. We split our sample into training/validation and test samples that maintain the temporal ordering of the full sample. The rolling sample splitting scheme gradually shifts forward in time to incorporate more recent data while keeping the total number of time periods fixed (i.e., a five-year window). Each pass uses a five-year window of training/validation data and assesses the out-of-sample performance using a one-year window of testing data (e.g., 2010-2014 for training/validation and 2015 for testing in the first pass of rolling window).

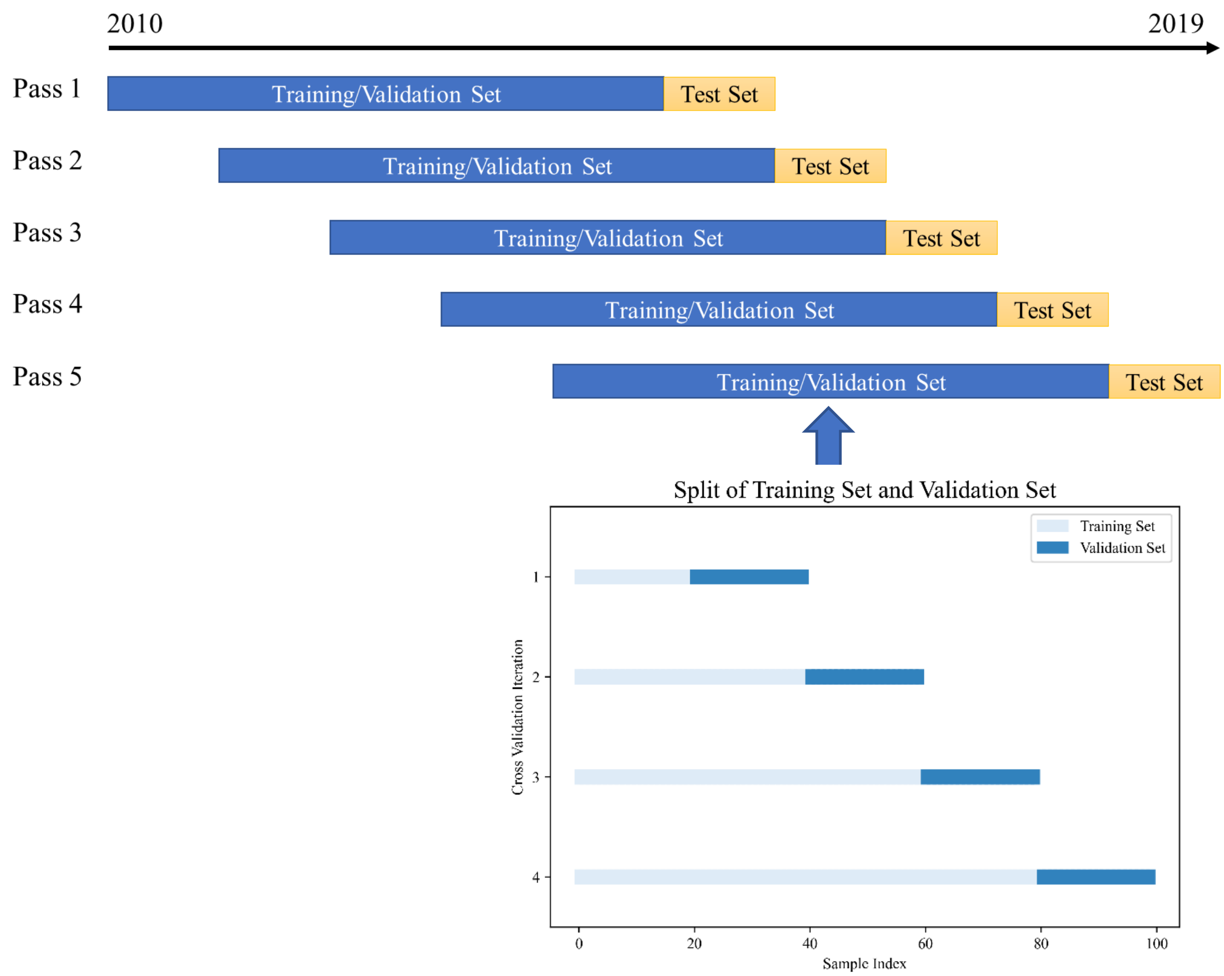
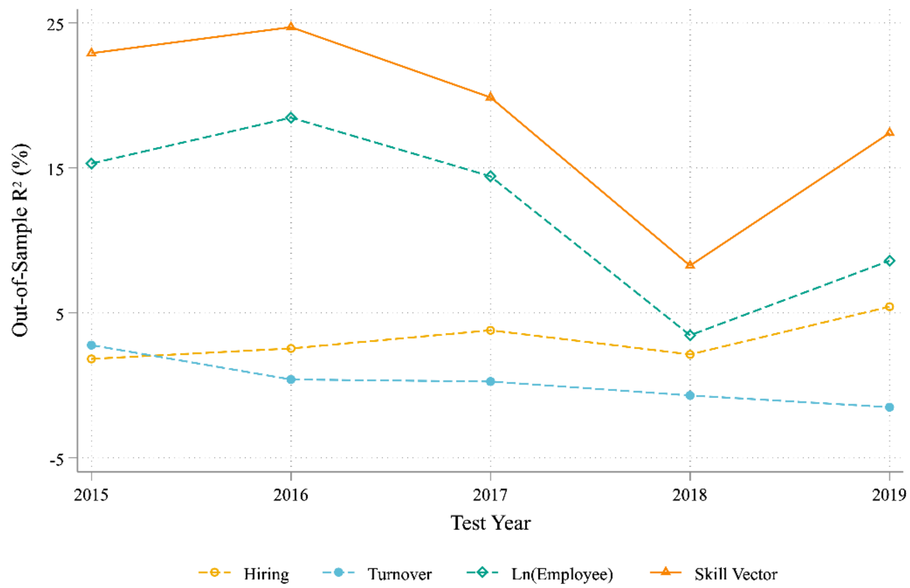


Figure 5: Predictive Performance of Skill Vector

This figure presents the out-of-sample R^2 in percentage of various model across test years. Using XGBoost models built on a five-year training/validation window preceding each test year, we evaluate out-of-sample performance with specific predictors annually. The analysis yields a series of out-of-sample R2 values, each corresponding to a rolling window and predictor set. Each line indicates the predictive performance of a predictor set. Panel A shows the predictive performance of skill vector and benchmark variables (*Ln*(*Employee*), *Hiring*, and *Turnover*) and Panel B shows the incremental predictive performance of skill vector over benchmark variables.

