Skills Capital

Hoa Briscoe-Tran, Eliezer M. Fich, and Xinjie Ma*

July 7, 2026

Abstract

We propose a new measure of firm-level skills capital: the labor-market value of the skills embedded in a firm's workforce. We estimate and validate time-varying skill prices from job-posting wage data and aggregate these prices across skills held by each firm's employees using resume data. Our measure captures the transferable, externally priced skills component of human capital. Despite concerns that valuable skills raise workers' outside options and expose firms to turnover and the loss of firm-specific human capital, we find that firms with greater skills capital have higher Tobin's Q, stronger sales growth, better innovation outcomes, and lower employee turnover, even though they exhibit lower short-run profitability. These results are robust to a Bartik-style instrumental variables design that uses firms' predetermined skill exposures and economy-wide changes in skill prices. The evidence suggests that skills capital is not merely a labor cost: it is an economically important intangible asset that complements R&D and organizational investments, contributes to firm valuation and growth, and shapes firms' incentives to retain skilled workers. Our paper advances the measurement of employee skills at the firm level and shows that labor-market-valued skills constitute a distinct and value-relevant component of corporate intangible capital.

Keywords: human capital, skills, labor market, growth, innovation, valuation.
JEL Classification: G12, G32, J24, M41, O34

* Hoa Briscoe-Tran is with Monash University (email: hoa.briscoe-tran@monash.edu), Eli Fich is with Drexel University (email: emf35@drexel.edu) and Xinjie Ma is with the University of Iowa (email: xinjie-ma@uiowa.edu). This paper has benefited from comments by Jason Chen.

1. Introduction

Employees' skills are central to modern firms, yet their value remains difficult to measure. This measurement problem is increasingly important because firms' market values are now driven heavily by intangible assets, while financial statements still expense many investments in knowledge, organizational capability, and labor. Regulators and investors have also placed greater emphasis on human capital disclosure, but existing disclosures are largely qualitative and do not reveal the labor-market value of the skills embedded in a firm's workforce. Moreover, "human capital" is a broad construct that combines transferable skills, education, experience, firm-specific knowledge, collaboration, culture, routines, and organizational processes. This makes it difficult to determine whether firms with more valuable workers are more valuable because of the portable skills employees bring to the firm, because of firm-specific human capital, or because of other unobserved attributes. We address this gap by focusing on a narrower and economically interpretable component of human capital: skills capital, defined as the labor-market value of the skills embedded in a firm's workforce. Our central research question is whether externally priced employee skills represent a value-enhancing intangible asset of the firm.

The answer is theoretically ambiguous. On the one hand, skills capital can increase firm value if transferable skills raise productivity, improve the firm's ability to adopt new technologies, complement physical and organizational capital, and expand growth opportunities. In this view, the labor-market value of skills is not merely a wage bill; it is a replacement-cost measure of a productive input that can generate rents when combined with the firm's other assets. This logic is consistent with the broader view that intangible investments should be treated as capital when they create future benefits (Corrado, Hulten, and Sichel, 2005) and with evidence that job-posting skill requirements contain information about wages and firm performance beyond standard labor-market classifications (Deming and Kahn, 2018). It also relates to work on organizational capital, which argues that firms derive value from intangible capabilities embodied partly in employees and key talent (Eisfeldt and Papanikolaou, 2013). If transferable skills complement firm-specific

assets, firms with greater skills capital should have higher valuations, stronger growth, and better innovation outcomes.

On the other hand, valuable transferable skills may weaken the firm's claim on the cash flows generated by its workforce. Skills that are highly valued in the external labor market raise workers' outside options, increase retention- and replacement-related costs, and may allow employees to capture a larger share of the surplus. Even though many workers may underestimate the value of their outside options (Jäger, Roth, Roussille, and Schoefer, 2024), if a meaningful share of workers responds by leaving, the resulting turnover can disrupt production and destroy firm-specific knowledge. In this view, skills capital differs from owned physical capital because firms do not own the workers who embody it (e.g., Hart and Moore, 1990; Matsa, 2018; Nishesh, Ouimet, and Simintzi, 2024). Prior work highlights this tension: labor mobility can increase operating leverage and risk for shareholders (Donangelo, 2014) and increases in mobility for skilled workers reduce firm value by increasing labor costs and weakening firms' rents over workers (Shen, 2021). These arguments predict that skills capital may have a limited or even negative relation to firm value.

We therefore treat the relation between skills capital and firm value as an open empirical question. We construct and validate time-varying skill prices from job-posting wage data and aggregate these prices across the skills held by each firm's employees using resume data. This approach isolates the transferable, externally priced component of employee human capital and distinguishes it from broader organizational capital. We then test whether skills capital is significantly associated with firm valuation, operating performance, innovation, and employee turnover. The competing hypotheses are sharp: if skills capital is a productive intangible asset that complements firms' other assets, it should be positively associated with Tobin's Q, growth, and innovation; if it mainly raises outside options and labor costs, it should reduce profitability, increase turnover, and weaken shareholder value.

The data favors the first view. Using valuation measures in Lee, Shin, and Stulz (2021), we find that greater skills capital commands meaningfully higher firm valuations. A one-standard-deviation increase in skills capital intensity, defined as skills capital scaled by total assets, is

associated with approximately a 1.05 increase in asset-based Tobin's Q. This effect is economically sizable, representing 43% of the standard deviation of Q and 46% of its sample average. The result remains positive and significant using Total Q that directly considers intangible capital (Peters and Taylor, 2017), so the value of skills capital is not an artifact of the omission of intangibles under accounting rules.

Skills capital intensity also predicts stronger sales growth and higher R&D intensity across many subsequent quarters, consistent with firms growing and investing in an innovation pipeline instead of simply incurring a wage cost. Patent filings and real patent value per dollar of assets are both higher in firms with more skills capital intensity, and all these effects are robust to the inclusion of firm, industry-quarter, and state-quarter fixed effects. Contrary to the concern that workers with valuable skills leave firms for outside opportunities, skills capital intensity is associated with lower employee turnover, with an effect that is largest contemporaneously and fades over time. The only "negative" result we find is that skills capital intensity is associated with lower current and subsequent returns on assets (ROA). This pattern is consistent with skills capital complementing higher firm expenditures on R&D and SG&A, all of which are expensed (ROA-reducing) under generally accepted accounting principles, a point similarly emphasized in the accounting measurement literature on intangible investment (e.g., Brynjolfsson, Rock, and Syverson, 2021). Finally, analysts appear to understand the positive value effect of skills capital, as analyst recommendations are more bullish for skill-intensive firms, and the effect persists over five quarters ahead.

To address endogeneity concerns, we construct a Bartik (1991)-style instrument in a panel setup following Ma (2025) and Green and Vallee (2025). The instrument interacts each firm's predetermined skill shares and quantities from an early base period with economy-wide changes in skill prices estimated on an external sample that excludes firms in our sample, scaled by the firm's assets at $t-1$. These components satisfy the standard pre-determination requirement: the skill shares and quantities are fixed at the base period, and the price variation is plausibly exogenous as it is identified from job postings by firms outside of our main sample. Because these

price shifts are driven by economy-wide forces and not by any individual firm's decisions, they are unlikely to reflect a firm's own investment choices or contemporaneous demand shocks, supporting the identifying assumption that the firm's historical skill composition is uncorrelated with current unobservable shocks to firm value, conditional on firm and time fixed effects. Results using this instrument are consistent with the OLS estimates and support a causal interpretation of skills capital value.

Our paper contributes to several literatures. First and most directly, it relates to the growing body of work that uses employee-level data to study firm performance. Agrawal, Hacamo, and Hu (2021) use LinkedIn CV data to show that rank-and-file labor flows predict abnormal stock returns. Fedyk and Hodson (2023) use an employer-employee matched dataset to examine the firm-level consequences of technical human capital in five technology-intensive domains. They find that all five are associated with higher contemporaneous Tobin's Q but negatively forecast future returns and future profitability, a pattern they attribute to investor overvaluation of currently popular technologies instead of genuine productivity gains. A common feature of these studies, and of related work measuring human capital from job-posting skill requirements (Deming and Kahn, 2018; Campello, Gao, and Xu, 2024), resume or LinkedIn skill profiles (Babina, Fedyk, He, and Hodson, 2024; Dorn et al., 2025), or employment counts that distinguish higher- from lower-skill workers (e.g., Fonseca and Van Doornik, 2022), is that they count workforce attributes without assigning dollar values to individual skills. We move from counting to valuation by pricing each skill at its market wage premium and aggregating across the firm's workforce, producing a dollar-valued, firm-level measure of transferable human capital. This distinction matters empirically. Unlike Fedyk and Hodson, we do not find overvaluation: firms with more skills capital earn higher valuations that are accompanied by higher sales growth, more R&D investment, and more patents. These results suggest that skills capital captures productive workforce capabilities that the market recognizes and rewards, instead of a manifestation of investor overvaluation.

Second, our findings advance the literature on intangible capital and firm value. Over a century ago, Marshall (1890) observed that *"the older economists took too little account of the fact that*

the human faculties are as important a means of production as any other kind of capital." The observation remains apt: a longstanding challenge in this literature is that human capital investments do not appear on the balance sheet, making it difficult to assess the productive value of a firm's workforce from public information. Abraham and Mallatt (2022) survey the three main approaches to measuring human capital (indicator, cost, and income-based) and argue that income-based approaches, which value investments by their discounted future earnings consequences, are particularly informative about how skill investments translate into productive capacity. Our measure brings this income-based logic to the firm level by using labor-market prices to value a firm's transferable human capital, much as Ewens, Peters, and Wang (2025) use merger prices to infer intangible capital.

