The Value of Teamwork for Firms' Human Capital

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ABSTRACT

We study the importance of teamwork in predicting firm performance. Drawing on classical economic theories on the division of labor, we argue that one of the main contributors to firm-level human capital resources and firm performance is teamwork, namely the cooperation among employees with specialized knowledge. Using firms' online job posting requirements, we construct a novel measure of teamwork that details firm-level human capital profiles. We employ machine learning models and assess how well teamwork predicts future firm performance in out-of-sample tests. We find that teamwork outperforms other human-capital-related variables in predicting future performance. Furthermore, we document that teamwork has superior predictive power for firms engaged in complex tasks and characterized by effective employee communication.

Keywords: human capital; teamwork; complementarity; machine learning; XGBoost

JEL classification: J23; J24; M41; M54

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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

Classical economics (e.g., Smith, 1776) emphasizes the division of labor and task specialization as significant contributors to national economic growth, which is borne out in empirical tests using cross-cultural data (e.g., Basu, Kirk, and Waymire 2009). Modern production processes often involve collaboration between specialized employees with diverse skill sets. Firms encourage collaboration to develop internal human capital, thereby creating a competitive advantage and enhancing firm performance. Given the increasing complexity of production processes, collaboration has likely gained importance for firm performance. However, large-sample research investigating the within-firm interactions among team members and their skills is scarce, likely because of limited data, and thus, we do not know whether and how well classical economic theories explain firm performance.

We empirically examine how much teamwork matters for firm performance and when it matters more. Teamwork, as we conceptualize it, is the cooperation of specialized employees and encompasses both labor-division-induced employee skill specialization and team-member-collaboration-induced employee skill complementarities. We postulate that teamwork has important economic implications for firm performance. Moreover, we argue that its importance depends on the complexity of the firm’s production requirements and the effectiveness of employee communication and coordination. Complex job tasks raise employees’ costs to master broad expertise and proficiency and make team-based workflows that encourage employee specialization and collaboration more valuable. And teamwork can only generate value when employees actively communicate and collectively integrate their expertise. Our findings have implications for managers' decisions regarding human capital investment, including whom to hire and how to organize the teams (Brickley, Smith, and Zimmerman 2016).

Despite the significance of human capital, U.S. financial statements contain little relevant data beyond the number of employees and the ratio of CEO-to-typical-worker compensation. We propose a new approach that leverages job requirements posted by firms on online platforms to investigate the importance of teamwork in predicting firm performance.

Our study proceeds in three main steps. In step one, we collect comprehensive data from job postings and construct a teamwork measure that captures firm-level human capital profiles. Using all job postings issued by the focal firm in a year, we construct a skill vector that contains the frequency of each unique skill sought by the firm that year. Crucially, we also assess the frequency of unique two-skill pairs to capture intra-employee and inter-employee skill complementarities in local functional teams and across teams. Assuming that all job postings are filled, this teamwork measure provides detailed insights into firms' human capital on an annual basis, including both the additive sum of employees' specialized knowledge and the multiplicative sum of the firm-level human capital generated through employee interactions.

In step two, we address "how much" teamwork matters by examining how well the teamwork measure predicts future firm performance out of sample. This analysis involves a large set of variables (over 1,400) with potentially complex interactions and possibly nonlinear effects on firm performance. To handle this complexity, we choose a machine learning model instead of specifying a complex OLS regression model. We stress that our analysis does not explore causal relationships between human capital resources and firm performance. Rather, we focus on the out-of-sample prediction power of our teamwork measure on one-year ahead operating performance. Specifically, we employ extreme gradient boosting (XGBoost) models and use cross-validation in the training/validation data to optimize model parameters. To assess the prediction performance of the teamwork models, we compare them with benchmark models that use other variables related to human capital, such as employee count and turnover. We find that the out-of-sample R^2 values of teamwork models range from 8.65% to 22.88%, depending on the test years. Moreover, teamwork outperforms benchmark models built with human-capital-related variables such as employee count and turnover in the out-of-sample prediction analysis. We also observe substantial improvements in the prediction performance of the benchmark models when teamwork is included.

Moving to the third step, we address the question of "when" teamwork matters more by analyzing the prediction performance of the teamwork measure in subsamples where teamwork is expected to have a greater impact on firm performance. Specifically, we investigate whether the predictive power of teamwork measure varies with task complexity and employee communication. Our results show that teamwork exhibits higher prediction performance for firms with lower routine task indexes, higher Tobin's Q ratios, and those operating in high-tech industries. Additionally, teamwork performs better for firms characterized by a more intensive teamwork culture, a higher requirement for teamwork skills in job postings, and a smaller number of business segments and geographical locations. Collectively, these findings indicate that our teamwork measure possesses stronger predictive power for future firm performance when firms face more complex tasks and exhibit more efficient employee communication, consistent with the notion that teamwork is particularly valuable under these circumstances.

We contribute to the economic and management literatures on specialization and complementarity by documenting the value of employee specialization and complementarity in forecasting future firm operating performance, especially when firms face more complex tasks and exhibit enhanced communication practices. By underscoring the pivotal role of effective communication, we also shed light on how organizations can design and implement a management control system that can significantly shape the nature of teamwork within an organization. We extend the human capital literature by leveraging skill requirements in firms' job postings and creating a new measure that comprehensively and granularly describes firms' human capital profiles. Moreover, we contribute to the broad application of machine learning in accounting research by combining a state-of-the-art machine learning model with firms' job posting data to document the predictive power of teamwork on firm operating performance.

II. THEORETICAL DEVELOPMENT

Firm-level human capital

Corporate executives frequently exclaim that employees are their firms' most crucial assets (Fulmer and Ployhart 2014). Individual employees possess specialized knowledge and skills for various job tasks, establish their expertise in specific domains, and help achieve their firms' business objectives.

However, a firm's human capital resides not only within its individual employees but also extends to the collective capabilities and synergies created at the team or firm level. Due to the division of labor, employees collectively contribute to the overall firm objective by performing different roles that are interconnected through interdependency (Raveendran, Silvestri, and Gulati 2020). Therefore, firm-level human capital is not merely the additive sum of individuals' human capital, but a function of both individual employees and their synergy (Thompson 1967).

Complementarity is deeply embedded in the theory of why firms exist and how they operate (e.g., Milgrom and Roberts 1995). Classical economic theory on the complementarity between capital and labor posits that when the amount of physical capital increases, it enhances the productivity of labor, particularly skilled labor.[1] Such complementarity between different factors of production is arguably more critical for human capital (Neffke 2019). Consequently, managing human capital in firms entails coordinating specialized employees to maximize complementarity and efficiently produce goods and services (Becker and Murphy 1992; Garicano 2000).

Firm as a team of teams

When coordinating a group of complementary specialized employees, firms must consider the tradeoff between coordination costs and team size (Becker and Murphy 1992). As the number of specialists increases, the costs of coordinating the team grow, evidenced by principal-agent conflicts, free riding, and communication difficulties (Cohen and Levinthal 1990; Becker and Murphy 1992; Adams, Akyol, and Verwijmeren 2018). Consequently, firms often divide their workforce into small groups and adopt a multi-level structure, particularly in today's complex and fast-paced economy (Mintzberg 1978). Increasing global competition and advances in modern technology push the emergence of teams as the core building blocks of organizations (e.g., Wuchty, Jones, and Uzzi 2007; Kozlowski and Bell 2013).

During the 19th and early 20th centuries, firms generally organized people by functional department (i.e., U-form) to gain operational efficiencies (Porter 1985).[2] By grouping similar

[1] 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).
[2] 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 typical issue is that the within-firm communication can then become rigid due to the high degree of standardization and formalization (Madsen 2011).

roles together, firms can achieve economies of scale, facilitate within-function communication, and simplify management control over employees (Chandler 1962). This specialization-based approach clarifies employees' roles and responsibilities, enables them to work within their own realm of expertise, and provides more opportunities for skill development and expertise honing (Daft 1978). Finally, the departments complement each other: the expertise in each function, when combined, results in enhanced business performance (Teece 1986).

As 20th century firms grew larger and became more diversified, they often introduced an additional level in the organizational structure and divided the firm into semi-autonomous divisions or segments (i.e., M-form) (Chandler 1977). Each division, typically consisting of multiple functional departments, is responsible for a distinct business or geographic area.[3] By the early 1990s, nearly all large firms in the United States had adopted some variation of the multi-divisional structure due to its associated performance gains (Palmer, Jennings, and Zhou 1993). The M-form structure allows firms to decentralize decision-making and maintain flexibility in day-to-day operations. While central management provides overall strategic direction for the firm, each division operates semi-independently, tailoring its strategy to the specific market needs, tracking its own performance, and staying productive even if other divisions fail (Williamson 1975). In this sense, a firm can be viewed as a team of teams, with employees collaborating within their respective departments, divisions, and the overall organization.

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

Teamwork and firm performance

We study teamwork, which is firm-level human capital in specialized employee collaboration.[4] We argue that productive within-firm teamwork encompasses two components: employee specialization and coordination at all levels (Becker and Murphy 1992). Moreover, to conceptualize and operationalize teamwork, we delve deeper into the origins of employees' human capital. The economics and management literatures view an individual's human capital as her stock of knowledge and skills that can help achieve economic outcomes (Becker 1964; Beck, Francis, and Gunn 2018). Therefore, firm-level human capital is measured as the collective skills of employees and other contracted individuals who work for a specific firm, with their stand-alone skills as the micro-foundations (Coff and Kryscynski 2011; Foss 2011; Ployhart, Nyberg, Reilly, and Maltarich 2014).[5]

Importantly, the combination of individual skills within a firm is *not* a simple linear function. As a result of teamwork, individual skills constitute firm-level human capital in two ways: additively and interactively (Ployhart and Moliterno 2011; Ployhart et al. 2014). First, individual workers can increase output additively as the sum of their skills and efforts.[6] Second, individual skills can be combined interactively through cooperation, resulting in new and collective firm-level human capital. Coordination across individuals, across departments, and

[4] 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.

[5] 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 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) accounting goodwill.

[6] Firms can optimize production efficiency by coordinating employee specialization and assigning job roles to employees with comparative advantage (Smith 1776; Rivkin and Siggelkow 2003). For simplicity, this paper takes firms' matching between job roles and employee skills as given.

across divisions can transform individual skills into synergy so that the whole is greater than the sum of its parts (Ployhart and Moliterno 2011; Ethiraj and Garg 2012).[7] Team players with diverse skill sets complement one another and contribute more to team performance (Fang and Hope 2021). Synergies between teams arise when complementary skills are used to successfully implement and complete a project. For example, management research argues that the successful commercialization of an innovation requires complementary assets such as manufacturing, marketing, and after-sales service (Teece 1986). Intrafirm knowledge sharing across semi-autonomous divisions also contributes to firm performance (Seavey, Imhof, and Westfall 2018).[8]

When teamwork adds more value

The impact of teamwork on productivity varies across different contexts. In sports like baseball, team production primarily relies on the simple aggregation of individual efforts. However, basketball requires more coordinated actions, strategic positioning, and effective communication among teammates to create opportunities and maximize team performance (Wolfe et al. 2005). We could observe similar variations in business settings, where customer service call centers predominantly represent a simple aggregation of individual efforts while sell-side analyst teams do not (Fang and Hope 2021). For firms, the value of teamwork is greatly influenced by two factors: task complexity and ease of communication among employees (e.g., Ployhart and Moliterno 2011).

[7] The whole can also be less than the sum of the parts. As mentioned, the coordination costs increases with the team size. High levels of specialization in teams may impede the development of a common language (Cohen and Levinthal 1990; Becker and Murphy 1992; Adams, Akyol, and Verwijmeren 2018). Team work can also create moral hazard problems when it is difficult to discern an individual's contribution to team output a.k.a. the free rider problem (Holmstrom 1982). 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).

[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).