Panel A: Individual Predictors



Panel B: Incremental Predictive Performance

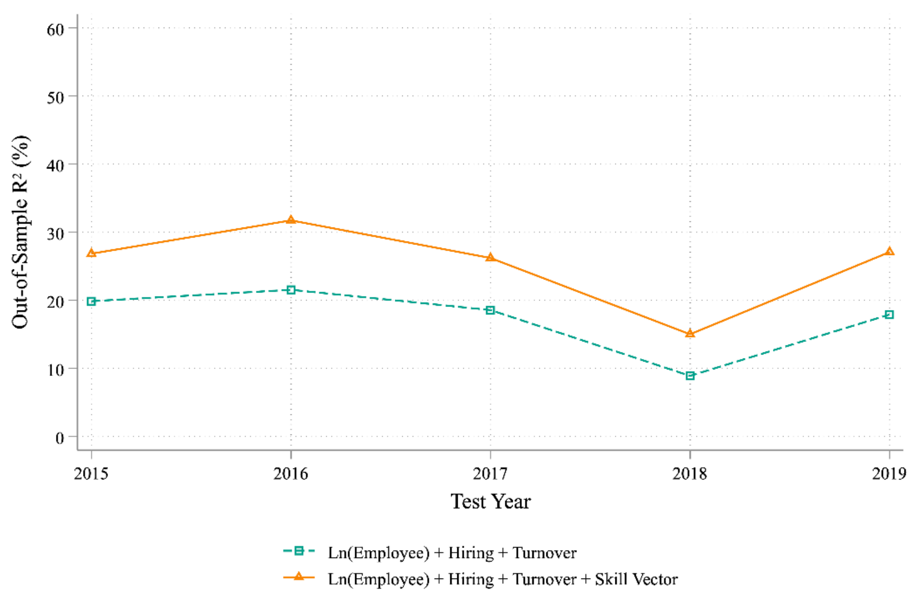


Figure 6: Predictive Performance of Expertise and Expertise with Teamwork

This figure presents the out-of-sample R^2 in percentage of various model across test years. Using XGBoost models built on a five-year training/validation window preceding each test year, we evaluate out-of-sample performance with specific predictors annually. The analysis yields a series of out-of-sample R2 values, each corresponding to a rolling window and predictor set. Each line indicates the predictive performance of a predictor set.

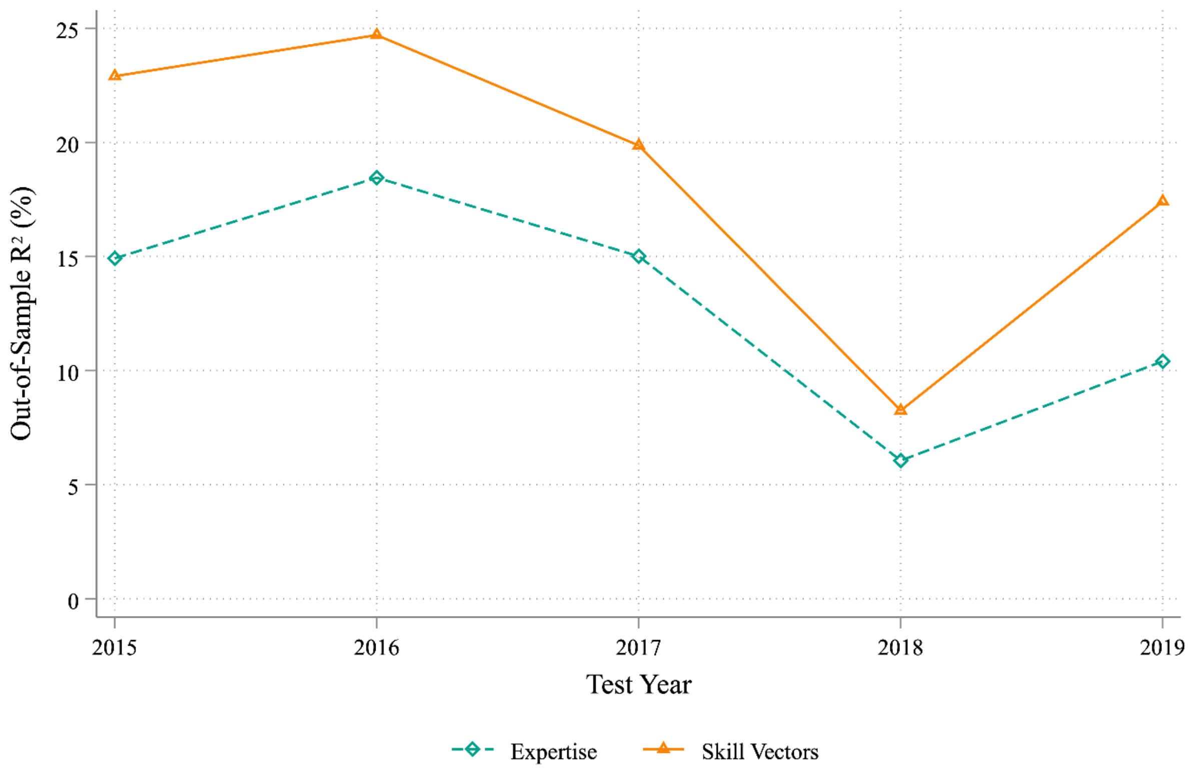
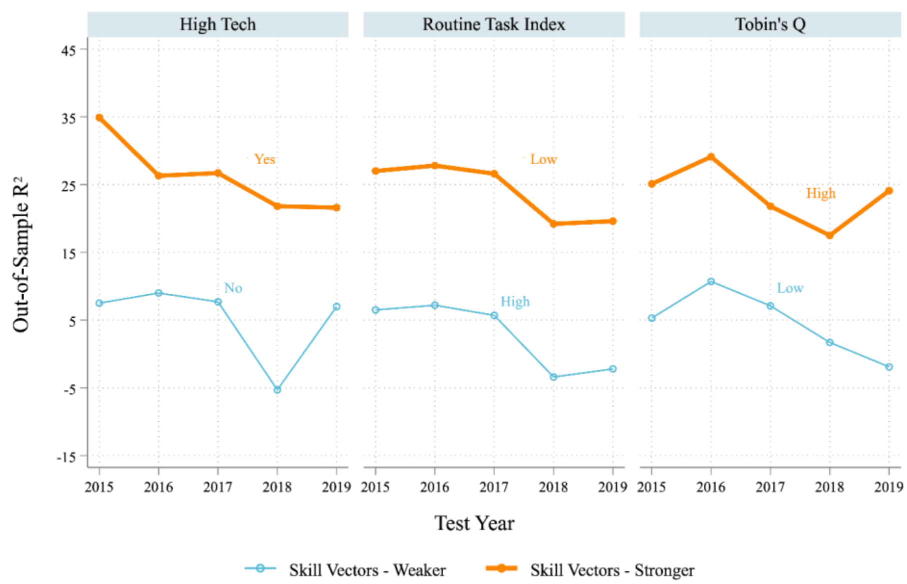