Corrado, Hulten, and Sichel (2005) argue that firms' investments in knowledge and organizational capabilities should be treated as capital, and subsequent empirical work has shown that conventional accounting practices systematically undervalue these assets (Lev, 2019). Peters and Taylor (2017) construct a Total Q measure that augments the standard denominator with estimated intangible capital, and we show that skills capital remains value-relevant even after this adjustment. This robustness matters because, as Morck, Shleifer, and Vishny (1988) note, Tobin's Q is high when the firm has valuable intangible assets beyond physical capital, including monopoly power, goodwill, a stock of patents, or good managers. Interpreted broadly, "good managers" likely includes the skilled workforce those managers have assembled, which is precisely the asset our measure quantifies. The fact that skills capital retains its predictive power across Tobin's Q, equity-based Q, and Total Q, and is also reflected in sales growth, innovation output, and analyst recommendations, guards against the concern that any single valuation measure captures too many confounds. Eisfeldt and Papanikolaou (2013) develop a model of organizational capital embedded in key employees and show that it commands a risk premium in the cross-section of returns; our paper provides complementary evidence that the labor-market value of skills captures a distinct and economically large component of this organizational intangible.

Third, the results herein advance the literature on labor and innovation. The finding that skills capital predicts R&D intensity and patent activity across all forward quarters suggests a durable innovation investment channel: firms with more valuable skills capital deploy those skills to generate new knowledge, creating a complementarity between human capital and innovation that amplifies the productivity gains from either input alone. This complements work by Ma, Wang, and Wu (2025), who show that firms make strategic decisions about the scope of innovation to influence the general versus firm-specific composition of inventors' human capital. Whereas their evidence focuses on how firms design innovation to manage worker mobility, our results suggest that the externally priced, transferable component of that human capital is highly predictive of firm-level innovation outcomes. Taken together, the innovation, R&D, and patent results establish that skills capital is not simply consumed as a current input but generates cumulative knowledge assets.

Fourth, our paper speaks to the literature on labor mobility and firm performance. Donangelo (2014) shows that labor mobility amplifies firms' exposure to systematic risk and commands a return premium, and Shen (2021) finds that relaxing mobility constraints for skilled workers reduces firm value. Our turnover evidence sheds new light on this picture: firms with more skills capital have lower, not higher, turnover, despite their workers commanding larger wage premiums in external labor markets. This suggests that market-valued skills strengthen worker-firm matching, either because firms work harder to retain skilled employees or because employees value working alongside skilled co-workers (e.g., Wallskog, 2025), offsetting the turnover effect of their stronger outside options.

The retention benefit is especially important because skills capital is not static. Dinerstein, Megalokonomou, and Yannelis (2022) provide evidence that human capital depreciates when workers are not actively engaged in employment, implying that firms retaining skilled workers can preserve and compound their skills capital, while firms with high turnover face continuous depreciation of their workforce's productive value. Skills can also lose value when technologies change. Hombert and Matray (2026) document that workers who joined the ICT sector during the

1990s technology boom experienced substantial long-run earnings losses as their accumulated skills rapidly became obsolete. Relatedly, Eisfeldt, Schubert, Zhang, and Taska (2026) show that the release of ChatGPT increased the market values of firms whose workforces were more exposed to Generative AI, highlighting how technology shocks can quickly reprice workforce attributes. Together, these findings underscore the need to measure skills using their time-varying labor-market value. Our paper fills this gap by valuing firms' workforce skills at prevailing market prices, allowing skills capital to reflect both accumulation and depreciation over time. As AI capabilities expand, real-time measurement of skill premiums will become increasingly important for understanding whether AI-driven changes strengthen or threaten firms' competitive positions.

Finally, our study connects to the emerging literature on human capital disclosure. Adams, Akyol, and Verwijmeren (2018) exploit Regulation S-K's 2009 requirement that firms disclose the skills of their directors to show that greater commonality in director skill sets is associated with better firm performance. The SEC has more recently expanded human capital disclosure requirements for the broader workforce, but existing mandated disclosures remain largely qualitative (e.g., Dey, Haslag, Sensoy, and White, 2022). Our measure provides a market-based, economically interpretable metric (the aggregate dollar value of a firm's transferable skills stock) that could serve as a more informative disclosure benchmark. The evidence that this measure predicts valuation, innovation, growth, and retention suggests it contains material information about firm prospects that investors could find particularly useful.

The remainder of the paper proceeds as follows. Section 2 describes the construction of our skills capital measure, including the estimation of skill prices from job postings and the aggregation of those prices across firm workforces using resume data. Section 3 presents the main empirical tests linking skills capital to firm valuation, operating performance, innovation, and employee outcomes. Section 4 addresses endogeneity using the Bartik-style instrumental variables design. Section 5 concludes.

2. Measuring Skills Capital

Our approach involves three steps. In the first step, we estimate the labor-market price of each individual skill by running quarterly hedonic wage regressions on a large sample of job postings that report advertised salaries. The estimated coefficients represent the annual wage premium that each skill commands in the external labor market, net of education and experience. In the second step, we validate these estimated skill prices against independent benchmarks: realized occupation-level wages from a government establishment survey, occupational complexity ratings as a proxy for labor supply constraints, and labor market demand conditions. In the third step, we aggregate the validated skill prices across each firm's workforce using resume data that link workers to employers and occupations. The result is a firm-quarter measure of skills capital: the total labor-market value of the transferable skills held by the firm's employees.

2.1. Measuring Individual Skills' Labor Market Value

We measure skill prices from online job postings provided by Lightcast, which systematically collects and parses job advertisements from thousands of U.S. online sources. Our sample spans 2010Q1 through 2024Q4 and covers 363.96 million postings, of which 88.88 million (24.42%) include advertised salary information. Each posting records the job title, employer, location, required skills, required education, and minimum years of experience. Lightcast applies a proprietary natural language processing algorithm to standardize skill mentions into a common taxonomy. We use the second most granular skill classification, and our sample covers 442 distinct skills. On average, a posting lists 9.74 skills (standard deviation 7.26). We observe an average of 6.07 million postings per quarter, ranging from 1.62 million at the start of the sample to 10.72 million at its peak. Salaries are annualized and deflated to real values in 2010 dollar terms using the Bureau of Labor Statistics Consumer Price Index for All Urban Consumers (CPI-U, all items, seasonally adjusted) and winsorized at the 1st and 99th percentiles.

Table 1 reports summary statistics for the job-posting sample. Panel A presents posting-level variables. The mean real advertised salary is $50.57 thousand (standard deviation $32.85 thousand); the distribution is right-skewed, with a median of $38.96 thousand and a 75th percentile of $63.66 thousand. Postings list an average of 9.74 skills, and 15.32% originate from staffing firms on behalf of client firms. Panel B shows the distribution of experience and education requirements. Most postings (54.48%) are for entry-level positions requiring no prior experience; 20.32% require one to two years, 18.18% require three to five years, and the remaining 7.01% require six or more years. On the education dimension, 67.45% of postings require at most a high school diploma or GED, 5.08% require an associate degree, 24.37% require a bachelor's degree, and 3.11% require graduate education, including master's degrees, Ph.D.s, and professional degrees. Panel C reports sample-wide characteristics, including 88.88 million salary observations, covering 442 distinct skills.

We estimate quarterly skill prices using a two-stage Heckman (1979) selection model with a Non-Negative Least Squares (NNLS) constraint. The selection problem arises because salary disclosure is not random: employers that choose to advertise wages likely differ systematically from those that do not, and the skills associated with transparent-pay jobs may differ from those in opaque-pay jobs.

In the first stage, we estimate a probit model for whether a posting includes salary information, using all 442 skill indicators, five experience categories (zero, one to two, three to five, six to nine, and ten or more years), five education levels, and an indicator for whether the posting is made by a staffing firm on behalf of a client firm. The staffing-firm indicator serves as a potential instrumental variable and is excluded from the second-stage wage equation. The predicted index from this first stage yields the inverse Mills ratio, which we include as a control in the second stage. This correction accounts for potential selection in salary disclosure under either of two assumptions. First, as in the standard Heckman (1979) framework, the correction is identified under joint normality of the selection and wage errors. This distributional assumption is not directly verified, but it is commonly used in settings where the outcome is observed only for a

selected sample, such as Boyer, Nadauld, Vorkink, and Weisbach (2023), who estimate private equity indices using infrequent and incomplete secondary-market transactions.

Second, even without normality, identification can be achieved by an instrument for the first stage regression. Our baseline specification uses an indicator for whether a job is posted by a staffing company as the instrumental variable. This variable is relevant because staffing firms differ systematically in their disclosure practices and are more likely to advertise wages, reflecting both standardized posting templates and the need to attract applicants for client positions. The exclusion restriction requires that, conditional on skills, experience requirements, education requirements, and other controls, staffing-company status affects advertised salary only through the disclosure decision. The rich set of controls, especially detailed skill indicators and education and experience requirements, helps absorb the main determinants of wage levels and makes a direct staffing-company wage effect less likely. We use the instrumented Heckman specification as our baseline, and report robustness results from a specification without the instrument.

In the second stage, we regress the real advertised salary on skill indicators and controls, restricting attention to postings with salary data and at least one skill requirement. The control vector includes experience category indicators, education level indicators, and the inverse Mills ratio. We impose non-negativity on all skill coefficients, which is a natural restriction, since no skill can rationally command a negative wage premium in a competitive labor market. Formally stated, we estimate coefficients as follows:

$$\hat{\beta}_t = \mathrm{argmin}_{\beta \geq 0} \, || \, \tilde{w}_{jt} - \tilde{S}_{jt}'\beta \, ||^2$$

where $\tilde{w}_{jt}$ and $\tilde{S}_{jt}$ are the residuals from the projections of real salary and skill indicators onto the controls. We solve this quadratic program using coordinate descent (2,000 maximum iterations, convergence threshold 10^{-8}) and estimate it separately for each quarter, producing a panel of skill prices $\hat{\beta}_{st}$ for skill s in quarter t.