As job tasks increase in complexity, the costs associated with acquiring relevant skills and knowledge also rise. Consequently, complex tasks can make it difficult for an individual to possess broad expertise and proficiency, increasing the returns to specialization (Einstein 1934; Jones 2009; Jones 2021). Heightened specialization naturally fosters a higher degree of interdependence and coordination among employees that eases the aggregation of specialized knowledge (Jones 2009). Therefore, complex tasks engender intensive workflows and necessitate close temporal synchronization (Thompson 1967; Ployhart and Moliterno 2011). Employees are required to adapt their behaviors and coordinate their actions with fellow team members.

The ease of employee communication is also crucial because teamwork can only generate value when employees work interdependently, communicate effectively, trust one another, share knowledge, and collectively integrate their 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, Kala, and Nyshadham 2023).[9] Adhvaryu et al. (2023) suggest that providing on-the-job soft skill training to Indian garment workers can boost productivity by 13.5%. A significant part of this increase is due to the emphasis on teamwork and collaboration skills in the training.

[9] Management control system 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), financial incentives (Chen, Williamson, and Zhou 2012; Kachelmeier, Wang, and Williamson 2019; Glover and Xue 2020), and personnel control (Autrey, Jackson, Klevsky, and Drasgow 2023).

Task complexity and ease of communication are not independent of each other. Complex tasks demand employee specialization and collaboration. Therefore, firms with complex tasks will design their structures, allocate job tasks, and promote collaborative culture in a way that effectively leverages employee specialization. Over time, the organizational structure and corporate culture will adapt or adjust how the tasks are structured.

Measuring firm-level human capital and teamwork

Within U.S. financial reporting, disclosed employee data is largely confined to employee counts and the CEO-to-typical-worker pay ratio. This limitation is significant given human capital's role in generating economic benefits. The 2020 SEC amendment to Regulation S-K (Reg S-K) highlights the importance of human capital disclosure for investors and other stakeholders (Arif, Yoon, and Zhang 2022; Bourveau, Chowdhury, Le, and Rouen 2022; Demers, Wang, and Wu 2022; Haslag, Sensoy, and White 2022). In line with this, the FASB proposed an Accounting Standards Update (ASU) in July 2023 on expense disaggregation disclosures (subtopic 220-40), aiming to provide more detailed employee compensation information.

Likely due to such data limitations, early studies on firm-level human capital focus on specific contributors of human capital such as the board of directors (Adams, Akyol, and Verwijmeren 2018), top executives' human capital (Chen, Huang, Meyer-Doyle, and Mindruta 2021), and rank-and-file employees (Dou, Khan, and Zou 2016). Others roughly quantify the stock of firm-level human capital using accounting data such as Selling, General, and Administrative (SG&A) expense (Eisfeldt and Papanikolaou 2013).

More recent studies examine the performance implication of human capital investment in specific functions. For example, human investment in the tax function contributes to firms' tax planning activities (Chen, Cheng, Chow, and Liu 2020; Barrios and Gallemore 2022). Tambe (2014) documents that firms' investments in big data lead to faster productivity growth. Darendeli et al. (2022) measure firms' investment in green jobs and link this to firm operating performance and green innovations. Lee, Mauer, and Xu (2018) take a more holistic approach to examine firms' occupation composition and document that the across-firm occupation-composition relatedness is a key factor in mergers and acquisitions.

Different from prior studies, we take a more comprehensive and granular approach to propose a new measure of firms' human capital resources using employee skill requirements in job postings. Using skills (rather than occupations) as the basis to model teamwork lets us better understand the multidimensionality and heterogeneity of teamwork in firm-level human capital. First, individuals' human capital is multidimensional (Lise and Postel-Vinay 2020). They develop bundles of different skills via training, education, and exploration. Also, the needs for individual human capital are heterogeneous across firms. Even for the same occupation, employees may use different combinations of skills with different weights attached to the skills depending on firms' needs (Lazear 2009).

III. MEASURING TEAMWORK USING JOB POSTINGS

Main data

Our main data come from Burning Glass Technologies (BGT). BGT is an employment data analytics firm that provides data on online job postings and skills in demand, sourcing from over 40,000 online job boards and company websites. After removing duplicate job postings, BGT uses its proprietary algorithm to extract and standardize job-level characteristics in each job posting, such as employer name, job title, job location, and skill requirements.

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 (the last year of job postings data we obtain). We use the crosswalk file provided by BGT to merge the job postings data with the financial data from Compustat and require the subsequent-year *Return on Assets* (ROA_{t+1}) to be non-missing. The final sample consists of 15,226 firm-year observations.

Table 1 Panels B and C report the number of firm-year observations by year and by Fama-French 30 industry, respectively. The number of observations increases slightly over the years, consistent with BGT gradually expanding its coverage. Also, the industry distribution of our final sample is similar to that of the Compustat universe. The most populated industries are banking, services, business equipment, and healthcare.

Teamwork Measure using Skill Vectors

Teamwork encompasses the collective skills and knowledge possessed by individual employees within the firm. To measure teamwork, we begin with the foundational elements of human capital, namely the skills and knowledge of each employee. We obtain the job-posting-level skill requirement data from BGT, assuming that the skill requirements in each job posting represent individual-level employees' skill endowments for the focal firm.[10] To limit the dimensionality of our predictors to a manageable level, we use skill family cluster, the coarsest level of skill requirements coded by BGT using its own proprietary algorithm.

We construct the teamwork measure by aggregating job-posting-level skill requirements to the firm-year level. To mitigate the influence of outliers, we exclude the skills and skill pairs

[10] We take the skill requirements in the job posting as the components of focal firm's human capital rather than trying to capture individuals' total skill endowment from their resume. The reason is that firm-level human capital resources are composed of individual skills that are valuable to the focal firm's business operations. For example, when an accountant plays the piano well, the latter skill is not directly relevant to firm business operations and should not be included in our measurement of teamwork.

required by less than 2 percent of job postings. In the aggregation process, we first count the total number of every skill required in all job postings issued by firm i in year t. We then measure the simple additive sum of employees' skills within each firm-year. Specifically, we group the job postings by firm and year and aggregate the skill requirements of firm i in year t by counting the frequency of each unique skill and scaling them by the total number of skills.[11] Next, assuming that firms will design job requirements and post job advertisements based on the synergistic effects within a certain combination of skills, we capture the multiplicative effects of employee skills by counting unique skill pairings at various levels. Counting the co-occurrences of skills allows us to explore the synergies that emerge when specific skills are combined. This approach aligns with a fundamental rationale rooted in the concept of labor division since Smith (1776), which posits that combining skills at a lower level leads to the creation of synergies at a higher level (see Figure 1).

We measure the skill complementarities at the individual, department, division, and firm levels by counting co-occurrences of skill pairs in the following ways. First, we assume one job posting represents one employee and measure the complementarity across skills within the same *individual* by counting the co-occurrences of unique skill pairs (e.g., Python and writing) within the same job posting, aggregating the count of all job postings to the firm-year level, and scaling them by the total number of skills.[12]

Second, we measure the complementarity across individuals within the same *department*. We define a department as a group of individuals working within the same occupation and the

[11] 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.

[12] 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.

same geographic area, 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 the total number of skills. Note that in measuring the complementarities at a higher level, we disregard the skill pairs that were counted at lower levels to avoid double counting. For example, assuming that job posting No. 1 required skills A, B, and C and job posting No. 2 required skills B, C, and D, we count A&B, B&C, A&C, B&D, and C&D as within-individual skill pairs and A&D as the within-department across-individual skill pair. As a result, the measured skill complementarity is contingent upon the heterogeneity of employee skills. For example, if the skill requirements are similar across individuals within a department, we would observe a smaller number of unique skill pairs at the department level.

Third, we measure the complementarity across departments within the same *division*. Because we cannot precisely isolate firms' business segments using job posting data, 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 the total number of skills.

Last, we measure the complementary across divisions within the same *firm* by counting the co-occurrences of unique skill pairs across two different divisions within the same firm and scaling them by the total number of skills. Note that under this research design, firms with more than one hiring MSA, especially retailers, would have more non-zero values for the skill pairs at the firm level.

As a result, our measure of teamwork is a multi-dimensional skill vector for each firm-year observation. Table 2 Panel A shows the number of predictors by category. The skill vector contains 1 variable of total skill requirement count, 27 unique skill counts representing the additive sum of employee skills, and 1,371 unique skill pair counts representing skill complementarity across different levels. Table 2 Panels B to F list the top 10 most frequently required skills or skill pairs by category and present summary statistics.

We caveat several limitations associated with our measure. First, our assessment of skill-based human capital relies on the skills specified in online job postings. However, it is important to recognize that firms, particularly their HR teams, may have access to additional labor-related information from alternative sources such as resumes or job interviews, which are not captured in our measure. Second, our current measure of skill complementarities is constrained by the co-occurrences of skill pairs, determined by computational limitations. Firms can achieve even greater synergy by combining multiple skills in various ways. Therefore, our measure of synergy serves as a conservative estimate, representing a lower bound of the potential synergy that can be generated through the interaction of different skills within a firm. Last, as a common caveat of research using job postings, the skills identified in job postings reflect the skills demanded by firms but may not align with the actual skills acquired through the recruitment process.

IV. PREDICTING FIRM PERFORMANCE USING MACHINE LEARNING METHOD

We evaluate our firm-level teamwork measure by employing machine learning models to examine its ability to predict future operating performance (ROA_{t+1}), which is a joint test of the importance of human capital resources and the validity of our measure. The complexity of our prediction analysis is notable, as our firm-level teamwork measure encompasses a substantial set of over 1,400 variables. These variables are likely to exhibit nonlinear interactions, and the relationships between these variables and firm performance can be intricate and lack well-defined patterns. Hence, trying to construct an elaborate OLS regression model will likely be suboptimal. Thus, we opted for a machine learning approach, which provides greater flexibility and predictive capacity, especially when dealing with large and intricate 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 prediction power of our teamwork measure on one-year ahead operating performance (Bao et al. 2020; Brown, Crowley, and Elliott; Ding et al. 2020; Bertomeu, Cheynel, Floyd, and Pan 2021; Chen, Cho, Dou, and Lev 2022).

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 teamwork measure. 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 its superior performance and high speed in solving regression, classification, and ranking problems (Tantri 2021; Zheng 2021; Li and Zheng 2023).[13]

XGBoost, like other machine learning algorithms, relies on a set of parameters that require optimization to achieve the best prediction performance. This optimization process is not guided

[13] 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.

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 prediction 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.[14] 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.[15] In the n^{th} iteration, the XGBoost model is trained using the first *n* folds and validated on the $(n+1)^{th}$ fold (see Figure 2). For example, in the 2^{nd} iteration, the training set is the first two folds, and the validation set is the 3^{rd} fold. In this way, we ensure that the validation data is more recent than the training data to avoid look-ahead 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.[16] Last, the fine-tuning process chooses the optimal parameter combination that maximizes the model's average performance over the four iterations.

[14] 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.
[15] 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.
[16] There are 4 iterations in each 4-split time-series cross-validation process to train an XGBoost model. Moreover, we grid search for 15 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 1,080 (=4*15*6*3) times for each training and validation attempt.

Performance evaluation

To test the predictive performance of our teamwork measure, 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 3). The results of our analysis will comprise a sequence of out-of-sample R^2s, one for each rolling window.

Benchmark selection

To further assess the out-of-sample performance of our teamwork measure, we compare it with two benchmarks. The first benchmark is the number of employees, which is chosen due to its wide data availability from Compustat. However, as a simple aggregate measure, the number of employees offers limited information on the composition and quality of human capital.

We add a second benchmark, employee turnover, which is constructed using employment data gathered from online platforms. Li et al. (2022) use this measure and document a negative association between current employee turnover and future operating performance. We construct firm-year level employee turnover rate based on resume data from Revelio Labs. The Revelio Labs resume data include individuals' demographic data, educational background, and employment history (e.g., start and end dates of a job position, employer name, and job title). We follow Li et al. (2022) and calculate the turnover rate as the employee outflow scaled by the number of employees of a firm at the beginning of a year.

We repeat the above-mentioned method to train the XGBoost models of these two benchmarks separately and jointly and evaluate their out-of-sample prediction performance.