Figure 7: Predictive Performance of Skill Vector by Task Complexity

This figure presents the out-of-sample R^2 in percentage of each model across test years, partitioned by three proxies of task complexity: *High Tech*, *Routine Task Index*, and *Tobin's Q*. Orange line indicates the predictive performance for firms with more complexity. Blue line indicates the predictive performance for firms with less complexity. Panel A shows the predictive performance of skill vector and Panel B shows the predictive performance of the expertise component.

Panel A: Skill Vectors



Panel B: Expertise

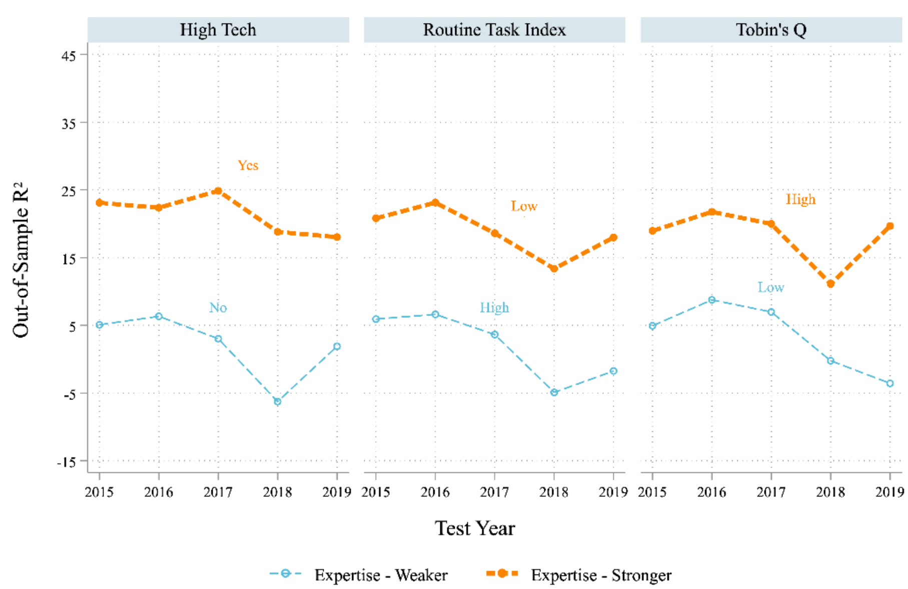
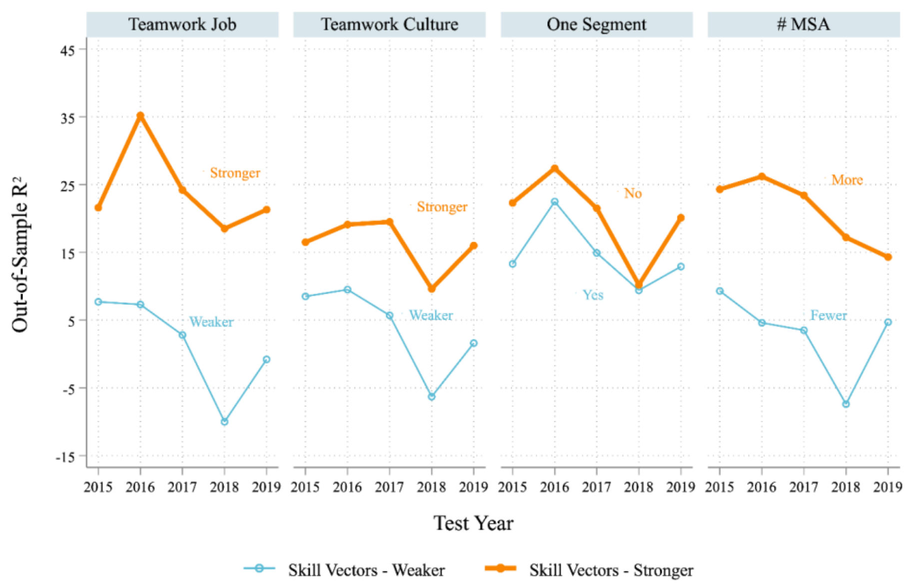


Figure 8: Predictive Performance of Skill Vector by Ease of Communication

This figure presents the out-of-sample R^2 in percentage of each model across test years, partitioned by four proxies of ease of communication: *Teamwork Job*, *Teamwork Culture*, *One Segment*, and *# MSA*. Orange line indicates the predictive performance for firms with more communication ease. Blue line indicates the predictive performance for firms with less communication ease. Panel A shows the predictive performance of skill vector and Panel B shows the predictive performance of the expertise component.