We assess the sensitivity of the estimated skill prices to the modelling choices used in the estimation procedure. Since our baseline specification combines a Heckman selection correction with non-negativity constraints, we compare these estimates with three alternative specifications:

Heckman without the non-negativity constraints, non-negative least squares without the Heckman correction, and OLS without either correction. The correlations between the baseline skill prices and the three alternative estimates all exceed 0.95, indicating that the estimated price structure is highly stable across methods.

Each estimated coefficient $\hat{\beta}_{st}$ represents the annual wage premium, in constant 2010 dollars, that a job requiring skill s commands over an otherwise identical posting, net of education, experience, and selection into salary disclosure. This is the price of skill s in the external labor market at time t: the amount a typical firm is willing to pay extra to hire a worker who brings that skill to an arm's-length employment transaction. Aggregating these prices across a firm's workforce, as described in Section 2.3, yields a market-valued replacement cost of the firm's transferable human capital skills.

2.2. Results and Validation of Individual Skill Values

The Non-Negative Least Squares (NNLS) procedure produces sparse solutions: in a typical quarter, more than half of the 442 skills receive a zero coefficient, indicating that once education, experience, and selection are held constant, their marginal contribution to advertised wages is indistinguishable from zero. Across all 26,520 skill-quarter pairs in the sample, the mean estimated annual premium is $1,918, though this average is pulled toward zero by the predominance of zero-coefficient skill-quarter cells. Among the skills that receive positive premiums, the rankings are economically sensible. Table 2 reports the five highest time-averaged premiums: Electronic Trading ($15,167), Hardware Description Languages ($14,067), Cryptocurrency ($11,719), Cardiology ($11,667), and Ground Freight Transportation ($11,451). These high premium categories capture specialized and, in some cases, regulated forms of human capital, spanning financial technology, engineering, healthcare, and logistics. For example, Hardware Description Languages reflects technical expertise used to design and verify digital hardware, while Ground Freight Transportation typically involves commercial driver credentials, hazardous materials and tank vehicle qualifications, and compliance with rules governing the movement of oversized,

heavy, or otherwise high-risk freight. The breadth of these categories suggests that skill premiums are not confined to a single sector but arise across multiple domains of specialized labor demand.

Skill prices also vary substantially over time, which is central to our identification strategy. The variation appears economically sensible (see Figure 1). For example, electronic trading commands a large premium early in the sample, consistent with its scarcity during the diffusion of automated and algorithmic trading, but the premium declines as the skill becomes more widely adopted. Cryptocurrency-related premiums are much more volatile, reflecting the boom-bust nature of crypto demand. By contrast, cardiology exhibits a relatively persistent premium, consistent with regulated specialist skills whose supply adjusts slowly. Ground freight transportation shows a rising premium over much of the sample, consistent with the growing importance of logistics, e-commerce, and supply-chain capacity. Overall, the time-series patterns suggest that the estimated skill prices capture meaningful changes in labor-market demand rather than arbitrary noise.

We validate our estimated skill prices against three benchmarks. Because directly comparable estimates of individual skill prices are not available, we begin with national occupation wage benchmarks from the Occupational Employment and Wage Statistics (OEWS). These data provide a useful external benchmark because they measure realized compensation from an independent establishment survey, rather than advertised salaries in job postings. For each occupation and year, we compute a weighted skill premium by averaging the estimated skill prices across all skills that appear in that occupation's job postings, where the weight for each skill is its share of postings within the occupation. This weighted premium measures the labor market value of the typical skill bundle required by employers hiring for that occupation.

Figure 2 compares this occupation-level skill premium with OEWS occupation wages. Each panel groups the observations into 100 equal-sized bins; the solid line reports a quadratic fit. The top panel shows a strongly positive raw relation. The bottom panel removes year fixed effects to isolate variation across occupations within the same year. The positive relation remains, and its slope is nearly unchanged. Because OEWS wages are based on realized compensation from an

independent data source, the close alignment between the two series supports the interpretation that our estimates capture meaningful labor market prices, rather than artifacts of the wage posting environment.

We next validate the estimates at the individual skill level using proxies for skill (supply) scarcity as well as skill demand. If estimated premiums capture scarcity, they should be higher for skills that are more difficult to obtain. We proxy for this difficulty using the O*NET job zone classification, which ranks occupations from 1, requiring little preparation, to 5, requiring extensive preparation and advanced education. With quarter and skill fixed effects absorbed, the within-skill, within-quarter coefficient on job zone exposure is 2,861, with a standard error of 705, and is significant at the 1% level. A one standard deviation increase in occupational complexity is associated with a $1,202 higher quarterly premium, as reported in Table 3, Panel A, column 1.

A good estimate of skill premiums should also rise when market demand for a skill increases, holding fixed differences across skills and common time effects constant. We test this prediction using demand intensity, measured from the posting frequency of each skill. Skills that experience increases in posting frequency also exhibit contemporaneous increases in estimated premiums. The coefficient on demand intensity is 195, with a standard error of 68, and is significant at the 1% level, corresponding to a $744 increase per standard deviation, as reported in Table 3, Panel B, column 1.

Overall, our skill premium estimates align with national statistics on occupation wages and vary sensibly with proxies for the supply and demand of individual skills. These patterns provide validation that the estimates capture economically meaningful variation in the labor market value of skills, rather than statistical artifacts of the hedonic regression. Online Appendix Table OA1 reports additional summary statistics on mean wage premiums by broad skill family.

2.3. Firm-Level Aggregation and Statistics

We construct firm-level skills capital by aggregating individual skill prices over a firm's workforce using resume data (from Revelio Labs), which record each worker's current employer and occupation. For firm i in quarter t:

$$SC_{it} = \sum_{s \in S} \sum_{o \in O} e_{iot} f_{ost} \hat{\beta}_{st}$$

where e_{iot} is the number of employees in occupation o at firm i in quarter t, f_{ost} is the fraction of Lightcast postings in occupation o during quarter t that list skill s, and $\hat{\beta}_{st}$ is the estimated quarterly wage premium for skill s. The occupation-skill fractions f_{ost} translate occupation-level headcounts into an implied skill portfolio using the contemporaneous hiring requirements posted by employers in each occupation, thereby linking the workforce stock observable through resumes to the skill prices estimated from posted vacancies.

Two features of this construction are worth emphasizing. First, SC_{it} changes over time through both changes in a firm's workforce composition and changes in economy-wide skill prices. The latter variation, driven by forces outside any individual firm's control, underlies the Bartik identification strategy in Section 4. Second, the measure is explicitly contemporaneous in its pricing: it values skills at current market replacement cost, not at the historical wages actually paid to employees. This distinction matters because a firm retaining workers whose skills have appreciated in the market holds more valuable human capital than its historical payroll reflects.

We scale SC_{it} by lagged book assets to form the main empirical variable, skills capital intensity, which measures the market-valued transferable skill stock per dollar total assets and facilitates cross-sectional comparisons across firms of different sizes.

After requiring non-missing values for total assets, net sales, market capitalization, capital expenditures, and return on assets, and dropping financial firms (Fama–French industry 45) and regulated utilities (Fama–French industry 31), our main regression sample contains 200,403 firm-quarter observations spanning 2010Q1 through 2024Q4.

Skills capital exhibits wide cross-sectional dispersion. In dollar terms, the mean firm holds $61.13 million in skills capital, but the median is $4.93 million and the 75th percentile is $26.47 million; the distribution is heavily right-skewed, with a 99th percentile of $1,004 million. After scaling by assets, skills capital has a mean of 2.47% relative to total assets. We use this scaled measure throughout the empirical analysis and report further summary statistics in Table 4. All continuous variables are winsorized at the 1st and 99th percentiles.

3. The Value of Skills Capital

This section examines whether skills capital is associated with firm value and performance. We begin by describing the empirical design, including the regression specification, outcome variables, and fixed-effect structure. We then present the main valuation result and examine the channels through which skills capital may contribute to firm value: sales growth, profitability, innovation, complementary investment, employee retention, and analyst recommendations.

3.1. Empirical Design

We test whether skills capital is associated with firm value and performance by estimating:

$$Y_{i,t+k} = \alpha + \beta SkillsCapital_{i,t} + \gamma' X_{i,t} + \delta_i + \delta_{t\times j} + \epsilon_{i,t+k}$$

where $Y_{i,t+k}$ is an outcome for firm i at horizon k $\in$ {0, 1, 2, 3, 4, 5} quarters ahead, $SkillsCapital_{i,t}$ is the firm's skills capital divided by lagged total assets (expressed as a percentage), and δ_i and $\delta_{t\times j}$ denote firm and interacted time fixed effects. Following the seminal work of Yermack (1996) where firm value is the main dependent variable, the control vector $X_{i,t}$ includes current-quarter ROA, its first and second lags, the natural logarithm of the market value of equity, capital expenditures scaled by assets, and the number of business segments. Beyond Yermack (1996), we include tests with firm fixed effects, industry × quarter fixed effects as well as location × quarter fixed effects, and cluster standard errors by firm and calendar quarter.

We study ten outcome variables spanning various dimensions of firm performance. For valuation, we use asset-based Tobin's Q as the primary measure, defined as the market value of

equity plus book assets minus book equity, divided by book assets. For operating performance, we use four-quarter sales growth and ROA. For innovation, we examine R&D expenditures, patent filings, and patent value. For investment more broadly, we examine SG&A excluding R&D and capital expenditures, each scaled by lagged assets. Finally, we study the firm-level employee turnover rate and the consensus analyst recommendation score.

We report three increasingly demanding columns. Column (1) includes quarter and SIC2 industry fixed effects, exploiting cross-sectional variation among firms within industry-quarter cells. Column (2) replaces industry fixed effects with firm fixed effects, so identification comes from within-firm changes in skills capital over time. Column (3), our preferred specification, retains firm fixed effects and replaces the quarter fixed effect with quarter × SIC2 and quarter × headquarters state fixed effects, thereby absorbing time-varying shocks common to firms operating in the same industry or state.