V. EMPIRICAL RESULTS

Predicting future firm performance

In this section, we apply the models derived from the training/validation sample to predict future performance during the test period.[17] Table 3 reports the out-of-sample R^2 results of the test sample in each of the five rolling windows and online appendix Table OA2 reports the MSE and MAE results for robustness. When employing our teamwork measure as the predictor, the out-of-sample R^2 values range from 8.65% to 22.88%, with an average of 17.52% across the five test samples. To provide a better understanding of these figures, we compare the prediction performance of the teamwork models (row 1) with those of benchmark models (rows 2-4). The results consistently demonstrate that the teamwork measure significantly outperforms other variables related to human capital in forecasting future firm performance across all five rolling windows. For example, Table 3 shows that the average out-of-sample R^2 is 12.86% for models with the number of employees, 1.57% for models with turnover, and 13.68% for models with both the number of employees and turnover.[18] We further assess if teamwork enhances the model's predictive power beyond existing benchmark variables. Upon integrating the teamwork

[17] 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. The values are relatively stable over time and do not cluster at the lower or upper bounds, suggesting that the allowed range for each parameter is typically not binding.
[18] Note that we evaluate the prediction 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.

measure into the benchmark models (rows 5-7), we observe a substantial improvement in predictive performance. For instance, the average out-of-sample R2 of models employing employee count nearly doubles (from 12.86% to 24.96%) with the inclusion of the teamwork measure. This highlights the teamwork measure's ability to unveil additional insights not captured by existing human-capital-related variables.

To enhance the interpretability of our teamwork models and make transparent the items responsible for prediction performance, we quantify the importance of each predictor within the teamwork measure using SHapley Additive exPlanations (SHAP). SHAP values use 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 (Lundberg, Erion, and Lee 2019). Based on the magnitude of feature attributions, we estimate each predictor’s importance by averaging the absolute SHAP values across the test data in five rolling windows.[19] Table 4 Panel A presents the top 10 predictors with the highest average absolute SHAP values across all rolling windows.[20] Among these predictors, several relate to skill combinations at different levels, such as health care combined with science and research, analysis combined with health care, business combined with customer and client support, and customer and client support combined with industry knowledge. Furthermore, individual skills also exhibit significant importance in

[19] Permutation importance is an alternative to SHAP values. Based on the decrease in model performance rather than the magnitude of feature attributions, permutation importance of a predictor is computed as the R2 decrease when that predictor is randomly shuffled (Altmann, Toloşi, Sander, and Lengauer 2010). Table OA3 in the online appendix shows the top 10 most important predictors and cumulative feature importance by group based on permutation importance. 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.

[20] 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 0.88, 0.60, 0.61, and 0.62, suggesting that the predictor importance is reasonably stable over time.

predicting future performance, including maintenance, repair, and installation, supply chain and logistics, customer and client support, industry knowledge, and business.

To comprehensively assess the collective importance of all predictors within our teamwork measure, we categorize them into five groups: individual skills, skill pairs at the individual level, skill pairs at the department level, skill pairs at the division level, and skill pairs at the firm level. Table 4 Panel B shows the sum of predictor importance by group.[21] In aggregate, skill pairs at the individual level contribute the most in forecasting future performance, followed by stand-alone individual skills.

When teamwork is more valuable

We next examine whether the predictive performance of our teamwork measure is contingent upon the levels of task complexity and ease of communication among employees. 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 out-of-sample prediction accuracy.[22] Given that the benefits of teamwork are amplified when tasks are complex and when communication among employees is smooth, we expect that the prediction performance of our teamwork measure increases with task complexity and ease of communication.

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

[21] The approach to calculating grouped feature importance is not well defined in machine learning literature (Au et al. 2021). Therefore, we follow prior literature and sum the predictors to calculate the cumulative importance by group (Bertomeu, Cheynel, Floyd, and Pan 2021; Chen, Cho, Dou, and Lev 2022). Note that the summed cumulative importance may overestimate the group importance, especially if there is multicollinearity.

[22] For robustness, we check the sub-sample prediction performance using the parameter values of the main models without retraining the models. Online appendix Table OA4 shows that the results are robust to this research design modification.

(Freund 2022). It is particularly pronounced in high-tech industries characterized by extensive research and development endeavors. Therefore, we use the routine task index, Tobin's Q, and a high-tech industry indicator as proxies to capture the multifaceted nature of task complexity (Francis, Philbrick, and Schipper 1994; Peters and Taylor 2017; Tuzel and Zhang 2021).

Table 5 Panel A presents the out-of-sample R^2 values of teamwork measure for low task complexity and high task complexity subsamples. As shown in the shaded area, we find that the R^2 values are consistently higher in the high task complexity subsamples across all test years and partitions compared to their low task complexity counterparts. For example, the average R^2 is 21.58% for the subsample with low routine task index and 2.74% for the subsample with high routine task index, 22.16% for the subsample with high Tobin's Q and 8.36% for the subsample with high Tobin's Q, and 26.08% for high-tech industries and 8.06% for non-high-tech industries. These findings suggest that our teamwork measure exhibits stronger predictive power for firms engaged in complex tasks, consistent with the notion that teamwork contributes more value in such contexts.

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, the structure of the firm also influences 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 unique hiring MSAs in all job postings by the focal firm in a given year (*# MSA*).

Table 5 Panel B presents the out-of-sample R^2 values of the teamwork measure for low and high communication-ease subsamples. The shaded results consistently show higher R^2 values in the high communication-ease subsamples compared to their low communication-ease counterparts. For example, the average R^2 is 15.20% (2.22%) for the subsample with high (low) teamwork culture and 21.36% (0.58%) for the subsample with more (fewer) teamwork skill requirements. Moreover, the teamwork measure shows better prediction performance for subsamples with fewer geographical locations (18.76% vs. 3.90%) and only one business segment (19.42% vs. 11.59%). These findings collectively suggest that our teamwork measure demonstrates enhanced predictive power when the firm's social environment and structure foster effective communication among employees.

We then continue to explore whether the prediction performance of the teamwork measure is contingent upon *both* task complexity and ease of communication. To facilitate this analysis, we employ the principal component method of factor analysis to condense the proxies of each dimension into a single factor. Table 6 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-

high. For each subsample, we retrain the models to fine-tune the model parameters and evaluate the out-of-sample prediction accuracy.

Given that a higher value of complexity factor indicates higher task complexity and a higher value of communication factor indicates a higher ease of communication, we expect that the teamwork measure will exhibit the best predictive performance in the high-high subsample. Table 6 Panel B presents the out-of-sample R^2 values of teamwork measure for each subsample.[23] Consistent with our expectation, the values of out-of-sample R^2 are the highest in the high-high subsamples for all five test years. For example, in the test year 2019, the R^2 is -12.86% for the low-low subsample, 1.45% for the high-low subsample, 1.04% for the low-high subsample, and 15.02% for the high-high subsample. Overall, these results demonstrate that our teamwork measure exhibits superior prediction performance for firms with complex tasks and effective employee communication.

VI. ADDITIONAL ANALYSIS

High-skills vs low-skills

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

[23] Without factor analysis, we find consistent results when partitioning the sample into four subsamples using other proxies. Online appendix Table OA5 presents the results of other two-by-two subsample analysis with and without retraining the models to fine-tune the model parameters.

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 teamwork 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.

Table 7 reports out-of-sample R^2 values of 5 different versions of teamwork measures created using job posting data with each job zone assignment. As shown in the shaded area, we find that the R^2 values are consistently higher in the subsamples of greater job zone scores. For example, the average R^2 is 17.16% for the teamwork measure based on Job Zone 5 data and is much greater than the average R^2 of 0.72% for the teamwork measure based on Job Zone 1 data. These findings suggest that our teamwork measure exhibits stronger predictive power for high-skill occupations, consistent with the notion that teamwork contributes more value when job tasks are complex.

Specialization and complementarity

While separating specialization and complementarity is conceptually and empirically challenging, we examine whether *both* parts of teamwork contribute to the predictive performance in the subsample analysis. Due to the division of labor, an employee contributes to the collective human capital of a firm by specializing in a specific domain with her skill endowments to fulfill her job requirements. We label such human capital as the specialization component, which is captured by the vectors of unique skills or skill pairs at the individual level. Then, we label the remaining component (i.e., the skill pairs at the department, MSA, and firm levels) in the skill vector as the complementarity component. To test whether both specialization and complementarity components contribute to the predictive power of human capital on firm performance, we retrain XGBoost models using the specialization and complementarity components one at a time for each subsample and evaluate the prediction performance.

Table 8 reports the prediction performance separately for specialization and complementarity components of teamwork by task complexity and ease of communication. Consistent with the previous subsample analysis, we use routine task index, Tobin's Q, and a high-tech industry indicator as proxies for task complexity and use teamwork culture, teamwork skill requirements, number of MSAs, and a one-business-segment indicator as proxies for ease of communication. In Panel A of Table 8, we present the out-of-sample R^2 values for the specialization component. The shaded area highlights that the R^2 values for the specialization component consistently exhibit higher values in subsamples characterized by high task complexity and high communication ease across all test years. Moving to Panel B of Table 8, we present the out-of-sample R^2 values for the complementarity component of teamwork. Once again, the shaded results consistently show higher R^2 values for the complementarity component in subsamples with high task complexity and high communication ease across all test years.

We further test whether *both* specialization and complementarity components of teamwork have superior prediction performance in the high task complexity and high ease of communication subsamples. As in the previous two-by-two subsample analysis, we divide the entire sample into four subsamples using both complexity factor and communication factor. Table 9 Panel A presents the out-of-sample R^2 values of the specialization component for each subsample. Consistent with our expectations, we observe that the subsamples with high complexity factor scores and high communication factor scores consistently exhibit the highest values of out-of-sample R^2 across all five test years. Similarly, Table 9 Panel B presents the out-of-sample R^2 values of the complementarity component for each subsample. We again find that the complementarity component achieves the best prediction performance in the subsamples with high complexity factor scores and high communication factor scores across all five test years.

Overall, our findings suggest that both the specialization and complementarity components of our teamwork measure add more value for firms with complex tasks and effective employee communication. These results emphasize the importance of considering both aspects of teamwork when examining the relationship between teamwork and firm outcomes. By incorporating both specialization and complementarity, our measure provides a more comprehensive understanding of the impact of teamwork on firm performance.

VII. CONCLUSION

This study sheds light on the importance of teamwork 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 overlooked due to limited data availability.

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

Overall, this study underscores the significance of teamwork for firm performance, particularly in the context of complex tasks and effective employee communication. The 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, 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 expand the scope of measuring human capital beyond traditional metrics. We also extend the literature on the application of machine learning in accounting literature.

REFERENCES

Adams, R. B., A. C. Akyol, and P. Verwijmeren. 2018. Director skill sets. *Journal of Financial Economics* 130 (3): 641–662.

Adhvaryu, A., N. Kala, and A. Nyshadham. 2023. Returns to On-the-Job Soft Skills Training. *Journal of Political Economy* 131 (8): 2165–2208.

Alchian, A. A., and H. Demsetz. 1972. Production, Information Costs, and Economic Organization. *The American Economic Review* 62 (5): 777–795.

Anand, V., R. Brunner, K. Ikegwu, and T. Sougiannis. 2019. Predicting Profitability Using Machine Learning. Working Paper.

Arif, S., Y. S. (Johnny) Yoon, and H. (Helen) Zhang. 2022. The Information Content of Mandatory Human Capital Disclosures - Initial Evidence. Working Paper.

Arnold, M. C., R. L. Hannan, and I. D. Tafkov. 2018. Team Member Subjective Communication in Homogeneous and Heterogeneous Teams. *The Accounting Review* 93 (5): 1–22.

———. 2020. Mutual Monitoring and Team Member Communication in Teams. *The Accounting Review* 95 (5): 1–21.

Au, Q., J. Herbinger, C. Stachl, B. Bischl, and G. Casalicchio. 2021. Grouped Feature Importance and Combined Features Effect Plot. Working Paper.