Panel A: Skill Vectors



Panel B: Expertise

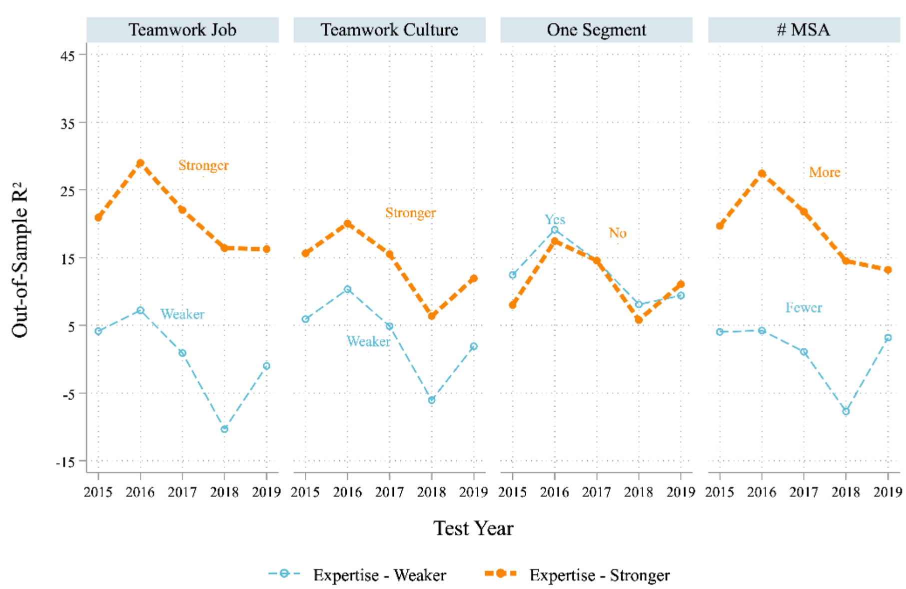
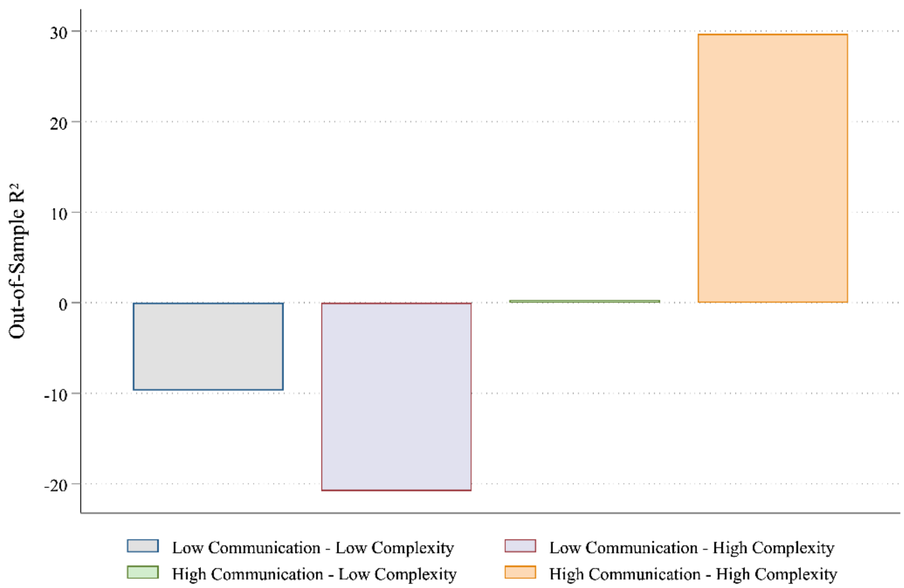


Figure 9: Predictive Performance of Skill Vector in Two-by-two Subsamples

This figure presents the out-of-sample R^2 in percentage of each model across test years, partitioned by both complexity and communication factors. Each bar presents the average predictive performance of skill vector across test years for each subsample. Panel A shows the predictive performance of skill vector and Panel B shows the predictive performance of the expertise component.

Panel A: Skill Vectors



Panel B: Expertise

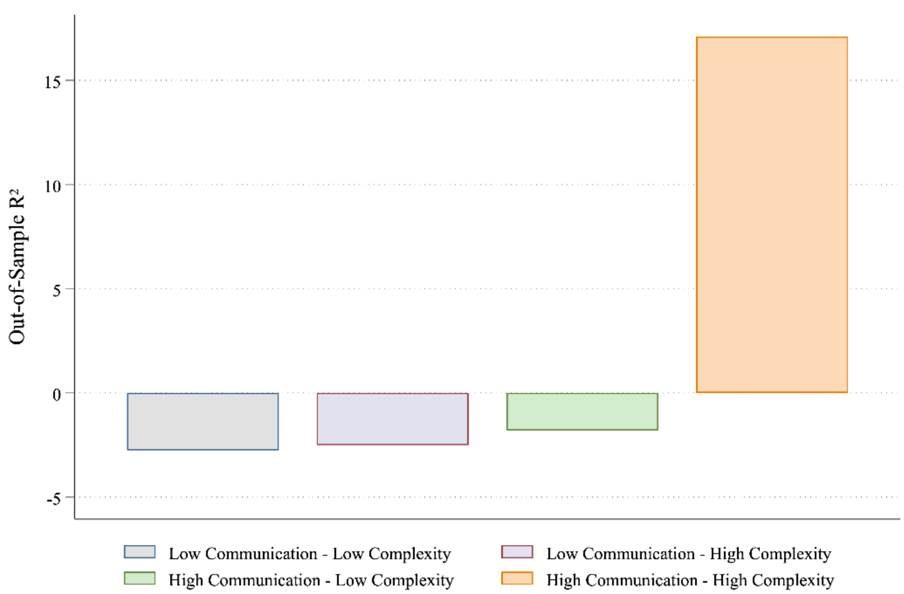


Figure 10: Predictive Performance of Skill Vector by Job Zone

This figure presents the out-of-sample R^2 in percentage of each XGBoost model by job zone. Each bar presents the average predictive performance across test years of skill vector constructed using occupations in each job zone. O*NET groups occupations into one of five job zones based on levels of education, experience, and training necessary to perform the occupation. Zone 1 indicates the lowest requirement and Zone 5 indicates the highest requirement.