3.2. Results on Firm Value

Table 5 presents estimates of the relation between skills capital and Tobin's Q across the three specifications. The coefficient on skills capital increases from 0.15 in column (1) to 0.23 in column (2) and 0.24 in column (3), each estimated with a standard error of roughly 0.01. The increase in the coefficient from column (1) to columns (2) and (3) suggests that controlling for time-invariant firm heterogeneity strengthens the estimated association. In the preferred specification, a one-standard-deviation increase in skills capital (4.38% of lagged assets) is associated with a 1.05 unit increase in Tobin's Q, equivalent to 43% of the sample standard deviation.[1] In Online Appendix Table OA2, we show that the relation between skills capital and firm value remains similar when skills capital is reconstructed using alternative sets of skill prices.

As additional robustness, the Online Appendix Table OA3 replicates the analysis using equity-based Q and Total Q (Peters and Taylor, 2017), which augments the conventional denominator

[1] Throughout, we compute economic magnitudes using the overall sample standard deviation from Table 4. Economic significance remains large when we use within-firm standard deviations instead.

with estimates of knowledge and organizational capital. The positive association between skills capital and firm value remains statistically significant under both alternative measures, indicating that the main result is not driven by the omission of internally generated intangible assets from book value**.**

3.3. How Does Skills Capital Affect Firm Value?

What sustains the valuation premium documented in Table 5? We examine accounting performance, innovation, investment, employee retention, and analyst assessments in turn.

Table 6 suggests that the valuation premium is accompanied by subsequent firm growth. In Panel A, the coefficient on *Skills Capital* in the sales growth regression is 0.76 contemporaneously, rises to 1.58 at (t+3), and moderates to 1.26 at (t+5), with all six estimates significant at the 1% level. A one-standard-deviation increase in skills capital is associated with 3.33 percentage points of additional sales growth at (t), rising to 6.92 percentage points at the (t+3) peak. The delayed response is consistent with skills capital supporting investments whose operating benefits materialize gradually.

Panel B presents a different pattern for profitability. The coefficient on *Skills Capital* in the ROA regression is negative and significant up to five quarters ahead. It is −0.008 at (t), −0.005 at (t+1), and attenuates monotonically to −0.002 by (t+4) and (t+5). A one-standard-deviation increase in skills capital corresponds to roughly a 0.04 reduction in contemporaneous ROA, compared with a sample mean of −0.02. This persistent but declining relation is consistent with models of intangible investment in which productive labor expenditures are expensed rather than capitalized under GAAP (Corrado, Hulten, and Sichel, 2005; Lev, 2019). In this interpretation, firms with greater skills capital bear recurring accounting charges associated with maintaining and deploying skilled labor, even as higher valuation and subsequent sales growth suggest that these expenditures are economically productive.

Table 7 shows that firms with greater skills capital invest more heavily in innovation. Panel A reports that the coefficient on *Skills Capital* in the R&D/Assets regression is 0.18

contemporaneously and remains positive through (t+5), declining gradually to 0.06. A one-standard-deviation increase in skills capital is associated with a 0.79 percentage-point increase in R&D intensity, relative to a sample mean of 1.45%. The persistence of the relation suggests that skills capital is associated with an ongoing innovation program rather than a one-time increase in research spending.

Patent outcomes provide complementary evidence. Patent filings per dollar of assets increase significantly through all horizons, although the magnitude attenuates at (t+4) and (t+5). Patent value also rises: the contemporaneous coefficient is 0.07, implying a one-standard-deviation effect of 0.31 percentage points relative to a sample mean of 1.42%, and remains statistically significant through (t+3). The joint pattern of higher R&D, more patent filings, and greater patent value is consistent with skills capital being associated with meaningful knowledge production.

Table 8 indicates that firms with greater skills capital (intensity) also invest more heavily in complementary organizational and physical assets. Panel A shows that SG&A excluding R&D increases by 0.73 contemporaneously and remains significantly positive through (t+5), albeit lower at 0.31. A one-standard-deviation increase in skills capital is associated with a 3.20 percentage-point increase in SG&A relative to assets. Panel B reports a similarly persistent relation for capital expenditures: the coefficient is 0.04 contemporaneously, remains 0.03 from (t+1) through (t+4), and declines to 0.02 at (t+5), with all estimates significant at the 1% level. These results suggest that firms with greater skills capital intensity invest persistently in the organizational and physical infrastructure needed to deploy skilled labor effectively.

Employee turnover exhibits a different but informative pattern. As shown in Table 9, the contemporaneous coefficient on *Skills Capital* is −0.11, corresponding to a one-standard-deviation reduction of 0.48 percentage points, or 11.8% of the sample standard deviation of turnover. The coefficient remains significantly negative over all subsequent horizons, declining from −0.05 at (t+1) to −0.02 at (t+5). Although workers with valuable skills have stronger outside options, firms with greater skills capital intensity exhibit lower turnover. One possible explanation is that these firms create stronger complementarities between worker skills and firm-specific assets or provide

non-wage amenities that improve retention. Persistent retention may further reinforce the firm's stock of skills because skill depreciation accelerates during periods of non-employment (Dinerstein, Megalokonomou, and Yannelis, 2022).

Finally, skills capital intensity is positively associated with analyst assessments as shown in Table 10. The coefficient on *Skills Capital* in the analyst recommendation regression is 0.03 contemporaneously and 0.02 at each of the five subsequent horizons, with all estimates significant at the 1% level. A one-standard-deviation increase in skills capital corresponds to a 0.13 increase in the recommendation score, where the score ranges from 1 (strong sell) to 5 (strong buy) with a sample mean of 3.60. Because analyst recommendations reflect forward-looking assessments rather than current accounting performance alone, the persistence of the association suggests that analysts incorporate information contained in firms' skill composition when evaluating future performance.

Taken together, the evidence suggests that skills capital behaves as a productive intangible asset rather than simply a labor cost. Firms with greater skills capital experience stronger subsequent sales growth, invest more heavily in innovation and complementary organizational assets, exhibit lower employee turnover, and receive more favorable analyst assessments. At the same time, skills capital is associated with persistently lower ROA, consistent with the accounting treatment of labor-related intangible investment as a current expense rather than a capitalized asset. Overall, the evidence is consistent with skills capital contributing to durable competitive advantage through sustained investment, innovation, and operating performance.

4. Addressing potential endogeneity

4.1. Empirical design

The OLS estimates in Section 3 may be biased if unobserved firm-level attributes simultaneously determine both skills capital accumulation and the outcome variables such as firm value. For example, a firm pursuing an aggressive growth strategy might hire workers with high-

value skills and increase R&D investments at the same time, generating a positive association between skills capital and innovation that does not necessarily reflect the effect of skills capital itself. To address this concern, we construct a Bartik-style shift-share measure that isolates variation in skills capital driven by economy-wide changes in skill prices, following the general logic in Bartik (1991) and Ma (2025).

The intuition is as follows. For each firm, we measure its baseline skill composition using job postings and resume data from 2010–2011, before the estimation period used in the shift-share analysis.[2] We then hold this baseline skill composition fixed and interact it with the market price of each skill, where skill prices are estimated from an external sample that excludes the public firms in our sample. Our shift-share design in a panel setup is closest to Green and Vallee (2025).[3] The resulting shift-share measure is scaled by the firm's lagged assets at t−1. Because the price variation is estimated outside the focal sample with public firms, it is less likely to reflect the firm's own investment decisions, hiring shocks, or contemporaneous performance. Section 2.3 shows that skills capital changes over time through two channels: changes in the firm's workforce composition and changes in economy-wide skill prices. The shift-share measure operates exclusively through the second channel, removing the endogenous hiring margin.

One remaining concern is that large firms may have sufficient labor-market presence to influence the market price of certain skills, even when the public firms in our sample are excluded from the price estimation. This concern is especially relevant if a small number of dominant firms account for a large share of demand for specialized skills and therefore affect the wage premiums used to construct the shift-share measure. To address this possibility, we repeat the analysis after excluding firms whose total assets are at or above the 90th percentile of the sample distribution. The results are robust to this exclusion, suggesting that the findings are not driven by firms with unusual market power in skill-specific labor markets.

[2] We exclude 2010 and 2011 from the final estimation sample, so the identifying variation comes from predetermined firm skill exposures interacted with subsequent economy-wide skill-price movements.

[3] Specifically, in a panel setup like Green and Vallee (2025), rather than using changes in skill prices as the shift, we use the current skill price while including firm fixed effects. The firm fixed effects absorb baseline differences across firms, so identification comes from within-firm changes in skill prices, consistent with the usual interpretation of shift-shares.

We estimate regressions of each outcome variable directly on the shift-share predicted component of skills capital, including the same controls and fixed effects (firm, quarter×SIC2, quarter×state) used in the most stringent OLS specification. This approach has the advantage of being agnostic about the precise functional form of the first stage. If the OLS estimates are driven by reverse causality or omitted variables, the estimates based on predetermined skill exposures and external skill-price movements should be attenuated toward zero or change sign.

4.2. Results

Table 11 reports estimates across all ten outcome categories and six horizons (t through t+5). The valuation results are robust to the shift-share construction. The coefficient on Tobin's Q is 0.27 at t, significant at 1%, and remains highly significant across all forward horizons, declining gradually to 0.15 at t+5. Thus, the component of skills capital predicted by predetermined firm skill exposure and external skill-price movements is positively associated with firm value. This pattern is inconsistent with the interpretation that the baseline valuation result is driven solely by contemporaneous firm-specific hiring decisions or reverse causality from firm value to skills capital.

The temporal profile of the sales growth result is also preserved. The coefficient starts at 0.60 at t, climbs to 1.55 at t+3, and drops to 1.34 at t+5, with all estimates statistically significant. The hump-shaped pattern mirrors the baseline OLS estimates in Table 6, Panel A, and is consistent with the effect of skills on revenue building over several quarters. The estimates for ROA remain negative and statistically significant.