Autrey, R. L., K. E. Jackson, E. Klevsky, and F. Drasgow. 2023. Connectors: A Catalyst for Team Creativity. *The Accounting Review*: 1–24.

Bao, Y., B. Ke, B. Li, Y. J. Yu, and J. Zhang. 2020. Detecting Accounting Fraud in Publicly Traded U.S. Firms Using a Machine Learning Approach. *Journal of Accounting Research* 58 (1): 199–235.

Barney, D., and D. L. Flesher. 1994. Early nineteenth-century productivity accounting: the Locust Grove Plantation slave ledger. *Accounting, Business & Financial History* 4 (2): 275–294.

Basu, S., M. Kirk, and G. Waymire. 2009. Memory, transaction records, and The Wealth of Nations. *Accounting, Organizations and Society* 34 (8): 895–917.

Basu, S., X. Ma, and H. Briscoe-Tran. 2022. Measuring Multidimensional Investment Opportunity Sets with 10-K Text. *The Accounting Review* 97 (1): 51–73.

Basu, S., and G. Waymire. 2008. Has the importance of intangibles really grown? And if so, why? *Accounting and Business Research* 38 (3): 171–190.

Beck, M. J., J. R. Francis, and J. L. Gunn. 2018. Public Company Audits and City-Specific Labor Characteristics. *Contemporary Accounting Research* 35 (1): 394–433.

Becker, G. S. 1964. *Human capital: A theoretical and empirical analysis, with special reference to education.* New York: Columbia University Press.

Becker, G. S., and K. M. Murphy. 1992. The Division of Labor, Coordination Costs, and Knowledge. *The Quarterly Journal of Economics* 107 (4): 1137–1160.

Bertomeu, J., E. Cheynel, E. Floyd, and W. Pan. 2021. Using machine learning to detect misstatements. *Review of Accounting Studies* 26 (2): 468–519.

Bourveau, T., M. Chowdhury, A. Le, and E. Rouen. 2022. Human Capital Disclosures. Working Paper.

Brickley, J. A., C. W. Smith, and J. L. Zimmerman. 2016. *Managerial economics and organizational architecture*. Sixth edition. The McGraw-Hill series in economics. New York, NY: McGraw-Hill Education.

Brown, N. C., R. M. Crowley, and W. B. Elliott. What are You Saying? Using topic to Detect Financial Misreporting. *Journal of Accounting Research*.

Brüggen, A., C. Feichter, and M. G. Williamson. 2018. The Effect of Input and Output Targets for Routine Tasks on Creative Task Performance. *The Accounting Review* 93 (1): 29–43.

Chandler, A. D. 1962. *Strategy and Structure: Chapters in the History of the American Industrial Enterprise*. MIT Press.

———. 1977. *The Visible Hand: The Managerial Revolution in American Business*. Harvard University Press.

Chen, C. X., M. G. Williamson, and F. H. Zhou. 2012. Reward System Design and Group Creativity: An Experimental Investigation. *The Accounting Review* 87 (6): 1885–1911.

Chen, T., and C. Guestrin. 2016. XGBoost: A Scalable Tree Boosting System. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 785–794. KDD ’16. New York, NY, USA: Association for Computing Machinery.

Chen, X., Y. H. (Tony) Cho, Y. Dou, and B. Lev. 2022. Predicting Future Earnings Changes Using Machine Learning and Detailed Financial Data. *Journal of Accounting Research* 60 (2): 467–515.

Coff, R., and D. Kryscynski. 2011. Invited Editorial: Drilling for Micro-Foundations of Human Capital–Based Competitive Advantages. Ed. J. B. Barney, D. J. Ketchen, and M. Wright. *Journal of Management* 37 (5): 1429–1443.

Cohen, W. M., and D. A. Levinthal. 1990. Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative Science Quarterly* 35 (1): 128–152.

Daft, R. L. 1978. A Dual-Core Model of Organizational Innovation. *Academy of Management Journal* 21 (2): 193–210.

Demers, E., V. X. Wang, and K. Wu. 2022. Corporate Human Capital Disclosures: Early Evidence from the SEC’s Disclosure Mandate. Working Paper.

Ding, K., B. Lev, X. Peng, T. Sun, and M. A. Vasarhelyi. 2020. Machine learning improves accounting estimates: evidence from insurance payments. *Review of Accounting Studies* 25 (3): 1098–1134.

Einstein, A. 1934. *The World as I See it*. Covici, Friede.

Eisfeldt, A. L., and D. Papanikolaou. 2013. Organization Capital and the Cross-Section of Expected Returns. *The Journal of Finance* 68 (4): 1365–1406.

Ethiraj, S. K., and P. Garg. 2012. The Division of Gains from Complementarities in Human-Capital-Intensive Activity. *Organization Science* 23 (3): 725–742.

Fang, B., and O.-K. Hope. 2021. Analyst teams. *Review of Accounting Studies* 26 (2): 425–467.

Fehr, E., and S. Gächter. 2000. Cooperation and Punishment in Public Goods Experiments. *The American Economic Review* 90 (4): 980–994.

Flesher, D. L., and T. K. Flesher. 1980. Human Resource Accounting in Mississippi Before 1865. *Accounting and Business Research* 10 (sup1): 124–129.

Foss, N. J. 2011. Why micro-foundations for resource-based theory are needed and what they may look like. *Journal of Management* 37 (5): 1413–1428.

Francis, J., D. Philbrick, and K. Schipper. 1994. Shareholder Litigation and Corporate Disclosures. *Journal of Accounting Research* 32 (2): 137.

Freund, L. 2022. Superstar Teams: The Micro Origins and Macro Implications of Coworker Complementarities. Working Paper.

Fulmer, I. S., and R. E. Ployhart. 2014. "Our Most Important Asset": A Multidisciplinary/Multilevel Review of Human Capital Valuation for Research and Practice. *Journal of Management* 40 (1): 161–192.

Garicano, L. 2000. Hierarchies and the Organization of Knowledge in Production. *Journal of Political Economy* 108 (5): 874–904.

Gibbons, R., and M. Waldman. 2004. Task-specific human capital. *American Economic Review* 94 (2): 203–207.

Glover, J. C., and H. Xue. 2020. Team Incentives and Bonus Floors in Relational Contracts. *The Accounting Review* 95 (6): 181–212.

Gong, Y., T.-Y. Kim, D.-R. Lee, and J. Zhu. 2013. A Multilevel Model of Team Goal Orientation, Information Exchange, and Creativity. *Academy of Management Journal* 56 (3): 827–851.

Griliches, Z. 1969. Capital-Skill Complementarity. *The Review of Economics and Statistics* 51 (4): 465–468.

Guiso, L., P. Sapienza, and L. Zingales. 2015. The value of corporate culture. *Journal of Financial Economics* 117 (1). NBER Conference on the Causes and Consequences of Corporate Culture: 60–76.

Haslag, P. H., B. A. Sensoy, and J. T. White. 2022. Human Capital Disclosure and Workforce Turnover. Working Paper.

Holmstrom, B. 1982. Moral Hazard in Teams. *The Bell Journal of Economics* 13 (2): 324–340.

Ichniowski, C., K. Shaw, and G. Prennushi. 1997. The Effects of Human Resource Management Practices on Productivity: A Study of Steel Finishing Lines. *American Economic Review* 87 (3): 291–313.

Jones, B. F. 2009. The Burden of Knowledge and the "Death of the Renaissance Man": Is Innovation Getting Harder? *The Review of Economic Studies* 76 (1): 283–317.

———. 2021. The Rise of Research Teams: Benefits and Costs in Economics. *Journal of Economic Perspectives* 35 (2): 191–216.

Kachelmeier, S. J., L. W. Wang, and M. G. Williamson. 2019. Incentivizing the Creative Process: From Initial Quantity to Eventual Creativity. *The Accounting Review* 94 (2): 249–266.

Klein, A., and G. Speckbacher. 2020. Does Using Accounting Data in Performance Evaluations Spoil Team Creativity? The Role of Leadership Behavior. *The Accounting Review* 95 (4): 313–330.

Kozlowski, S. W. J., and B. S. Bell. 2013. Work groups and teams in organizations. In *Handbook of psychology: Industrial and organizational psychology, Vol. 12, 2nd ed*, 412–469. Hoboken, NJ, US: John Wiley & Sons, Inc.

Lafortune, J., E. Lewis, and J. Tessada. 2019. People and Machines: A Look at the Evolving Relationship between Capital and Skill in Manufacturing, 1860–1930, Using Immigration Shocks. *The Review of Economics and Statistics* 101 (1): 30–43.

Lazear, E. P. 2009. Firm-specific human capital: A skill-weights approach. *Journal of Political Economy* 117 (5): 914–940.

Lee, K. H., D. C. Mauer, and E. Q. Xu. 2018. Human capital relatedness and mergers and acquisitions. *Journal of Financial Economics* 129 (1): 111–135.

Li, F., and X. Zheng. 2023. Carbon emission and asset prices: new evidence from machine learning. Working Paper.

Li, K., F. Mai, R. Shen, and X. Yan. 2021. Measuring Corporate Culture Using Machine Learning. Ed. I. Goldstein. *The Review of Financial Studies* 34 (7): 3265–3315.

Li, Q., B. Lourie, A. Nekrasov, and T. Shevlin. 2022. Employee Turnover and Firm Performance: Large-Sample Archival Evidence. *Management Science* 68 (8): 5667–5683.

Lise, J., and F. Postel-Vinay. 2020. Multidimensional Skills, Sorting, and Human Capital Accumulation. *American Economic Review* 110 (8): 2328–2376.

Lundberg, S. M., G. G. Erion, and S.-I. Lee. 2019. Consistent Individualized Feature Attribution for Tree Ensembles. arXiv.

Madsen, P. E. 2011. How Standardized Is Accounting? *The Accounting Review* 86 (5): 1679–1708.

Marshall, A. 1890. *Principles of Economics*. London: Palgrave Macmillan UK.

McChrystal, G. S., T. Collins, D. Silverman, and C. Fussell. 2015. *Team of Teams: New Rules of Engagement for a Complex World*. Illustrated edition. New York, New York: Portfolio.

Mesmer-Magnus, J. R., and L. A. DeChurch. 2009. Information sharing and team performance: A meta-analysis. *Journal of Applied Psychology* 94: 535–546.

Milgrom, P., and J. Roberts. 1995. Complementarities and fit strategy, structure, and organizational change in manufacturing. *Journal of Accounting and Economics* 19 (2–3): 179–208.

Mintzberg, H. 1978. *The Structuring of Organizations*. Englewood Cliffs, N.J: Pearson.

Myers, S. C. 1977. Determinants of corporate borrowing. *Journal of Financial Economics* 5 (2): 147–175.

Neffke, F. M. H. 2019. The value of complementary co-workers. *Science Advances* 5 (12): eaax3370.

Ostrom, E., J. Walker, and R. Gardner. 1992. Covenants with and without a Sword: Self-Governance Is Possible. *American Political Science Review* 86 (2): 404–417.

Peters, R. H., and L. A. Taylor. 2017. Intangible capital and the investment-q relation. *Journal of Financial Economics* 123 (2): 251–272.

Ployhart, R. E., and T. P. Moliterno. 2011. Emergence of the Human Capital Resource: A Multilevel Model. *The Academy of Management Review* 36 (1): 127–150.

Ployhart, R. E., A. J. Nyberg, G. Reilly, and M. A. Maltarich. 2014. Human Capital Is Dead; Long Live Human Capital Resources! *Journal of Management* 40 (2): 371–398.

Porter, M. E. 1985. *Competitive Advantage: Creating and Sustaining Superior Performance*. Free Press.

Raveendran, M., L. Silvestri, and R. Gulati. 2020. The Role of Interdependence in the Micro-Foundations of Organization Design: Task, Goal, and Knowledge Interdependence. *Academy of Management Annals* 14 (2): 828–868.

Rivkin, J. W., and N. Siggelkow. 2003. Balancing Search and Stability: Interdependencies Among Elements of Organizational Design. *Management Science* 49 (3): 290–311.