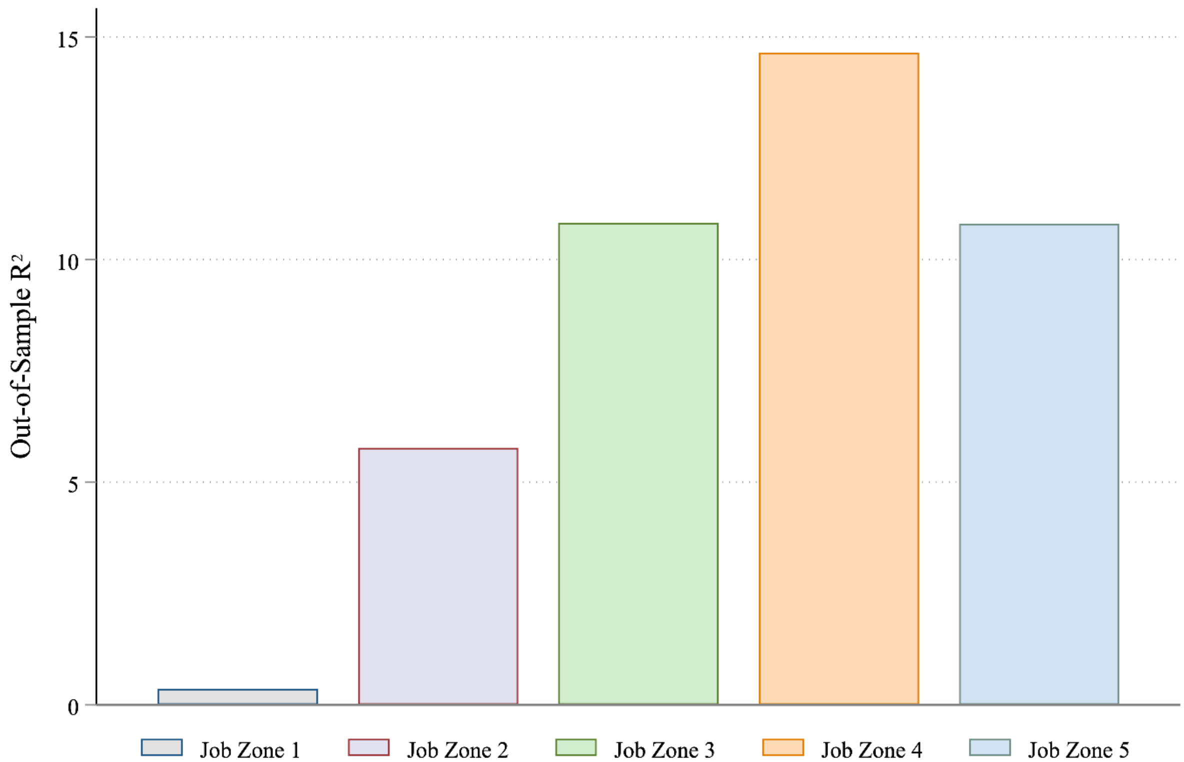


Table 1: Sample

Panel A reports the sample selection process. Panel B shows the number of firm-level job posting data by year. Panel C provides the number of firm-level job posting data by Fama French 12 industry.

Panel A: Sample selection

Source/Filter	**No. of Observations**
(1) All job postings collected by Burning Glass from 2010 to 2019	233,098,988
(2) Aggregating job posting data to the firm year level	37,017
(3) Requiring turnover and hiring rate data available from Revelio Lab	15,244
(4) Requiring non-missing ROA$_{t+2}$ from Compustat	15,141
(5) Requiring non-missing employee count data from Compustat	14,866
(6) Requiring at least 10 job postings for each firm year observation	13,069

Panel B: Firm-year level job posting data by year

Year	Frequency	Percentage
2010	899	6.88
2011	986	7.54
2012	1,089	8.33
2013	1,290	9.87
2014	1,338	10.24
2015	1,375	10.52
2016	1,395	10.67
2017	1,482	11.34
2018	1,635	12.51
2019	1,580	12.09
Total	13,069	100.00

Panel C: Firm-year level job posting by Fama French 12 industry

	Our Sample		Compustat
Industry	#	%	%
Consumer NonDurables	819	5.38	3.78
Consumer Durables	586	3.85	2.15
Manufacturing	1,703	11.19	6.99
Oil and Gas	509	3.34	4.93
Chemicals	425	2.79	2.10
Business Equipment	2,653	17.43	15.60
Telecom	353	2.32	2.52
Utilities	494	3.25	3.51
Retail	1,658	10.89	6.78
Healthcare	1,325	8.70	15.02
Finance	2,634	17.30	21.54
Other	1,874	12.31	15.08
Total	13,069	100.00	100.00

Table 2: Summary Descriptives

Panel A shows the number of predictors by category. Panels B and C provide lists of the top 10 most populated individual skills and skill pairs at various levels. All predictor values, with the exception of the total skill count, are normalized by the annual total skill count for each firm and presented as percentages.