The innovation results are likewise broadly consistent with the baseline evidence. The R&D/Assets coefficient is 0.17 at t and decays to 0.06 at t+5, with all six estimates significant at 1%. Patent filings per dollar of assets are also positively associated with the shift-share measure through (t+3), although the estimates become weaker at longer horizons. Patent filing value,

however, is weaker: the coefficient of 0.04 at t is only marginally significant, and the forward estimates are statistically indistinguishable from zero.[4]

The investment results further support the baseline patterns. SG&A excluding R&D starts at 0.72 (versus 0.73 in OLS) and decays to 0.39, with all six estimates significant at 1%. Capex/Assets is 0.04 at t and stable near 0.03 through t+5, matching the OLS profile closely. These estimates suggest that firms with higher externally shifted skills capital also undertake greater complementary organizational and physical investment. The results are therefore difficult to attribute solely to contemporaneous firm-specific hiring decisions or anticipated investment programs that mechanically raise both realized skills capital and future investment.

The employee-retention results are also consistent with the baseline evidence. The coefficients on turnover are negative across all horizons: −0.11 at (t), −0.14 at (t+1), −0.13 at (t+2) and (t+3), and −0.12 and −0.11 at (t+4) and (t+5), all significant at the 1% level. The persistence of these estimates reinforces the conclusion that skills capital is associated with lower subsequent turnover. Relative to the baseline OLS estimates, the shift-share estimates are farther from zero at longer horizons, a pattern consistent with measurement error in realized skills capital attenuating the OLS association. We therefore interpret the shift-share evidence as strengthening the qualitative conclusion that skills capital is associated with greater employee retention, rather than as a structural magnitude comparison with the OLS coefficients.

Analyst recommendations are also positively related to the shift-share measure. The coefficient is 0.04 at (t) and stabilizes at 0.03 across all five forward horizons, with all estimates significant at the 1% level. This persistence suggests that financial intermediaries incorporate the productive value of skill-intensive workforces into their assessments. The result is difficult to explain solely by firms simultaneously improving analyst relations and accumulating realized skills capital, because the variation in Table 11 comes from predetermined skill exposure interacted with external skill-price movements.

[4] This attenuation, however, is the single exception. For all the other nine outcome variables, the IV estimates reinforce the OLS results.

Overall, Table 11 corroborates the baseline findings using a shift-share predicted component of skills capital. Across the outcome categories, the estimates generally have the same sign and temporal profile as those in Section 3. The one partial exception is patent filing value, which is directionally consistent but imprecisely estimated. Taken together, the evidence suggests that the main results are unlikely to be driven entirely by reverse causality, omitted contemporaneous firm shocks, or endogenous hiring composition. Instead, externally shifted variation in firms' skill endowments is associated with higher Tobin's Q, stronger revenue growth, sustained R&D and patenting activity, greater complementary investment, lower employee turnover, and more favorable analyst recommendations.

5. Conclusion

This paper develops a novel firm-level measure of skills capital, defined as the aggregate labor-market value of the transferable, externally priced skills embedded in a firm's workforce, and shows that it is an economically important intangible asset. Firms with greater skills capital (intensity) command higher valuation. They grow faster, invest more in R&D, file more patents of greater value, and receive more bullish analyst recommendations that persist over many subsequent quarters. Employee turnover is lower, consistent with skills capital raising matching and retention incentives. The one seeming exception, lower ROA, reflects the accounting treatment of compensation and benefits as a current expense instead of an investment: skill-intensive firms appear less profitable under accrual accounting precisely because their key productive input is expensed rather than capitalized. Collectively, the evidence indicates that skills capital is not just a labor cost; it is a productive intangible that complements R&D and organizational investments and contributes persistently to firm value, innovation, and growth.

Our results carry implications for research and policy. For researchers, we provide a new construct, namely skills capital, and provide a validated empirical measure for its dollar value, which has the potential to facilitate future research on how skills capital interacts with other dimensions of human capital and organizational capital. For policymakers, our evidence supports

quantitative, market-based human capital disclosure: the SEC's expanded workforce disclosure requirements remain largely qualitative, yet our measure (constructible from observable job-posting and resume data and anchored in market wage premiums) predicts valuation, growth, innovation, and retention over multiple forward quarters, making it the kind of material forward-looking information that investors will find useful. The negative ROA finding additionally raises the question of whether the accounting treatment of skilled-labor wages (fully expensed in the period incurred regardless of their multi-year productive life) is well-calibrated for an economy in which human capital is a key driver of firm value, a mismatch that capitalization rules analogous to those discussed for R&D could address.

We hope the measure we propose provides a useful tool for researchers studying the determinants of firm value, for investors seeking to understand the human capital component of intangibles, for regulators grappling with how to bring financial reporting into alignment with the intangible economy, as well as for job seekers and students who wish to make an informed decision on what skills to accumulate through education and training.

References

Abraham, K.G., Mallatt, J., 2022. Measuring human capital. *Journal of Economic Perspectives*, 36, 103–130.

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

Agrawal, A., Hacamo, I., Hu, Z., 2021. Information dispersion across employees and stock returns. *Review of Financial Studies*, 34, 4785–4831.

Babina, T., Fedyk, A., He, A., Hodson, J., 2024. Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics*, 151, 103745.

Bartik, T.J., 1991. Who benefits from state and local economic development policies? Kalamazoo, MI: W.E. Upjohn Institute for Employment Research.

Boyer, B.H., Nadauld, T.D., Vorkink, K.P., Weisbach, M.S., 2023. Discount-rate risk in private equity: Evidence from secondary market transactions. *Journal of Finance*, 78, 835–885.

Brynjolfsson, E., Rock, D., Syverson, C., 2021. The productivity J-curve: How intangibles complement general purpose technologies. *American Economic Journal: Macroeconomics*, 13(1), 333–372.

Campello, M., Gao, J., Xu, Q., 2024. Personal taxes and firm skill hiring: Evidence from 27 million job postings. *Management Science*, 70(10), 7215–7241.

Corrado, C., Hulten, C., Sichel, D., 2005. Measuring capital and technology: An expanded framework. In: C. Corrado, J. Haltiwanger, D. Sichel, Eds. Measuring Capital in the New Economy. Chicago: University of Chicago Press, 11–46.

Deming, D.J., Kahn, L.B., 2018. Skill requirements across firms and labor markets: Evidence from job postings for professionals. *Journal of Labor Economics*, 36, S337–S369.

Dey, A., Haslag, P.H., Sensoy, B.A., White, J.T., 2022. Human capital disclosure and workforce turnover. Vanderbilt Owen Graduate School of Management Research Paper.

Dinerstein, M., Megalokonomou, R., Yannelis, C., 2022. Human capital depreciation and returns to experience. *American Economic Review*, 112, 3725–3762.

Donangelo, A., 2014. Labor mobility: Implications for asset pricing. *Journal of Finance*, 69, 1321–1346.

Dorn, D., Schoner, F., Seebacher, M., Simon, L., Woessmann, L., 2025. Multidimensional skills on LinkedIn profiles: Measuring human capital and the gender skill gap. IZA Discussion Paper No. 17896.

Eisfeldt, A.L., Papanikolaou, D., 2013. Organization capital and the cross-section of expected returns. *Journal of Finance*, 68, 1365–1406.

Eisfeldt, A.L., Schubert, G., Zhang, M.B., Taska, B., 2026. Generative AI and firm values. *Journal of Finance*, forthcoming.

Ewens, M., Peters, R.H., Wang, S., 2025. Measuring intangible capital with market prices. *Management Science*, 71(1), 407–427.

Fedyk, A., Hodson, J., 2023. Trading on talent: Human capital and firm performance. *Review of Finance*, 27, 1659–1698.

Fonseca, J., Van Doornik, B., 2022. Financial development and labor market outcomes: Evidence from Brazil. *Journal of Financial Economics*, 143(1), 550–568.

Green, D., Vallee, B., 2025. Measurement and effects of bank exit policies. *Journal of Financial Economics*, 172, 104129.

Hart, O., Moore, J., 1990. Property rights and the nature of the firm. *Journal of Political Economy*, 98, 1119–1158.
Heckman, J.J., 1979. Sample selection bias as a specification error. *Econometrica*, 47, 153–161.
Hombert, J., Matray, A., 2026. Innovation booms, easy financing, and human capital accumulation. Working paper. Available at SSRN: http://dx.doi.org/10.2139/ssrn.3187093
Jäger, S., Roth, C., Roussille, N., Schoefer, B., 2024. Worker beliefs about outside options. *Quarterly Journal of Economics*, 139, 1505–1556.
Lee, D.W., Shin, H.H., Stulz, R.M., 2021. Why does equity capital flow out of high Tobin's Q industries? *Review of Financial Studies*, 34, 1867–1906.
Lev, B., 2019. Ending the accounting-for-intangibles crisis. *Accounting Review*, 94, 333–352.
Ma, S., 2025. Technological obsolescence. *Review of Financial Studies*, forthcoming.
Ma, S., Wang, W., Wu, Y., 2025. Steering labor mobility through innovation. Working paper. Available at SSRN: http://dx.doi.org/10.2139/ssrn.4678261
Marshall, A., 1890. Principles of Economics. London: Macmillan. (Book IV, Chapter VII.)
Matsa, D.A., 2018. Capital structure and a firm's workforce. *Annual Review of Financial Economics*, 10(1), 387–412.
Morck, R., Shleifer, A., Vishny, R.W., 1988. Management ownership and market valuation: An empirical analysis. *Journal of Financial Economics*, 20, 293–315.
Nishesh, N., Ouimet, P., Simintzi, E., 2024. Labor and corporate finance. *Handbook of Corporate Finance*, 647–673.
Peters, R.H., Taylor, L.A., 2017. Intangible capital and the investment-Q relation. *Journal of Financial Economics*, 123, 251–272.
Shen, M., 2021. Skilled labor mobility and firm value: Evidence from green card allocations. *Review of Financial Studies*, 34, 4663–4700.
Wallskog, M., 2025. Entrepreneurial spillovers across coworkers. *Journal of Financial Economics*, 170, 104077.
Yermack, D., 1996. Higher market valuation of companies with a small board of directors. *Journal of Financial Economics*, 40, 185–211.