Seavey, S. E., M. J. Imhof, and T. J. Westfall. 2018. Audit Firms as Networks of Offices. *AUDITING: A Journal of Practice & Theory* 37 (3): 211–242.

Skinner, D. J. 1993. The investment opportunity set and accounting procedure choice: Preliminary evidence. *Journal of Accounting and Economics* 16 (4): 407–445.

Smith, A. 1776. *An Inquiry Into the Nature and Causes of the Wealth of Nations*. Strahan.

Smith, C. W., and R. L. Watts. 1992. The investment opportunity set and corporate financing, dividend, and compensation policies. *Journal of Financial Economics* 32 (3): 263–292.

Tantri, P. 2021. Fintech for the Poor: Financial Intermediation Without Discrimination. *Review of Finance* 25 (2): 561–593.

Taylor, F. W. 1911. *The Principles of Scientific Management*. New York and London: Harper & Brothers.

Teece, D. J. 1986. Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. *Research Policy* 15 (6): 285–305.

Thompson, J. D. 1967. *Organizations in Action: Social Science Bases of Administrative Theory*. Transaction Publishers.

Tuzel, S., and M. B. Zhang. 2021. Economic Stimulus at the Expense of Routine-Task Jobs. *The Journal of Finance* 76 (6): 3347–3399.

Williamson, O. E. 1975. *Markets and Hierarchies: A Study in the Internal Organizations*. New York, NY: Free Press.

Wolfe, R. A., K. E. Weick, J. M. Usher, J. R. Terborg, L. Poppo, A. J. Murrell, J. M. Dukerich, D. C. Core, K. E. Dickson, and J. S. Jourdan. 2005. Sport and Organizational Studies: Exploring Synergy. *Journal of Management Inquiry* 14 (2): 182–210.

Wuchty, S., B. F. Jones, and B. Uzzi. 2007. The Increasing Dominance of Teams in Production of Knowledge. *Science* 316 (5827): 1036–1039.

Zheng, X. 2021. How can Innovation Screening be Improved? A Machine Learning Analysis with Economic Consequences for Firm Performance. Working Paper.

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]
Teamwork	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]
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 $\mathrm{Ln}(T_{\mathrm{routine}})$-$\mathrm{Ln}(T_{\mathrm{Abstrct}})$-$\mathrm{Ln}(T_{\mathrm{nonroutine}})$. T_{routine}, T_{Abstrct}, and $T_{\mathrm{nonroutine}}$ 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 complementarity properties of human capital resources (HCR) under two different structures.

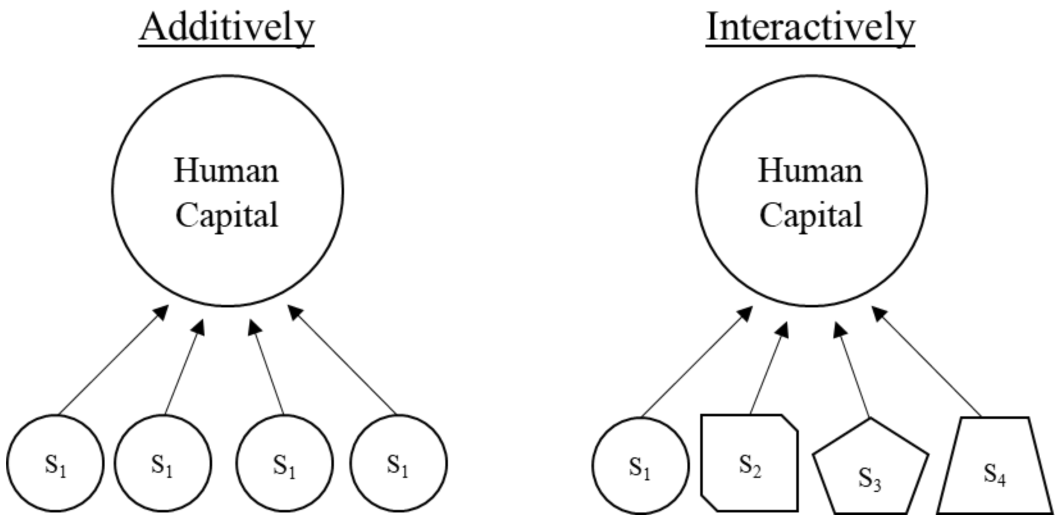

Figure 2: Illustration of Time Series Split Cross-Validation Approach

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.

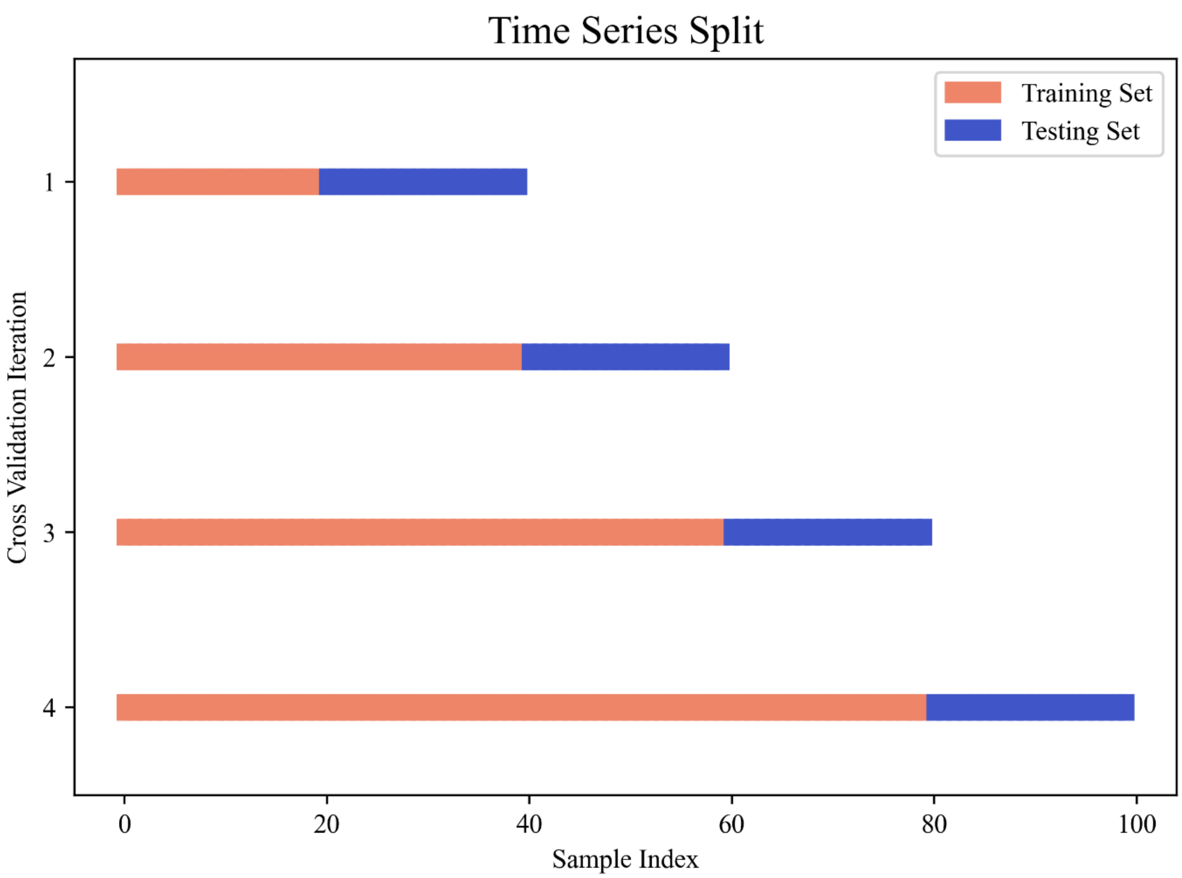

Figure 3: Illustration of the Rolling Scheme

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. 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 rolling window).

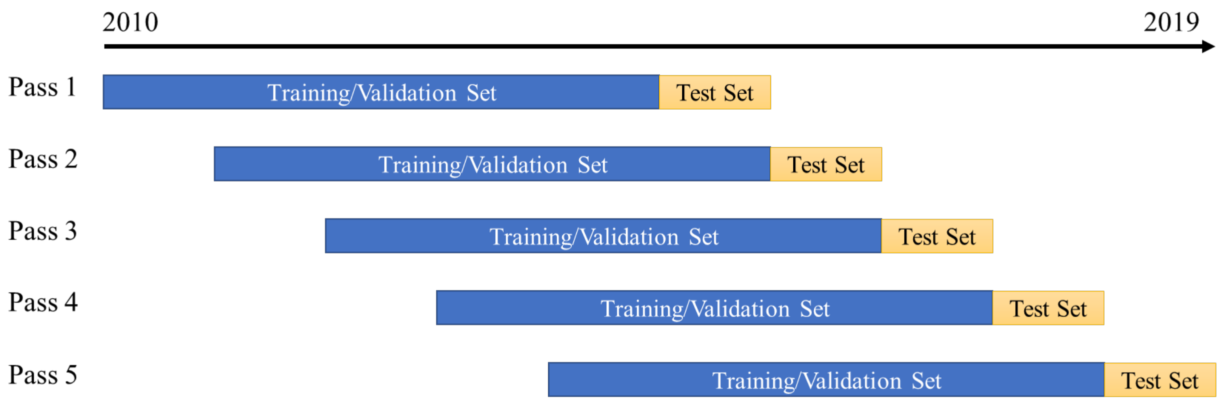

Table 1: Sample

Panel A reports the sample selection process. Panel B shows the number of firm-level job posting data by fiscal year for the final sample of 15,226. Panel C provides the number of firm-level job posting data by Fama-French 30-industry classification.

Panel A: Sample selection

Source/Filter	**No. of Observations**
(1) All job postings collected by Burning Glass Technologies from 2010 to 2019	233,098,988
(2) Aggregating job posting data to the firm year level	37,017
(3) Requiring financial data available from Compustat	15,244
(4) Requiring non-missing ROA_{t+1}	15,226

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

Fiscal year	Frequency	Percentage
2010	1,154	7.58
2011	1,249	8.20
2012	1,360	8.93
2013	1,491	9.79
2014	1,541	10.12
2015	1,606	10.55
2016	1,629	10.70
2017	1,692	11.11
2018	1,763	11.58
2019	1,741	11.43
Total	15,226	100.00

Panel C: Firm-year level job posting data by industry

Industry	Frequency	Percentage	Compustat Percentage
Food Products	281	1.85	1.94
Beer & Liquor	76	0.50	0.30
Tobacco Products	17	0.11	0.09
Recreation	238	1.56	1.69
Printing and Publishing	131	0.86	0.47
Consumer Goods	269	1.77	1.00
Apparel	254	1.67	0.76
Healthcare, Medical Equipment, Pharmaceutical Products	1,325	8.70	14.83
Chemicals	346	2.27	1.74
Textiles	49	0.32	0.15
Construction and Construction Materials	516	3.39	2.14
Steel Works Etc	167	1.10	0.92
Fabricated Products and Machinery	597	3.92	2.35
Electrical Equipment	194	1.27	1.24
Automobiles and Trucks	394	2.59	1.31
Aircraft, Ships, and Railroad Equipment	147	0.97	0.54
Precious Metals, Non-Metallic, and Industrial Metal Mining	112	0.74	2.47
Coal	28	0.18	0.30
Petroleum and Natural Gas	473	3.11	4.57
Utilities	494	3.24	3.61
Communication	360	2.36	2.59
Personal and Business Services	1,964	12.90	12.05
Business Equipment	1,362	8.95	7.60
Business Supplies and Shipping Containers	263	1.73	0.85
Transportation	424	2.78	2.80
Wholesale	524	3.44	2.52
Retail	800	5.25	3.28
Restaurants, Hotels, Motels	304	2.00	1.39
Banking, Insurance, Real Estate, Trading	2,632	17.29	20.73
Other	485	3.19	3.75
Total	15,226	100.00	100.00

Table 2: Summary Descriptives

Panel A shows the number of predictors by category. Panels B, C, D, E, and F provide lists of the top 10 most populated individual skills, skill pairs at the individual level, skill pairs at the department level, skill pairs at the MSA level, and skill pairs at the firm level, respectively, and descriptive statistics for the predictor values. Except for the total number of skills, all predictor values are scaled by the total number of skills.