Panel A: Number of predictors by category

Group	# Predictors
Total skill count (*# Skills*)	1
Individual skills	27
Skill pairs (individual level)	336
Skill pairs (department level)	333
Skill pairs (division level)	351
Skill pairs (firm level)	351

Panel B: Top 10 most frequently required individual skills (in %)

Predictor	Mean	Std.	25%	50%	75%
Information Technology	20.74	14.78	10.50	16.83	27.71
Business	11.44	5.00	8.28	11.35	14.39
Sales	9.79	10.25	2.68	6.29	13.28
Finance	9.43	7.95	4.36	7.07	11.71
Customer and Client Support	5.41	6.54	1.85	3.18	6.13
Supply Chain and Logistics	4.91	5.80	1.19	3.42	6.85
Administration	4.48	3.93	2.11	3.49	5.59
Marketing and Public Relations	4.38	4.26	1.53	3.26	5.78
Manufacturing and Production	3.52	4.63	0.41	1.52	5.16
Maintenance, Repair, and Installation	3.04	4.61	0.18	1.39	4.20

Panel C: Top 10 most frequently required skill pairs

At individual level	%	At department level	%
Business & Information Technology	0.91	*Finance & Information Technology*	0.40
Finance & Information Technology	0.87	*Finance & Marketing and Public Relations*	0.40
Business & Finance	0.70	*Finance & Human Resources*	0.39
Analysis & Information Technology	0.70	*Business & Finance*	0.37
Design & Information Technology	0.64	*Finance & Supply Chain and Logistics*	0.37
Information Technology & Sales	0.56	*Finance & Sales*	0.32
Administration & Information Technology	0.55	*Information Technology & Marketing and Public Relations*	0.28
Engineering & Information Technology	0.54	*Business & Information Technology*	0.28
Information Technology & Marketing and Public Relations	0.54	*Information Technology & Sales*	0.27
Marketing and Public Relations & Sales	0.53	*Administration & Finance*	0.26
At division level	**%**	**At firm level**	**%**
Information Technology & Sales	1.83	*Information Technology & Sales*	0.98
Finance & Maintenance, Repair, and Installation	1.43	*Finance & Maintenance, Repair, and Installation*	0.85
Engineering & Finance	1.35	*Finance & Sales*	0.66
Finance & Sales	1.26	*Maintenance, Repair, and Installation & Sales*	0.65
Information Technology & Maintenance, Repair, and Installation	1.22	*Information Technology & Maintenance, Repair, and Installation*	0.60
Finance & Information Technology	1.20	*Manufacturing and Production & Sales*	0.60
Design & Finance	1.17	*Finance & Manufacturing and Production*	0.57
Finance & Manufacturing and Production	1.01	*Engineering & Sales*	0.54
Finance & Science and Research	0.95	*Sales & Supply Chain and Logistics*	0.49
Human Resources & Information Technology	0.94	*Human Resources & Sales*	0.48

Table 3: Predictive Performance of Skill Vector

This table presents the out-of-sample R^2 in percentage for various models across test years. Using XGBoost models built on a five-year training/validation window preceding each test year, we evaluate out-of-sample performance with specific predictors annually. The analysis yields a series of out-of-sample R^2 values, each corresponding to a rolling window and predictor set. The predictors for the XGBoost model are listed by row, while each column represents a test year. Panel A shows the predictive performance of skill vector and benchmark variables (*Ln(Employee)*, *Hiring*, and *Turnover*) and Panel B shows the incremental predictive performance of skill vector over benchmark variables.

	Out-of-Sample R^2					
	Test Year					
Predictors	**2015**	**2016**	**2017**	**2018**	**2019**	**Avg.**
Panel A: Individual Predictors						
Ln(*Employee*)	15.30	18.46	14.41	3.45	8.59	12.04
Hiring	1.82	2.54	3.79	2.13	5.42	3.14
Turnover	2.77	0.40	0.26	-0.70	-1.51	0.24
Skill vector	22.90	24.70	19.86	8.25	17.41	18.63
Panel B: Incremental Predictive Value						
Ln(*Employee*) + *Hiring* + *Turnover*	19.85	21.53	18.55	8.89	17.90	17.34
Ln(*Employee*) + *Hiring* + *Turnover* + *Skill vector*	26.83	31.73	26.20	15.00	27.07	25.37

Table 4: Feature Importance

This table presents the feature importance of various predictors in our skill vector, calculated using the average SHapley Additive exPlanations (SHAP) values across all observations, multiplied by 100. Panel A presents the top 10 single predictors among all skill requirements with the highest average absolute SHAP values across all rolling windows. Panel B reports the cumulative importance of grouped predictor categories by summing their average absolute SHAP values.

Panel A: Top 10 single predictors

		Average Absolute SHAP	
	Predictor	Raw Values	%
1	*Science and Research (Individual Level)*	0.18	2.9
2	*Information Technology (Individual Level)*	0.15	2.5
3	*Industry Knowledge (Individual Level)*	0.14	2.4
4	*Analysis & Health Care (Individual Level)*	0.12	2.0
5	*Customer and Client Support & Industry Knowledge (Firm Level)*	0.12	1.9
6	*Supply Chain and Logistics (Individual Level)*	0.11	1.9
7	*Finance (Individual Level)*	0.11	1.8
8	*Business &Maintenance, Repair, and Installation (Division Level)*	0.10	1.6
9	*Health Care (Individual Level)*	0.09	1.6
10	*Customer and Client Support (Individual Level)*	0.09	1.5

Panel B: Grouped cumulative predictor importance

		Sum of Average Absolute SHAP	
Component	Group	Raw Values	%
Expertise	Total skill count (*# Skills*)	0.00	0.1
	Individual skills	1.30	21.7
	Skill pairs (individual level)	2.06	34.4
Teamwork	Skill pairs (department level)	0.83	13.8
	Skill pairs (division level)	1.05	17.5
	Skill pairs (firm level)	0.76	12.6

Table 5: Predictive Performance of Expertise and Expertise with Teamwork

This table presents the out-of-sample R^2 in percentage for various models across test years. Using XGBoost models built on a five-year training/validation window preceding each test year, we evaluate out-of-sample performance with specific predictors annually. The analysis yields a series of out-of-sample R^2 values, each corresponding to a rolling window and predictor set. The predictors for the XGBoost model are listed by row, while each column represents a test year.