Appendix A: Variable Definitions

Variable	Definition
Posting-Level Variables	
Real salary (2010 dollars)	Posted annual salary, taken as the midpoint if a range is disclosed, deflated to 2010 dollars.
Skills per posting	Number of distinct standardized skills listed in a job posting.
Has salary	Indicator equal to one if the posting reports salary information.
From staffing company	Indicator equal to one if the posting is placed by a staffing firm.
Education requirement	Minimum education requirement reported in the posting, coded as one of five categories: high school/GED, associate degree, bachelor's degree, master's degree, or Ph.D./professional degree.
Experience requirement	Minimum experience requirement reported in the posting, coded as one of five categories: 0, 1–2, 3–5, 6–9, or 10 or more years.
Skill-Premium Validation Variables	
Skill premium	Quarterly skill-level wage premium estimated from posting-level hedonic wage regressions.
Job Zone exposure	Employment-weighted average O*NET Job Zone score across occupations associated with a skill in a given skill-quarter. Job Zone ranges from 1 to 5, with higher values indicating greater preparation requirements.
Demand intensity	Skill's share of all job postings in a quarter, multiplied by 100.
Weighted skill premium	Occupation-year average of estimated skill premiums, weighted by each skill's posting share within the occupation-year.
Firm-Quarter Variables	
Skills capital	Firm-quarter Skills capital divided by lagged total assets, multiplied by 100. The measure aggregates quarter-specific skill premiums using the firm's posted occupation mix and the market-level occupation-skill mix.
Tobin's Q	Market value of equity plus book assets minus book equity, divided by book assets.
Sales growth	Year-over-year sales growth, defined as current quarterly sales divided by sales four quarters prior, minus one, multiplied by 100.
ROA	Income before extraordinary items divided by lagged total assets.
R&D/Assets	Research and development expense divided by lagged total assets, multiplied by 100.
Patent/Assets	Number of patent filings divided by lagged total assets, multiplied by 100.
Patent value/Assets	Real (2010) value of patent filings divided by lagged total assets, multiplied by 100.
SG&A/Assets	Selling, general, and administrative expense excluding R&D, divided by lagged total assets, multiplied by 100.
Capex/Assets	Capital expenditures divided by lagged total assets, multiplied by 100.
Turnover	Firm-level employee turnover rate, in percentage points.
Analyst rec.	Consensus analyst recommendation score; higher values indicate more favorable recommendations.
Log(MV)	Natural logarithm of market value of equity.
Segments	Number of Compustat business segments.

Figure 1: Time-Series of Estimated Skill Premiums for Selected High-Premium Skills

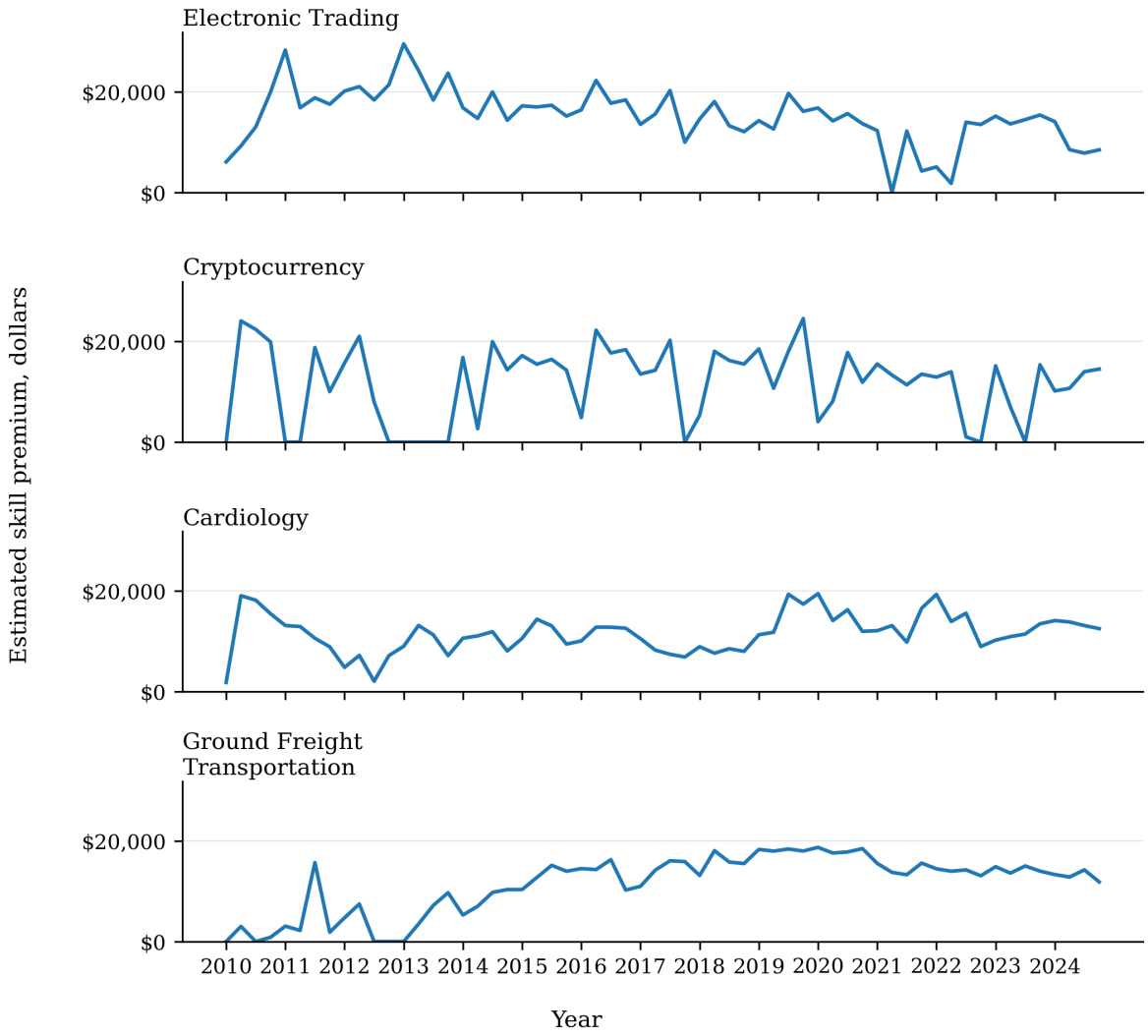
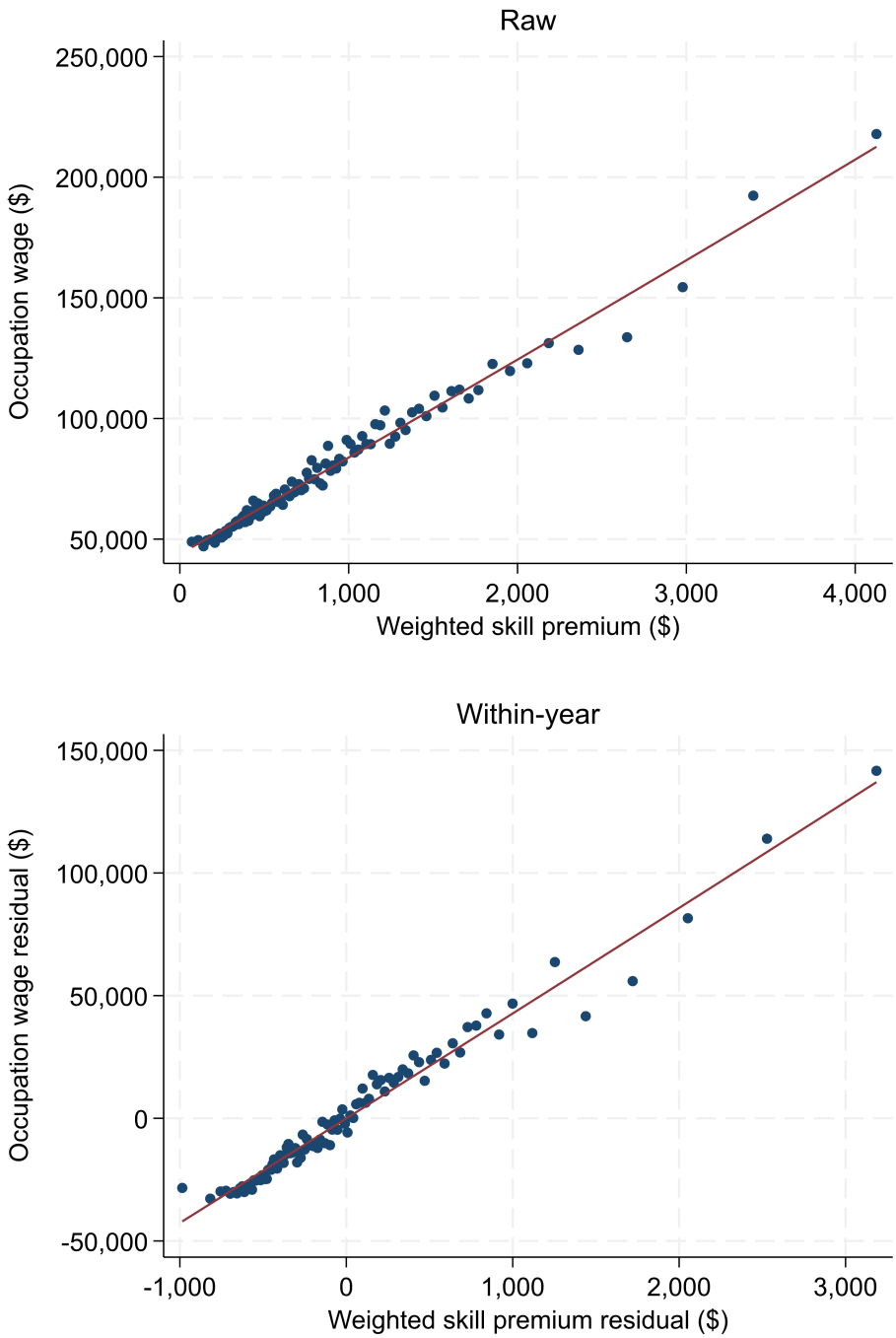


Figure 2: Occupation Wages and the Weighted Skill Premium



Notes: This figure plots the relationship between annual occupation wages and the posting-weighted average skill premium at the occupation-year level. For each occupation-year, the weighted skill premium is the average estimated skill premium across the skills appearing in the occupation's job postings, weighted by each skill's posting share. The top panel shows the raw relationship; the bottom panel plots residuals after partialling out year fixed effects, isolating within-year variation. Each point is one of 100 equal-sized bins; the solid line is a quadratic fit. Occupation wages are from the Occupational Employment and Wage Statistics (OEWS) and are inflation-adjusted. The sample spans 2010 to 2024.