Panel A: Number of predictors by category

Group	# of predictors
Total number of individual skills	1
Individual skills	27
Skill pairs at the individual level	336
Skill pairs at the department level	333
Skill pairs at the division level	351
Skill pairs at the firm level	351

Panel B: Top 10 most frequently required individual skills

Predictor	Mean	Std.	25%	50%	75%
Information Technology	0.0326	0.0621	0.0010	0.0075	0.0348
Business	0.0199	0.0317	0.0006	0.0047	0.0240
Sales	0.0190	0.0468	0.0003	0.0025	0.0145
Finance	0.0135	0.0269	0.0005	0.0033	0.0152
Customer and Client Support	0.0112	0.0300	0.0002	0.0015	0.0081
Supply Chain and Logistics	0.0094	0.0217	0.0001	0.0012	0.0080
Administration	0.0073	0.0145	0.0002	0.0015	0.0083
Marketing and Public Relations	0.0070	0.0140	0.0002	0.0014	0.0072
Health Care	0.0062	0.0296	0.0000	0.0003	0.0023
Manufacturing and Production	0.0058	0.0136	0.0000	0.0006	0.0042

Panel C: Top 10 most frequently required skill pairs at individual level

Predictor	Mean	Std.	25%	50%	75%
Business & Information Technology	0.0003	0.0009	0.0000	0.0001	0.0002
Analysis & Information Technology	0.0003	0.0008	0.0000	0.0001	0.0002
Finance & Information Technology	0.0003	0.0006	0.0000	0.0001	0.0002
Design & Information Technology	0.0002	0.0008	0.0000	0.0001	0.0002
Engineering & Information Technology	0.0002	0.0006	0.0000	0.0000	0.0002
Business & Finance	0.0002	0.0005	0.0000	0.0001	0.0002
Marketing and Public Relations & Sales	0.0002	0.0004	0.0000	0.0001	0.0002
Information Technology & Marketing and Public Relations	0.0002	0.0005	0.0000	0.0000	0.0002
Information Technology & Supply Chain and Logistics	0.0002	0.0004	0.0000	0.0000	0.0002
Design & Marketing and Public Relations	0.0002	0.0006	0.0000	0.0000	0.0001

Panel D: Top 10 most frequently required skill pairs at department level

Predictor	Mean	Std.	25%	50%	75%
Finance & Human Resources	0.0002	0.0006	0.0000	0.0000	0.0001
Finance & Marketing and Public Relations	0.0002	0.0006	0.0000	0.0000	0.0001
Finance & Information Technology	0.0002	0.0006	0.0000	0.0000	0.0001
Business & Finance	0.0002	0.0005	0.0000	0.0000	0.0001
Finance & Supply Chain and Logistics	0.0002	0.0006	0.0000	0.0000	0.0001
Finance & Sales	0.0001	0.0005	0.0000	0.0000	0.0001
Information Technology & Marketing and Public Relations	0.0001	0.0004	0.0000	0.0000	0.0001
Information Technology & Sales	0.0001	0.0005	0.0000	0.0000	0.0001
Business & Information Technology	0.0001	0.0004	0.0000	0.0000	0.0001
Human Resources & Supply Chain and Logistics	0.0001	0.0004	0.0000	0.0000	0.0001

Panel E: Top 10 most frequently required skill pairs at division level

Predictor	Mean	Std.	25%	50%	75%
Information Technology & Maintenance, Repair, and Installation	0.0010	0.0170	0.0000	0.0000	0.0002
Finance & Maintenance, Repair, and Installation	0.0010	0.0079	0.0000	0.0000	0.0003
Information Technology & Sales	0.0009	0.0080	0.0000	0.0000	0.0003
Information Technology & Legal	0.0008	0.0193	0.0000	0.0000	0.0001
Engineering & Finance	0.0008	0.0064	0.0000	0.0000	0.0002
Maintenance, Repair, and Installation & Sales	0.0007	0.0049	0.0000	0.0000	0.0003
Design & Finance	0.0007	0.0041	0.0000	0.0000	0.0002
Finance & Manufacturing and Production	0.0006	0.0037	0.0000	0.0000	0.0002
Business & Maintenance, Repair, and Installation	0.0006	0.0054	0.0000	0.0000	0.0002
Design & Sales	0.0006	0.0062	0.0000	0.0000	0.0002

Panel F: Top 10 most frequently required skill pairs at firm level

Predictor	Mean	Std.	25%	50%	75%
Information Technology & Sales	0.0007	0.0098	0.0000	0.0000	0.0002
Maintenance, Repair, and Installation & Sales	0.0005	0.0028	0.0000	0.0000	0.0001
Manufacturing and Production & Sales	0.0005	0.0032	0.0000	0.0000	0.0001
Finance & Maintenance, Repair, and Installation	0.0004	0.0051	0.0000	0.0000	0.0001
Engineering & Sales	0.0004	0.0027	0.0000	0.0000	0.0001
Sales & Supply Chain and Logistics	0.0004	0.0026	0.0000	0.0000	0.0001
Human Resources & Sales	0.0004	0.0023	0.0000	0.0000	0.0001
Finance & Sales	0.0003	0.0019	0.0000	0.0000	0.0001
Business & Sales	0.0003	0.0026	0.0000	0.0000	0.0001
Information Technology & Maintenance, Repair, and Installation	0.0003	0.0028	0.0000	0.0000	0.0001

Table 3: Prediction Performance of Teamwork

This table presents the out-of-sample R^2 in percentage of each XGBoost model. Each column indicates the test year. We build an XGBoost model using a five-year window of training/validation data (before each test year) and assess the out-of-sample performance using the data in each test year. The predictors used in building the XGBoost model are specified by rows. The results of our analysis will comprise a sequence of out-of-sample R^2s, one for each rolling window and one set of predictors.

		Test Year					
	Predictor	2015	2016	2017	2018	2019	**Average** Out-of-Sample R^2
(1)	Teamwork	19.94	16.72	22.88	19.38	8.65	17.52
(2)	*Ln*(Employee)	15.77	15.91	15.91	12.66	4.04	12.86
(3)	Turnover	3.10	2.12	0.59	1.01	1.04	1.57
(4)	*Ln*(Employee) + Turnover	16.25	16.51	15.26	12.67	7.73	13.68
(5)	Teamwork + *Ln*(Employee)	28.44	25.02	30.40	25.03	15.91	24.96
(6)	Teamwork + Turnover	14.98	21.50	21.14	20.21	9.91	17.55
(7)	Teamwork + *Ln*(Employee) + Turnover	27.31	28.57	29.58	25.63	14.79	25.17

Table 4: Feature Importance

This table presents the feature importance of different predictors for human capital. Feature importance is calculated as the average SHapley Additive exPlanations (SHAP) values across all observations and multiplied by 100. Panel A presents the top 10 most important single predictors among all skill requirements with the highest average SHAP values across all rolling windows. Panel B reports the grouped cumulative predictor importance of skill groups.

Panel A: Top 10 most important single predictors

Rank	Predictor	Average feature importance
1	Maintenance, Repair, and Installation	0.892
2	Health Care & Science and Research at the individual level	0.655
3	Total number of individual skills	0.650
4	Supply Chain and Logistics	0.472
5	Analysis & Health Care at the individual level	0.466
6	Customer and Client Support	0.424
7	Industry Knowledge	0.324
8	Business	0.228
9	Business & Customer and Client Support at the firm level	0.207
10	Customer and Client Support & Industry Knowledge at the firm level	0.188

Panel B: Grouped cumulative predictor importance

Group	Sum
Individual skills	3.77
Skill pairs at the individual level	5.49
Skill pairs at the department level	2.15
Skill pairs at the division level	2.51
Skill pairs at the firm level	1.74

Table 5: Prediction Performance of Teamwork in Subsamples

This table presents the out-of-sample R^2 in percentage of our teamwork measure in subsamples after retraining the models. Panel A partitions our sample by a firm's task complexity level. Panel B partitions our sample by a firm's ease of communication.

Panel A: Task complexity

		Test Year					**Average**
		2015	2016	2017	2018	2019	Out-of-Sample R^2
Routine Task Index	Low	25.54	17.90	26.48	22.05	15.92	21.58
	High	0.69	6.45	8.33	4.17	-5.95	2.74
Tobin's Q	Low	-6.25	9.00	15.65	17.01	6.36	8.36
	High	18.10	26.28	25.25	25.62	15.57	22.16
High Tech	=0	7.27	17.12	8.51	5.21	2.21	8.06
	=1	21.34	16.21	36.83	33.47	22.54	26.08

Panel B: Ease of communication

		Test Year					**Average**
		2015	2016	2017	2018	2019	Out-of-Sample R^2
Teamwork Culture	Low	2.76	3.06	7.96	2.82	-5.52	2.22
	High	9.40	15.32	22.10	17.82	11.35	15.20
Teamwork Job	Low	1.27	4.00	1.80	2.07	-6.23	0.58
	High	24.74	25.46	23.16	21.95	11.49	21.36
# MSA	Low	22.68	18.40	23.80	16.67	12.26	18.76
	High	5.52	6.01	5.00	5.44	-2.46	3.90
One Segment	=0	4.17	10.43	15.60	20.21	7.52	11.59
	=1	21.18	21.91	24.75	22.09	7.16	19.42

Table 6: Prediction Performance of Teamwork in Two-by-two Subsamples

This table presents the out-of-sample R^2 in percentage of our teamwork measure in two-by-two subsamples after retraining the models. Panel A presents factor loadings of proxies for task complexity and ease of communication using principal component analyses. Panel B partitions our sample into two-by-two subsamples based on the complexity factor and the communication factor.

Panel A: Factor loadings

Task complexity factor			Ease of communication factor	
Proxy	Factor loading		Proxy	Factor loading
Routine Task Index	-0.41		*Teamwork Culture*	0.56
Tobin's Q	0.10		*Teamwork Job*	0.36
High Tech	0.26		*# MSA*	-0.15
			One Segment	-0.19

Panel B: Out-of-sample R^2 in percentage

			Complexity factor	
Test Year			Low	High
2015	Communication factor	Low	-0.94	-2.24
		High	-3.53	15.18
2016	Communication factor	Low	2.43	0.19
		High	2.36	17.99
2017	Communication factor	Low	3.51	2.66
		High	-1.76	19.21
2018	Communication factor	Low	0.65	-1.15
		High	-0.72	22.34
2019	Communication factor	Low	-12.86	1.04
		High	1.45	15.02
Average	Communication factor	Low	-1.44	0.1
		High	-0.44	17.95

Table 7: Prediction Performance of Teamwork by Job Zone

This table presents the out-of-sample R^2 in percentage of our teamwork measure by job zone. Job zones group occupations into one of five categories 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	**Average**
Zone 1	0.07	1.86	1.51	1.87	-1.67	0.72
Zone 2	6.35	7.46	10.12	12.45	1.61	7.60
Zone 3	7.59	13.99	11.77	16.80	4.06	10.84
Zone 4	18.32	14.75	22.67	17.18	9.54	16.49
Zone 5	11.59	12.89	19.78	24.07	17.47	17.16

Table 8: Prediction Performance of Specialization and Complementarity in Subsamples

This table presents the out-of-sample R^2 in percentage of our specialization and complementarity components in subsamples after retraining the models. Panel A presents the prediction performance of specialization component by task complexity. Panel B presents the prediction performance of complementarity component by ease of communication.