		Out-of-Sample R^2					
		Test Year					
Label	Predictors	**2015**	**2016**	**2017**	**2018**	**2019**	**Avg.**
Expertise	*# Skills* + individual skills + Skill pairs (Individual level) + Interaction restrictions	14.92	18.45	15.01	6.06	10.41	12.97
Expertise with Teamwork (i.e., skill vector)	*# Skills* + individual skills + Skill pairs (All levels)	22.90	24.70	19.86	8.25	17.41	18.63

Online Appendix to "The Value of Human Capital for Firm Performance: Roles of Expertise and Teamwork"

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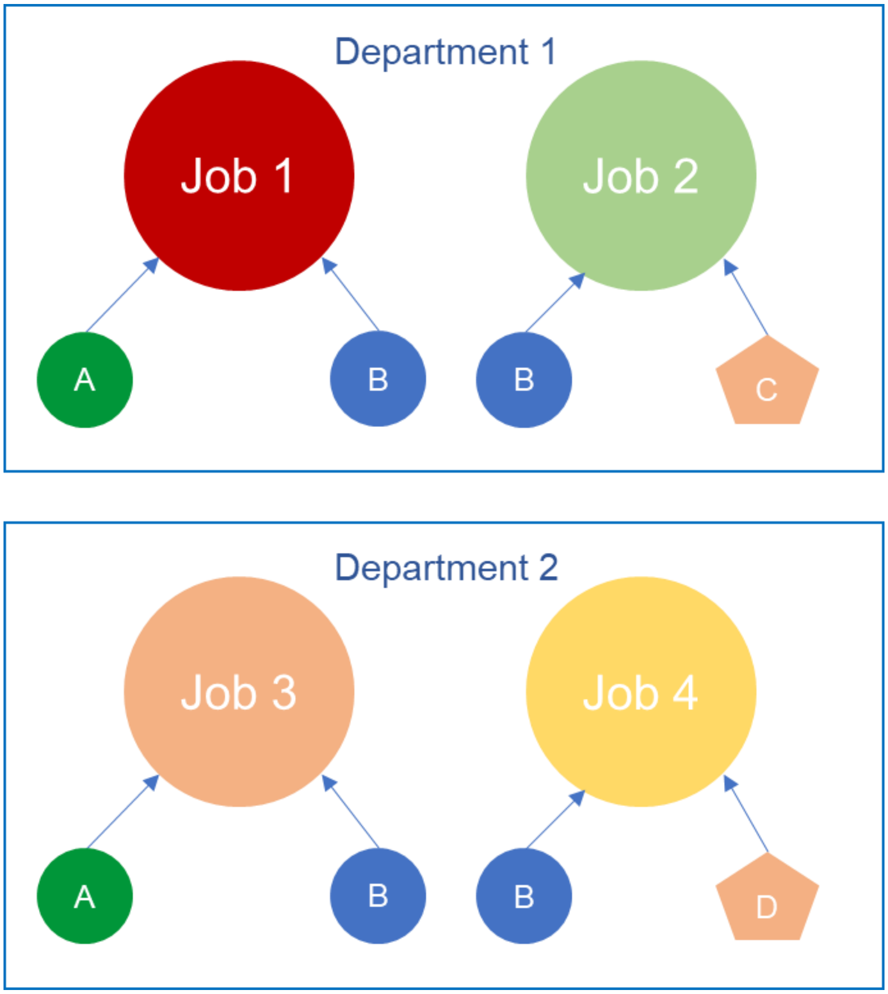
Figure OA1: Skill Count

This figure presents a simplified example of our skill vector.



Skill Level	Skill Count
Individual Standalone Skills	A (2)
	B (4)
	C (1)
	D (1)
Individual Skill Pairs	A×B (2)
	B×C (1)
	B×D (1)
Department Skill Pairs	A×C (1)
	A×D (1)
Division Skill Pairs	C×D (1)

Table OA1: Tuning Details for XGBoost Parameter

Panel A reports the search range of XGBoost parameter values. Panel B shows the chosen parameter values for the main XGBoost models for each test year. In the main XGBoost models, we use our skill vector to predict 2-year-ahead *ROA*.

Panel A: Search range of XGBoost parameter values

Number of trees	200, 400, 600, …, 2,000
Maximum depth of the tree	1, 2, 3, 4, 5, 6
Learning rate	0.001, 0.01, 0.1

Panel B: Chosen parameter values

	Predictor: Skill Vector	Test Year				
		2015	2016	2017	2018	2019
(1)	Number of trees	600	2,000	2,000	400	600
(2)	Maximum depth of the tree	6	5	4	2	3
(3)	Learning rate	0.01	0.001	0.001	0.01	0.01

Table OA2: Predictive Performance of Skill Vector

This table presents the out-of-sample predictive performance for various models across test years. Using XGBoost models built on a five-year training/validation window preceding each test year, we evaluate out-of-sample performance with specific predictors annually. The analysis yields a series of out-of-sample performance evaluation values, each corresponding to a rolling window and predictor set. The predictors for the XGBoost model are listed by row, while each column represents a test year. Panel A presents the out-of-sample MSEs and Panel B presents the out-of-sample MAEs of each XGBoost model.

Panel A: Out-of-sample MSE

		MSE					
		Test Year					
	Predictor	2015	2016	2017	2018	2019	Avg.
(1)	*Ln(Employee)*	0.007	0.007	0.008	0.010	0.009	0.008
(2)	*Hiring*	0.008	0.009	0.009	0.010	0.009	0.009
(3)	*Turnover*	0.008	0.009	0.010	0.010	0.010	0.009
(4)	*Skill vector*	0.007	0.007	0.008	0.010	0.008	0.008

Panel B: Out-of-sample MAE

		MAE					
		Test Year					
	Predictor	2015	2016	2017	2018	2019	Avg.
(1)	*Ln(Employee)*	0.057	0.057	0.059	0.067	0.061	0.060
(2)	*Hiring*	0.059	0.060	0.060	0.065	0.063	0.061
(3)	*Turnover*	0.058	0.060	0.060	0.066	0.064	0.062
(4)	*Skill vector*	0.053	0.054	0.056	0.066	0.058	0.057

Table OA3: Predictive Performance of Skill Vector by Task Complexity

This table presents the out-of-sample R^2 in percentage of each model across test years, partitioned by three proxies of task complexity: *High Tech*, *Routine Task Index*, and *Tobin's Q*. Shaded rows indicate the predictive performance for firms with more complexity. Panel A shows the predictive performance of skill vector and Panel B shows the predictive performance of the expertise component.