Table 1: Sample Characteristics for Estimating Skill-Level Wage Premiums

Panel A: Posting-level variables

Variable	N	Mean	SD	P1	P25	Median	P75	P99
Real salary (2010 $000s)	88,878,969	50.57	32.85	15.98	27.71	38.96	63.66	175.01
Skills per posting	363,961,893	9.74	7.26	0	4	9	14	31
Has salary	363,961,893	24.42	-	-	-	-	-	-
From staffing company	363,961,893	15.32	-	-	-	-	-	-

Panel B: Categorical regressors

Category	Share (%)	Category	Share (%)
Education		**Experience**	
High school or GED	67.45	0 years	54.48
Associate degree	5.08	1-2 years	20.32
Bachelor's degree	24.37	3-5 years	18.18
Master's degree	2.13	6-9 years	4.19
Ph.D. or professional degree	0.98	10+ years	2.82

Panel C: Sample dimensions

Value	Statistic
Number of postings (full sample)	363,961,893
Number of postings (with salary)	88,878,969
Number of distinct skills	442
Number of quarters	60
Postings per quarter (mean)	6,066,032
Postings per quarter (min-max)	1,617,292-10,719,211

Notes: This table reports descriptive statistics for the posting-level sample used to estimate skill-level wage premiums. Panel A reports posting-level variables. Panel B reports the distribution of education and experience requirements. Panel C summarizes sample coverage. Wage premiums are estimated separately each quarter using postings with salary information. The sample spans 2010-2024.

Table 2: Distribution of Estimated Skill Wage Premiums

Panel A: Top 5 Skills by Mean Wage Premium

	Skill	Family	Mean
1	Electronic Trading	Finance	15,167
2	Hardware Description Languages	Engineering	14,067
3	Cryptocurrency	Finance	11,719
4	Cardiology	Health Care	11,667
5	Ground Freight Transportation	Transportation, Supply Chain, and Logistics	11,451

Panel B: Summary statistics (skill-quarter level)

Variable	N	Mean	SD	P1	P25	Median	P75	P99
Skill premium ($)	26,520	1,918.16	3,668.24	0.00	0.00	0.00	2,478.72	17,036.06
Job Zone exposure	26,520	3.54	0.42	2.30	3.33	3.65	3.81	4.40
Demand intensity	26,520	2.07	3.82	0.01	0.31	0.82	2.07	23.89

Notes: This table summarizes estimated skill wage premiums. Panel A reports the five skills with the highest average quarterly wage premiums across the sample period. Panel B reports summary statistics for skill-quarter variables used in the validation analyses. Premiums are estimated from a hedonic wage regression run each quarter separately and winsorized at the 1st and 99th percentiles prior to averaging across quarters. Skill taxonomy follows the data provider's classification.

Table 3: Construct Validation of Estimated Skill Premiums

Panel A: Skill premium and Job Zone exposure

Dep. var.: Skill premium	(1) All occupations	(2) Top 30 occupations
Job Zone exposure$_t$	2,861.00***	1,890.22***
	(705.14)	(496.88)
Observations	26,520	26,520
Adjusted R^2	0.56	0.56
Quarter FE	Yes	Yes
Skill FE	Yes	Yes

Panel B: Skill premium and labor market demand

Dep. var.: Skill premium	(1)	(2)
Demand intensity$_t$	194.72***	
	(68.04)	
Demand intensity$_{t-1}$		162.73**
		(66.98)
Observations	26,520	26,078
Adjusted R^2	0.56	0.57
Quarter FE	Yes	Yes
Skill FE	Yes	Yes

Notes: This table evaluates whether estimated skill premiums capture economically meaningful variation in labor market value. Panel A examines the relation between skill premiums and occupational complexity measured using O*NET Job Zones. Panel B examines the relation between skill premiums and labor market demand. All continuous variables are winsorized at the 1st and 99th percentiles within quarter. Standard errors clustered by skill are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Descriptive Statistics for Firm-Level Skills capital and Outcome Variables

Variable	**N**	**Mean**	**SD**	**P1**	**P25**	**Median**	**P75**	**P99**
Skills capital ($mm)	200,403	61.13	311.72	0.01	0.87	4.93	26.47	1,004.08
Skills capital/Assets (%)	200,403	2.47	4.38	0.00	0.19	0.97	2.72	28.39
Tobin's Q	200,403	2.29	2.47	0.60	1.06	1.47	2.42	16.94
Sales growth (%)	186,903	12.90	42.85	-74.74	-4.11	6.05	19.65	256.93
ROA	200,403	-0.02	0.10	-0.62	-0.01	0.00	0.02	0.12
R&D/Assets (%)	200,403	1.45	3.28	0.00	0.00	0.00	1.33	19.39
Patent/Assets	200,401	0.12	0.51	0.00	0.00	0.00	0.00	3.79
Patent value/Assets (%)	200,401	1.42	5.67	0.00	0.00	0.00	0.00	41.33
SG&A/Assets (%)	200,403	4.99	8.20	-15.46	0.53	2.99	7.34	44.47
Capex/Assets (%)	200,403	0.89	1.39	0.00	0.08	0.43	1.06	8.44
Turnover	181,965	5.91	4.08	0.00	3.49	5.20	7.41	24.44
Analyst rec.	93,683	3.60	0.77	2.00	3.00	3.50	4.00	5.00
Log(MV)	200,403	6.49	2.30	1.40	4.85	6.58	8.09	11.87
Segments	200,403	2.17	1.72	1.00	1.00	1.00	3.00	8.00

Notes: This table reports descriptive statistics for firm-quarter variables used in the main analyses. All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix A.

Table 5: Skills capital and Firm Value

	(1)	(2)	(3)
Dep. var.: Tobin's Q	t	t	t
Skills capital/Assets$_t$	0.15***	0.23***	0.24***
	(0.01)	(0.01)	(0.01)
Log(MV)$_t$	0.34***	0.91***	0.93***
	(0.01)	(0.03)	(0.03)
Capex/Assets$_t$	0.09***	0.00	0.01
	(0.02)	(0.01)	(0.01)
Segments$_t$	-0.16***	-0.08***	-0.08***
	(0.01)	(0.01)	(0.01)
ROA$_t$	-4.65***	-2.38***	-2.33***
	(0.28)	(0.18)	(0.18)
ROA$_{t-1}$	-3.11***	-1.28***	-1.19***
	(0.21)	(0.13)	(0.13)
ROA$_{t-2}$	-3.56***	-1.40***	-1.30***
	(0.20)	(0.13)	(0.13)
Observations	200,403	200,296	200,006
Adjusted R^2	0.37	0.77	0.77
Quarter FE	Yes	Yes	
SIC2 FE	Yes		
Firm FE		Yes	Yes
Quarter × SIC2 FE			Yes
Quarter × State FE			Yes

Notes: This table reports panel regressions of Tobin's Q on firm-level Skills capital. Column (1) includes quarter and SIC2 fixed effects; column (2) includes firm and quarter fixed effects; column (3) includes firm, quarter×SIC2, and quarter×state fixed effects. All continuous variables are winsorized at the 1st and 99th percentiles. Standard errors clustered by firm and calendar quarter are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Skills capital and Accounting Performance

Panel A: Sales growth

Dep. var.: Sales growth	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+4	(6) t+5
Skills capital/Assets$_t$	0.76***	1.07***	1.35***	1.58***	1.41***	1.26***
	(0.14)	(0.14)	(0.15)	(0.17)	(0.17)	(0.16)
Log(MV)$_t$	7.49***	6.89***	5.29***	2.84***	0.68	-1.40***
	(0.46)	(0.44)	(0.42)	(0.40)	(0.42)	(0.48)
Capex/Assets$_t$	2.03***	2.26***	2.13***	1.90***	1.12***	0.51**
	(0.24)	(0.24)	(0.23)	(0.21)	(0.20)	(0.20)
Segments$_t$	-0.02	-0.14	-0.07	0.08	0.07	0.19
	(0.21)	(0.19)	(0.19)	(0.19)	(0.21)	(0.20)
ROA$_t$	118.52***	25.22***	15.33***	-3.03	-91.06***	-31.32***
	(6.86)	(4.60)	(4.72)	(4.62)	(6.58)	(4.43)
ROA$_{t-1}$	-6.97	-7.47	-15.51***	-91.25***	-17.48***	-24.64***
	(4.55)	(4.56)	(4.58)	(5.87)	(4.08)	(4.56)
ROA$_{t-2}$	-35.59***	-49.01***	-104.97***	-29.32***	-24.22***	-20.84***
	(4.93)	(4.65)	(6.27)	(4.21)	(4.57)	(4.49)
Observations	186,461	186,437	185,937	184,727	182,411	176,691
Adjusted R^2	0.24	0.22	0.23	0.22	0.22	0.21
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter × SIC2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter × State FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: ROA