Panel A: Out of sample R^2 for specialization

		Test Year					
		2015	2016	2017	2018	2019	Average
Routine Task Index	Low	24.78	14.82	23.58	18.94	9.47	18.32
	High	-3.52	6.86	9.52	5.69	-6.04	2.50
Tobin's Q	Low	-12.00	12.37	17.84	16.75	11.22	9.24
	High	20.58	22.93	23.97	23.70	9.90	20.22
High Tech	=0	3.94	16.97	7.47	4.39	2.83	7.12
	=1	16.09	17.42	29.93	29.50	21.03	22.80
Teamwork Culture	Low	4.45	2.19	6.85	3.04	-4.98	2.31
	High	6.42	13.20	18.43	17.82	10.37	13.25
Teamwork Job	Low	1.11	4.17	2.61	-0.48	-4.36	0.61
	High	20.39	25.18	20.55	20.10	12.70	19.78
# MSA	Low	19.26	18.05	20.24	15.93	12.16	17.12
	High	2.58	11.01	6.18	3.50	-2.47	4.16
One Segment	=0	9.34	11.79	15.32	18.82	13.84	13.82
	=1	19.70	20.93	19.16	18.69	5.45	16.79

Panel B: Out of sample R^2 for complementarity

		Test Year					
		2015	2016	2017	2018	2019	Average
Routine Task Index	Low	19.83	18.99	23.22	20.85	9.28	18.43
	High	-0.66	0.57	4.17	2.47	-5.27	0.25
Tobin's Q	Low	-0.05	5.18	6.03	9.88	-2.76	3.66
	High	15.39	20.82	25.94	25.02	11.13	19.66
High Tech	=0	3.87	9.54	5.80	4.86	-4.60	3.90
	=1	17.43	15.01	25.70	20.28	18.13	19.31
Teamwork Culture	Low	0.21	4.07	5.22	2.29	-5.64	1.23
	High	9.84	14.23	16.04	12.92	6.29	11.86
Teamwork Job	Low	-0.96	3.24	1.29	1.72	-6.67	-0.27
	High	24.74	20.28	20.69	23.59	6.49	19.16
# MSA	Low	14.40	11.97	16.33	17.79	4.12	12.92
	High	1.11	6.10	3.84	4.24	0.41	3.14
One Segment	=0	9.98	8.98	16.02	12.27	5.52	10.55
	=1	13.46	19.53	15.48	18.34	3.35	14.03

Table 9: Prediction Performance of Specialization and Complementarity in Two-by-two Subsamples

This table presents the out-of-sample R^2 in percentage of specialization and complementarity components after retraining the models. Panel A presents the prediction performance of specialization component with two-by-two subsamples based on the complexity factor and the communication factor. Panel B presents the prediction performance of complementarity component with two-by-two subsamples based on the complexity factor and the communication factor.

Panel A: Out of sample R^2 for specialization

			Complexity factor	
Test Year			Low	High
2015	Communication factor	Low	-1.66	1.54
		High	-3.98	9.48
2016	Communication factor	Low	4.47	0.33
		High	4.82	16.36
2017	Communication factor	Low	2.68	2.88
		High	-1.51	16.47
2018	Communication factor	Low	-0.24	-1.97
		High	-0.39	19.80
2019	Communication factor	Low	-11.94	1.16
		High	-3.45	14.57
Average	Communication factor	Low	-1.34	0.79
		High	-0.9	15.33

Panel B: Out of sample R^2 for complementarity

			Complexity factor	
Test Year			Low	High
2015	Communication factor	Low	-1.11	-5.4
		High	-2.33	13.48
2016	Communication factor	Low	3.11	-1.98
		High	-1.64	17.43
2017	Communication factor	Low	2.68	-1.88
		High	-1.59	13.91
2018	Communication factor	Low	0.05	0.24
		High	-4.16	16.94
2019	Communication factor	Low	-13.52	-0.6
		High	0.92	10.09
Average	Communication factor	Low	-1.76	-1.92
		High	-1.76	14.37

Online Appendix to “The Contribution of Teams to Firm Human Capital”

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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 teamwork measure to predict future *ROA*.

Panel A: Search range of XGBoost parameter values

Number of trees	200, 400, 600, …, 3000
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: Teamwork	Test Year				
		2015	2016	2017	2018	2019
(1)	Number of trees	1600	800	600	600	600
(2)	Maximum depth of the tree	3	3	6	5	3
(3)	Learning rate	0.01	0.01	0.01	0.01	0.01

Table OA2: Prediction Performance of Teamwork

Panel A of this table presents the out-of-sample MSEs of each XGBoost model. Panel B of this table presents the out-of-sample MAEs of each XGBoost model. Each column indicates the test year. We build an XGBoost model using a five-year window of training/validation data (before each test year) and assess the out-of-sample performance using the data in each test year. The predictors used in building the XGBoost model are specified by rows. The results of our analysis will comprise a sequence of out-of-sample MSEs, one for each rolling window and one set of predictors.

Panel A: Out-of-sample MSE

		Test Year					
	Predictor	2015	2016	2017	2018	2019	Average MSE
(1)	Teamwork	0.013	0.012	0.012	0.012	0.013	0.012
(2)	*Ln*(Employee)	0.015	0.014	0.014	0.014	0.013	0.014
(3)	Turnover	0.013	0.012	0.012	0.012	0.012	0.012
(4)	*Ln*(Employee) + Turnover	0.012	0.012	0.011	0.011	0.012	0.012

Panel B: Out-of-sample MAE

		Test Year					
	Predictor	2015	2016	2017	2018	2019	Average MAE
(1)	Teamwork	0.066	0.064	0.064	0.063	0.069	0.065
(2)	*Ln*(Employee)	0.066	0.065	0.066	0.064	0.066	0.066
(3)	Turnover	0.065	0.064	0.064	0.063	0.067	0.065
(4)	*Ln*(Employee) + Turnover	0.062	0.062	0.061	0.061	0.067	0.062

Table OA3: Permutation Feature Importance

This table presents the feature importance of different predictors for human capital. Permutation feature importance is calculated as the decrease in R^2 when the chosen feature is randomly shuffled. Panel A presents the top 10 most important single predictors among all skill requirements with the highest average R2 decreases across all rolling windows. Panel B reports the grouped cumulative predictor importance of skill groups.

Panel A: Top 10 most important single predictors

Rank	Predictor	Average feature importance
1	Health Care & Science and Research at the individual level	6.55
2	Analysis & Health Care at the individual level	4.78
3	Total number of individual skills	3.76
4	Customer and Client Support	2.64
5	Maintenance, Repair, and Installation	2.61
6	Business & Engineering at the division level	1.63
7	Information Technology & Science and Research at the individual level	1.47
8	Business	1.42
9	Supply Chain and Logistics	0.92
10	Health Care & Science and Research at the department level	0.81

Panel B: Grouped cumulative predictor importance

Group	Sum
Individual skills	10.78
Skill pairs at the individual level	19.95
Skill pairs at the department level	2.93
Skill pairs at the division level	3.99
Skill pairs at the firm level	2.76

Table OA4: Prediction Performance of Teamwork in Subsamples

This table presents the prediction performance of our teamwork measure in subsamples using the parameter values of the main models without retraining the models. Panel A partitions our sample by a firm's task complexity level. Panel B partitions our sample by a firm's ease of communication. Panel C partitions our sample by a firm's complexity factor and communication factor.

Panel A: Task complexity

		Test Year					Average
		2015	2016	2017	2018	2019	Out-of-Sample R^2
Routine Task Index	Low	26.65	21.14	26.82	23.03	13.21	22.17
	High	-3.59	0.16	6.00	5.08	-4.43	0.64
Tobin's Q	Low	-5.49	12.59	13.49	2.11	-4.58	3.62
	High	28.61	16.85	25.71	26.56	12.85	22.12
High Tech	= 0	7.77	9.63	5.15	0.98	-1.10	4.48
	= 1	27.95	19.43	34.54	33.94	20.61	27.30

Panel B: Ease of communication

		Test Year					Average
		2015	2016	2017	2018	2019	Out-of-Sample R^2
Teamwork Culture	Low	4.06	0.08	-3.44	-1.01	-2.12	-0.49
	High	16.68	14.41	19.74	20.16	10.26	16.25
Teamwork Job	Low	9.33	-0.36	15.70	8.52	1.03	6.85
	High	24.38	23.85	24.81	23.41	12.09	21.71
# MSA	Low	19.60	16.60	23.89	18.87	11.29	18.05
	High	4.06	0.08	-3.44	-1.01	-2.12	-0.49
One Segment	= 0	16.68	14.41	19.74	20.16	10.26	16.25
	= 1	9.33	-0.36	15.70	8.52	1.03	6.85

Panel C: Complexity factor and communication factor

			Complexity factor	
Test Year			Low	High
2015	Communication factor	Low	-25.61	8.22
		High	-1.14	24.28
2016	Communication factor	Low	-19.90	5.00
		High	-0.33	16.42
2017	Communication factor	Low	-11.43	0.97
		High	4.55	25.02
2018	Communication factor	Low	-7.02	-0.31
		High	-2.56	24.04
2019	Communication factor	Low	-9.04	0.29
		High	-3.77	12.78
Average	Communication factor	Low	-14.60	2.83
		High	-0.65	20.51

Table OA5: Prediction Performance of Teamwork in Two-by-two Subsamples

This table presents the results of other two-by-two subsample analyses with and without retraining the models.

Panel A: Routine Task Index and Teamwork Culture after retraining the models

			Routine Task Index	
Test Year			Low	High
2015	*Teamwork*	Low	0.83	-5.12
	Culture	High	18.90	-2.31
2016	*Teamwork*	Low	3.25	5.22
	Culture	High	18.53	3.46
2017	*Teamwork*	Low	1.54	10.00
	Culture	High	25.45	1.61
2018	*Teamwork*	Low	0.60	5.89
	Culture	High	24.69	9.47
2019	*Teamwork*	Low	3.75	-10.00
	Culture	High	15.15	-9.91
Average	*Teamwork*	Low	1.99	1.20
	Culture	High	20.55	0.47

Panel B: Routine Task Index and Teamwork Culture without retraining the models

			Routine Task Index	
Test Year			Low	High
2015	*Teamwork*	Low	13.29	-7.40
	Culture	High	22.65	-6.20
2016	*Teamwork*	Low	12.50	-18.03
	Culture	High	15.48	5.70
2017	*Teamwork*	Low	2.07	-11.27
	Culture	High	21.68	10.61
2018	*Teamwork*	Low	0.40	-2.71
	Culture	High	22.22	6.19
2019	*Teamwork*	Low	-0.07	-3.85
	Culture	High	12.84	-14.68
Average	*Teamwork*	Low	5.64	-8.65
	Culture	High	18.97	0.32

Panel C: Routine Task Index and Teamwork Job after retraining the models

			Routine Task Index	
Test Year			Low	High
2015	*Teamwork Job*	Low	10.90	-4.37
		High	17.22	-10.26
2016	*Teamwork Job*	Low	15.80	0.12
		High	17.66	4.27
2017	*Teamwork Job*	Low	7.51	-0.38
		High	26.58	3.92
2018	*Teamwork Job*	Low	-14.76	5.08
		High	28.94	3.00
2019	*Teamwork Job*	Low	-1.50	-11.80
		High	14.57	-1.05
Average	*Teamwork Job*	Low	3.59	-2.27
		High	20.99	-0.03

Panel D: Routine Task Index and Teamwork Job without retraining the models

			Routine Task Index	
Test Year			Low	High
2015	*Teamwork Job*	Low	18.08	-15.97
		High	27.77	5.36
2016	*Teamwork Job*	Low	-2.65	-13.29
		High	24.94	12.17
2017	*Teamwork Job*	Low	22.67	-1.23
		High	27.12	11.72
2018	*Teamwork Job*	Low	7.79	-4.94
		High	25.06	14.28
2019	*Teamwork Job*	Low	8.86	-8.95
		High	13.94	0.45
Average	*Teamwork Job*	Low	10.95	-8.88
		High	23.77	8.80

Panel E: Routine Task Index and # MSA after retraining the models

			Routine Task Index	
Test Year			Low	High
2015	*# MSA*	Low	27.68	-2.85
		High	0.23	0.00
2016	*# MSA*	Low	21.38	3.06
		High	-0.16	6.09
2017	*# MSA*	Low	27.33	6.94
		High	4.62	1.15
2018	*# MSA*	Low	20.65	0.66
		High	7.32	4.22
2019	*# MSA*	Low	17.67	-5.43
		High	16.71	-13.18
Average	*# MSA*	Low	22.94	0.47
		High	5.74	-0.34