Panel A: Expertise with Teamwork (i.e., skill vector)

		Out-of-Sample R^2					
		Test Year					
		2015	**2016**	**2017**	**2018**	**2019**	**Avg.**
Routine Task Index	Low	26.98	27.82	26.58	19.16	19.60	24.03
	High	6.49	7.23	5.75	-3.42	-2.16	2.78
Tobin's Q	Low	5.32	10.73	7.12	1.69	-1.93	4.59
	High	25.05	29.10	21.79	17.54	24.10	23.52
High Tech	=0	7.52	9.04	7.71	-5.34	6.96	5.18
	=1	34.91	26.34	26.68	21.78	21.59	26.26

Panel B: Expertise

		Out-of-Sample R^2					
		Test Year					
		2015	**2016**	**2017**	**2018**	**2019**	**Avg.**
Routine Task Index	Low	20.82	23.13	18.60	13.37	17.97	18.78
	High	5.92	6.62	3.64	-4.91	-1.74	1.91
Tobin's Q	Low	4.94	8.76	6.97	-0.23	-3.57	3.37
	High	18.95	21.76	19.99	11.10	19.67	18.29
High Tech	=0	5.08	6.33	3.02	-6.26	1.90	2.01
	=1	23.11	22.37	24.86	18.81	18.03	21.44

Table OA4: Predictive Performance of Skill Vector by Ease of Communication

This table presents the out-of-sample R^2 in percentage of each model across test years, partitioned by four proxies of ease of communication: *Teamwork Job*, *Teamwork Culture*, *One Segment*, and *# MSA*. Shaded rows indicate the predictive performance for firms with more communication ease. Panel A shows the predictive performance of skill vector and Panel B shows the predictive performance of the expertise component.

Panel A: Expertise with Teamwork (i.e., skill vector)

		Out-of-Sample R^2					
		Test Year					
		2015	**2016**	**2017**	**2018**	**2019**	**Avg.**
Teamwork Culture	Low	8.48	9.54	5.74	-6.26	1.65	3.83
	High	16.52	19.06	19.49	9.60	15.97	16.13
Teamwork Job	Low	7.74	7.33	2.81	-10.00	-0.83	1.41
	High	21.62	35.15	24.21	18.53	21.28	24.16
# MSA	Low	24.28	26.25	23.43	17.15	14.27	21.08
	High	9.34	4.61	3.55	-7.43	4.66	2.94
One Segment	=0	13.28	22.47	14.88	9.42	12.93	14.59
	=1	22.33	27.38	21.52	10.17	20.07	20.29

Panel B: Expertise

		Out-of-Sample R^2					
		Test Year					
		2015	**2016**	**2017**	**2018**	**2019**	**Avg.**
Teamwork Culture	Low	5.92	10.33	4.87	-6.05	1.91	3.39
	High	15.63	20.04	15.52	6.37	11.93	13.90
Teamwork Job	Low	4.14	7.22	0.90	-10.34	-0.99	0.19
	High	20.91	29.00	22.02	16.40	16.26	20.92
# MSA	Low	19.68	27.46	21.78	14.51	13.20	19.33
	High	4.03	4.23	1.10	-7.72	3.19	0.97
One Segment	=0	12.44	19.13	14.54	8.09	9.41	12.72
	=1	8.00	17.44	14.56	5.80	11.07	11.37

Table OA5: Predictive Performance of Skill Vector in Two-by-two Subsamples

This figure presents the out-of-sample R^2 in percentage of each model across test years, partitioned by both complexity and communication factors. Panel A presents factor loadings of complexity and communication factors after principal component analyses. Panel B shows the predictive performance of skill vector and Panel C shows the predictive performance of the expertise component after partitioning the sample into two-by-two subsamples with complexity and communication factors.

Panel A: Factor loadings

Task complexity factor		Ease of communication factor	
Proxy	Factor loading	Proxy	Factor loading
Routine Task Index	-0.37	*Teamwork Culture*	0.56
Tobin's Q	0.12	*Teamwork Job*	0.36
High Tech	0.37	*# MSA*	-0.15
		One Segment	-0.19

Panel B: Expertise with Teamwork (i.e., skill vector)

Test Year			Complexity factor Low	Complexity factor High
2015	Communication factor	Low	-33.58	1.54
		High	3.2	15.03
2016	Communication factor	Low	-0.39	-84.86
		High	4.98	39.47
2017	Communication factor	Low	10.74	27.33
		High	2.60	19.21
2018	Communication factor	Low	-0.48	-8.80
		High	0.91	28.25
2019	Communication factor	Low	-24.73	-3.54
		High	-10.08	38.42
Avg.	Communication factor	Low	-9.69	-20.81
		High	0.32	29.70

Panel C: Expertise

Test Year			Complexity factor Low	Complexity factor High
2015	Communication factor	Low	2.87	4.43
		High	0.07	17.77
2016	Communication factor	Low	1.54	2.15
		High	0.89	24.13
2017	Communication factor	Low	-0.80	0.72
		High	-4.13	19.11
2018	Communication factor	Low	-14.89	-4.23
		High	-3.67	12.30
2019	Communication factor	Low	-2.50	-12.08
		High	-5.73	12.17
Avg.	Communication factor	Low	-2.76	-1.80
		High	-2.51	17.10

Table OA6: Predictive Performance of Skill Vector by Job Zone

This table presents the out-of-sample R^2 in percentage of each XGBoost model by job zone. Each row presents the predictive performance of skill vector constructed using occupations in each job zone. O*NET groups occupations into one of five job zones based on levels of education, experience, and training necessary to perform the occupation. Zone 1 indicates the lowest requirement and Zone 5 indicates the highest requirement.

	Test Year					
Job Zone	**2015**	**2016**	**2017**	**2018**	**2019**	**Avg.**
Zone 1	1.22	2.73	1.11	-3.06	-0.19	0.36
Zone 2	4.90	8.05	9.70	1.80	4.42	5.77
Zone 3	12.46	14.84	13.16	3.78	9.90	10.83
Zone 4	17.27	17.34	15.70	8.25	14.67	14.64
Zone 5	12.13	13.17	11.99	6.32	10.43	10.81