Panel F: Routine Task Index and # MSA without retraining the models

			Routine Task Index	
Test Year			Low	High
2015	*# MSA*	Low	25.79	-8.45
		High	9.59	1.49
2016	*# MSA*	Low	21.03	-5.97
		High	9.61	3.32
2017	*# MSA*	Low	27.66	5.17
		High	13.86	2.92
2018	*# MSA*	Low	21.32	4.86
		High	21.01	-2.00
2019	*# MSA*	Low	15.05	-2.21
		High	6.14	-9.88
Average	*# MSA*	Low	22.17	-1.32
		High	12.04	-0.83

Panel G: Routine Task Index and One Segment after retraining the models

			Routine Task Index	
Test Year			Low	High
2015	*One Segment*	=0	18.11	-13.36
		=1	29.15	7.87
2016	*One Segment*	=0	14.69	0.92
		=1	25.96	7.35
2017	*One Segment*	=0	22.27	-1.34
		=1	27.94	10.22
2018	*One Segment*	=0	18.20	1.39
		=1	22.15	10.12
2019	*One Segment*	=0	12.82	-4.73
		=1	8.69	-4.02
Average	*One Segment*	=0	17.22	-3.43
		=1	22.78	6.31

Panel H: Routine Task Index and One Segment without retraining the models

			Routine Task Index	
Test Year			Low	High
2015	*One Segment*	=0	25.12	-14.62
		=1	27.61	2.65
2016	*One Segment*	=0	19.73	-7.75
		=1	21.25	7.89
2017	*One Segment*	=0	21.92	-2.62
		=1	34.64	16.43
2018	*One Segment*	=0	21.17	-1.11
		=1	26.03	12.96
2019	*One Segment*	=0	12.91	-6.18
		=1	13.67	-1.49
Average	*One Segment*	=0	20.17	-6.45
		=1	24.64	7.69

Panel I: Tobin's Q and Teamwork Culture after retraining the models

Test Year			*Tobin's Q* Low	High
2015	*Teamwork*	Low	-3.12	-1.59
	Culture	High	-4.30	9.67
2016	*Teamwork*	Low	1.67	5.10
	Culture	High	10.66	31.45
2017	*Teamwork*	Low	2.02	-5.14
	Culture	High	12.13	20.10
2018	*Teamwork*	Low	-4.97	-8.94
	Culture	High	22.31	26.60
2019	*Teamwork*	Low	-8.50	-6.06
	Culture	High	23.23	10.86
Average	*Teamwork*	Low	-2.58	-3.33
	Culture	High	12.80	19.74

Panel J: Tobin's Q and Teamwork Culture without retraining the models

Test Year			*Tobin's Q* Low	High
2015	*Teamwork*	Low	-14.91	-7.22
	Culture	High	-3.05	21.72
2016	*Teamwork*	Low	5.70	-23.11
	Culture	High	3.54	20.28
2017	*Teamwork*	Low	-4.60	-43.08
	Culture	High	14.93	20.60
2018	*Teamwork*	Low	-27.13	-17.09
	Culture	High	5.89	27.09
2019	*Teamwork*	Low	-24.37	-5.95
	Culture	High	4.12	11.46
Average	*Teamwork*	Low	-13.06	-19.29
	Culture	High	5.09	20.23

Panel K: Tobin's Q and Teamwork Job after retraining the models

Test Year			*Tobin's Q* Low	*Tobin's Q* High
2015	*Teamwork Job*	Low	-10.66	4.08
		High	4.78	25.97
2016	*Teamwork Job*	Low	-11.17	-2.35
		High	8.42	28.06
2017	*Teamwork Job*	Low	0.07	-0.43
		High	12.26	30.19
2018	*Teamwork Job*	Low	-11.33	4.03
		High	22.82	24.43
2019	*Teamwork Job*	Low	-14.25	-3.57
		High	20.17	15.91
Average	*Teamwork Job*	Low	-9.47	0.35
		High	13.69	24.91

Panel L: Tobin's Q and Teamwork Job without retraining the models

Test Year			*Tobin's Q* Low	*Tobin's Q* High
2015	*Teamwork Job*	Low	-8.53	2.77
		High	-1.29	33.05
2016	*Teamwork Job*	Low	15.73	-42.90
		High	9.01	34.09
2017	*Teamwork Job*	Low	1.95	4.96
		High	16.43	29.61
2018	*Teamwork Job*	Low	-25.55	4.96
		High	8.93	29.99
2019	*Teamwork Job*	Low	-26.97	3.49
		High	3.72	14.22
Average	*Teamwork Job*	Low	-8.67	-5.35
		High	7.36	28.19

Panel M: Tobin's Q and # MSA after retraining the models

			Tobin's Q	
Test Year			Low	High
2015	*# MSA*	Low	-2.68	25.44
		High	-8.25	-0.21
2016	*# MSA*	Low	-2.47	21.87
		High	0.94	0.34
2017	*# MSA*	Low	9.29	22.61
		High	0.93	16.11
2018	*# MSA*	Low	19.77	23.20
		High	-2.45	13.92
2019	*# MSA*	Low	-15.59	22.07
		High	-11.92	6.19
Average	*# MSA*	Low	1.67	23.04
		High	-4.15	7.27

Panel N: Tobin's Q and # MSA without retraining the models

			Tobin's Q	
Test Year			Low	High
2015	*# MSA*	Low	-0.02	27.74
		High	-22.92	8.21
2016	*# MSA*	Low	14.58	16.45
		High	-16.54	2.13
2017	*# MSA*	Low	15.69	28.30
		High	-14.80	11.26
2018	*# MSA*	Low	-0.05	28.90
		High	0.15	11.87
2019	*# MSA*	Low	2.78	15.94
		High	-27.09	5.16
Average	*# MSA*	Low	6.60	23.47
		High	-16.24	7.72

Panel O: Tobin's Q and One Segment after retraining the models

Test Year			*Tobin's Q* Low	High
2015	*One Segment*	=0	-17.91	14.92
		=1	2.41	9.74
2016	*One Segment*	=0	12.71	17.37
		=1	15.26	17.33
2017	*One Segment*	=0	16.92	13.70
		=1	11.89	36.24
2018	*One Segment*	=0	21.37	21.18
		=1	5.85	30.17
2019	*One Segment*	=0	17.55	9.09
		=1	-7.55	7.68
Average	*One Segment*	=0	10.13	15.25
		=1	5.57	20.23

Panel P: Tobin's Q and One Segment without retraining the models

Test Year			*Tobin's Q* Low	High
2015	*One Segment*	=0	-5.36	23.36
		=1	-5.68	33.80
2016	*One Segment*	=0	13.33	10.84
		=1	11.49	23.49
2017	*One Segment*	=0	15.41	12.27
		=1	9.13	40.60
2018	*One Segment*	=0	0.98	23.81
		=1	4.79	29.51
2019	*One Segment*	=0	-5.56	12.63
		=1	-2.82	13.10
Average	*One Segment*	=0	3.76	16.58
		=1	3.38	28.10

Panel Q: High Tech and Teamwork Culture after retraining the models

Test Year			High Tech =0	High Tech =1
2015	*Teamwork*	Low	6.20	3.41
	Culture	High	-2.97	20.75
2016	*Teamwork*	Low	8.82	-4.11
	Culture	High	0.59	16.36
2017	*Teamwork*	Low	8.97	-80.36
	Culture	High	3.04	26.00
2018	*Teamwork*	Low	4.66	-2.34
	Culture	High	1.31	29.87
2019	*Teamwork*	Low	-8.57	1.28
	Culture	High	2.37	19.95
Average	*Teamwork*	Low	4.02	-16.43
	Culture	High	0.87	22.59

Panel R: High Tech and Teamwork Culture without retraining the models

Test Year			High Tech =0	High Tech =1
2015	*Teamwork*	Low	4.70	-1.62
	Culture	High	5.95	19.94
2016	*Teamwork*	Low	-4.49	12.23
	Culture	High	9.01	13.34
2017	*Teamwork*	Low	-2.06	-13.90
	Culture	High	6.14	26.15
2018	*Teamwork*	Low	-3.28	8.13
	Culture	High	1.19	33.92
2019	*Teamwork*	Low	-3.87	-2.66
	Culture	High	0.89	17.28
Average	*Teamwork*	Low	-1.80	0.43
	Culture	High	4.64	22.13

Panel S: High Tech and Teamwork Job after retraining the models

Test Year			High Tech =0	High Tech =1
2015	*Teamwork Job*	Low	-3.01	-39.16
		High	12.83	25.42
2016	*Teamwork Job*	Low	8.17	-67.32
		High	17.80	27.08
2017	*Teamwork Job*	Low	3.47	11.79
		High	9.09	32.05
2018	*Teamwork Job*	Low	0.57	5.19
		High	7.74	28.79
2019	*Teamwork Job*	Low	-9.61	14.20
		High	6.22	26.01
Average	*Teamwork Job*	Low	-0.08	-15.06
		High	10.73	27.87

Panel T: High Tech and Teamwork Job without retraining the models

Test Year			High Tech =0	High Tech =1
2015	*Teamwork Job*	Low	-5.53	12.50
		High	12.01	32.11
2016	*Teamwork Job*	Low	-2.49	-22.81
		High	14.44	26.91
2017	*Teamwork Job*	Low	2.44	31.78
		High	6.36	32.14
2018	*Teamwork Job*	Low	-3.11	14.22
		High	2.79	35.29
2019	*Teamwork Job*	Low	-7.94	25.77
		High	2.82	18.86
Average	*Teamwork Job*	Low	-3.33	12.29
		High	7.68	29.06

Panel U: High Tech and # MSA after retraining the models

Test Year			High Tech =0	=1
2015	*# MSA*	Low	-4.47	20.36
		High	3.17	-0.16
2016	*# MSA*	Low	14.03	16.58
		High	9.89	6.46
2017	*# MSA*	Low	2.44	26.41
		High	7.35	4.27
2018	*# MSA*	Low	-0.36	31.33
		High	2.87	22.09
2019	*# MSA*	Low	-7.13	25.92
		High	-3.60	12.41
Average	*# MSA*	Low	0.90	24.12
		High	3.94	9.01

Panel V: High Tech and # MSA without retraining the models

Test Year			High Tech =0	=1
2015	*# MSA*	Low	5.34	22.33
		High	7.15	3.35
2016	*# MSA*	Low	7.68	15.06
		High	8.83	0.08
2017	*# MSA*	Low	0.84	34.66
		High	10.81	8.81
2018	*# MSA*	Low	-4.61	29.37
		High	6.84	35.67
2019	*# MSA*	Low	-0.99	22.07
		High	-2.28	6.61
Average	*# MSA*	Low	1.65	24.70
		High	6.27	10.90

Panel W: High Tech and One Segment after retraining the models

Test Year			*High Tech* =0	=1
2015	*One Segment*	=0	-5.84	14.32
		=1	12.76	27.12
2016	*One Segment*	=0	-0.03	7.62
		=1	25.15	22.11
2017	*One Segment*	=0	0.36	21.87
		=1	12.70	39.46
2018	*One Segment*	=0	-0.26	26.23
		=1	14.96	35.97
2019	*One Segment*	=0	0.47	19.09
		=1	3.38	25.39
Average	*One Segment*	=0	-1.06	17.82
		=1	13.79	30.01

Panel X: High Tech and One Segment without retraining the models

Test Year			*High Tech* =0	=1
2015	*One Segment*	=0	7.12	22.06
		=1	7.64	31.79
2016	*One Segment*	=0	1.14	22.14
		=1	16.30	13.92
2017	*One Segment*	=0	-1.45	32.54
		=1	15.48	35.10
2018	*One Segment*	=0	-2.65	34.92
		=1	6.91	31.40
2019	*One Segment*	=0	-0.95	19.20
		=1	-1.37	22.79
Average	*One Segment*	=0	0.64	26.17
		=1	8.99	27.00