Dep. var.: ROA	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+4	(6) t+5
Skills capital/Assets$_t$	-0.008***	-0.005***	-0.004***	-0.003***	-0.002***	-0.002***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log(MV)$_t$	0.007***	0.010***	0.009***	0.007***	0.006***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Capex/Assets$_t$	0.001*	0.001***	0.001***	0.001*	0.000	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Segments$_t$	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	200,006	199,362	198,184	196,398	192,967	187,392
Adjusted R^2	0.65	0.64	0.63	0.63	0.63	0.63
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter × SIC2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter × State FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports panel regressions of accounting performance on firm-level Skills capital. Panel A uses four-quarter sales growth as the dependent variable. Panel B uses ROA and excludes ROA from the control vector. Columns (1)–(6) report horizons t through t+5. All specifications include firm, quarter×SIC2, and quarter×state fixed effects. All continuous variables are winsorized at the 1st and 99th percentiles. Standard errors clustered by firm and calendar quarter are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Skills capital and Innovation Outcomes

Panel A: R&D/Assets

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.: R&D/Assets	t	t+1	t+2	t+3	t+4	t+5
Skills capital/Assets$_t$	0.18***	0.13***	0.10***	0.08***	0.07***	0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Log(MV)$_t$	0.05***	-0.04*	-0.04**	-0.04**	-0.04**	-0.04*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Capex/Assets$_t$	0.03***	0.00	0.01	0.00	0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Segments$_t$	0.00	0.00	-0.01	-0.01	-0.01*	-0.02*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ROA$_t$	-5.43***	-3.37***	-2.39***	-1.69***	-1.55***	-1.27***
	(0.31)	(0.23)	(0.22)	(0.20)	(0.20)	(0.21)
ROA$_{t-1}$	-1.99***	-1.48***	-1.03***	-1.14***	-0.84***	-0.76***
	(0.19)	(0.19)	(0.17)	(0.18)	(0.18)	(0.20)
ROA$_{t-2}$	-0.84***	-0.73***	-0.90***	-0.71***	-0.70***	-0.47***
	(0.18)	(0.17)	(0.18)	(0.17)	(0.18)	(0.16)
Observations	200,006	199,558	198,405	196,678	193,270	187,723
Adjusted R^2	0.83	0.82	0.82	0.81	0.81	0.81
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter × SIC2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter × State FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Skills capital and Innovation Outcomes (Continued)

Panel B: Patent Quantity

Dep. var.: Patent/Assets	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+4	(6) t+5
Skills capital/Assets$_t$	0.01***	0.01***	0.01***	0.01***	0.00**	0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log(MV)$_t$	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Capex/Assets$_t$	0.01***	0.00**	0.00*	0.00**	0.00*	0.00*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Segments$_t$	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ROA$_t$	0.04	0.04	0.00	-0.06	0.03	-0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)
ROA$_{t-1}$	0.01	-0.02	-0.05	0.04	-0.03	0.03
	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)
ROA$_{t-2}$	-0.04	-0.03	0.03	-0.02	0.04	0.01
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)
Observations	200,004	190,019	183,697	177,597	172,130	166,273
Adjusted R^2	0.45	0.46	0.46	0.46	0.47	0.47
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter × SIC2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter × State FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Skills capital and Innovation Outcomes (Continued)

Panel C: Patent Value

Dep. var.: Patent value/Assets	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+4	(6) t+5
Skills capital/Assets$_t$	0.07***	0.05***	0.04**	0.04**	0.02	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Log(MV)$_t$	-0.15***	-0.23***	-0.29***	-0.33***	-0.38***	-0.41***
	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Capex/Assets$_t$	0.08***	0.04**	0.05***	0.05***	0.05**	0.06***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Segments$_t$	-0.05**	-0.04*	-0.04	-0.04	-0.05*	-0.05*
	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
ROA$_t$	0.16	0.24	-0.15	-0.20	0.29	-0.04
	(0.27)	(0.27)	(0.31)	(0.26)	(0.26)	(0.32)
ROA$_{t-1}$	0.15	-0.10	-0.09	0.39*	-0.04	0.32
	(0.23)	(0.26)	(0.25)	(0.24)	(0.27)	(0.24)
ROA$_{t-2}$	-0.20	-0.08	0.28	-0.07	0.21	0.17
	(0.25)	(0.24)	(0.23)	(0.24)	(0.23)	(0.27)
Observations	200,004	190,019	183,697	177,597	172,130	166,273
Adjusted R^2	0.58	0.59	0.60	0.60	0.60	0.61
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter × SIC2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter × State FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports panel regressions of innovation outcomes on firm-level Skills capital. Panel A uses R&D/Assets, Panel B uses Patent/Assets, and Panel C uses Patent value/Assets. Columns (1)–(6) report horizons t through t+5. All specifications include firm, quarter×SIC2, and quarter×state fixed effects. All continuous variables are winsorized at the 1st and 99th percentiles. Standard errors clustered by firm and calendar quarter are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Observations in Panels B and C decline at t+1 due to patent publication lags.

Table 8: Skills capital and Investment

Panel A: SG&A/Assets

Dep. var.: SG&A/Assets	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+4	(6) t+5
Skills capital/Assets$_t$	0.73***	0.57***	0.48***	0.42***	0.37***	0.31***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Log(MV)$_t$	0.02	-0.22***	-0.32***	-0.36***	-0.38***	-0.42***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Capex/Assets$_t$	0.12***	0.03	0.01	-0.03	-0.03	-0.03
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Segments$_t$	-0.03	-0.05*	-0.05**	-0.06**	-0.07***	-0.07***
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
ROA$_t$	-4.09***	-2.93***	-2.13***	-1.19**	-1.30**	-1.93***
	(0.66)	(0.56)	(0.55)	(0.55)	(0.54)	(0.53)
ROA$_{t-1}$	-1.86***	-1.04**	-0.73	-1.09**	-1.50***	-1.27***
	(0.44)	(0.41)	(0.49)	(0.45)	(0.42)	(0.41)
ROA$_{t-2}$	-1.12**	-0.94*	-1.22***	-1.74***	-1.55***	-0.80*
	(0.46)	(0.52)	(0.44)	(0.46)	(0.45)	(0.44)
Observations	200,006	199,558	198,405	196,678	193,270	187,723
Adjusted R^2	0.82	0.81	0.81	0.80	0.80	0.80
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter × SIC2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter × State FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Skills capital and Investment (Continued)

Panel B: Capex/Assets

Dep. var.: Capex/Assets	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+4	(6) t+5
Skills capital/Assets$_t$	0.04***	0.03***	0.03***	0.03***	0.03***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log(MV)$_t$	0.18***	0.16***	0.14***	0.12***	0.10***	0.07***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Segments$_t$	0.00	0.00	0.00	0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ROA$_t$	0.15**	0.05	0.22***	0.22***	0.19***	0.12*
	(0.08)	(0.06)	(0.07)	(0.06)	(0.06)	(0.07)
ROA$_{t-1}$	-0.07	0.09	0.05	0.04	0.07	0.01
	(0.06)	(0.07)	(0.05)	(0.06)	(0.06)	(0.06)
ROA$_{t-2}$	0.06	0.05	-0.01	-0.03	-0.06	0.09
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Observations	200,006	197,526	196,325	194,576	191,272	185,689
Adjusted R^2	0.61	0.61	0.61	0.61	0.61	0.61
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter × SIC2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter × State FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports panel regressions of investment outcomes on firm-level Skills capital. Panel A uses SG&A/Assets, where SG&A excludes R&D. Panel B uses Capex/Assets and excludes contemporaneous Capex/Assets from the control vector. Columns (1)–(6) report horizons t through t+5. All specifications include firm, quarter×SIC2, and quarter×state fixed effects. All continuous variables are winsorized at the 1st and 99th percentiles. Standard errors clustered by firm and calendar quarter are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Skills capital and Employee Turnover

Dep. var.: Turnover	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+4	(6) t+5
Skills capital/Assets$_t$	-0.11***	-0.05***	-0.04***	-0.03***	-0.03**	-0.02*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Log(MV)$_t$	-0.30***	-0.18***	0.00	0.11***	0.20***	0.26***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
Capex/Assets$_t$	-0.08***	-0.06***	0.00	0.00	0.02	0.02
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Segments$_t$	-0.01	0.01	0.01	0.02	0.03	0.04**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
ROA$_t$	-1.98***	-2.31***	-2.51***	-2.06***	-1.42***	-1.08***
	(0.29)	(0.32)	(0.29)	(0.30)	(0.28)	(0.30)
ROA$_{t-1}$	-1.38***	-1.06***	-0.92***	-0.40	-0.58**	-0.45
	(0.32)	(0.26)	(0.24)	(0.24)	(0.29)	(0.27)
ROA$_{t-2}$	-0.68***	-0.27	0.29	0.03	0.12	0.21
	(0.25)	(0.26)	(0.24)	(0.27)	(0.28)	(0.31)
Observations	181,443	175,010	174,696	172,857	170,470	167,460
Adjusted R^2	0.32	0.37	0.37	0.37	0.36	0.37
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter × SIC2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter × State FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports panel regressions of employee turnover on firm-level Skills capital. The dependent variable is the firm-level employee turnover rate. Columns (1)–(6) report horizons t through t+5. All specifications include firm, quarter×SIC2, and quarter×state fixed effects. All continuous variables are winsorized at the 1st and 99th percentiles. Standard errors clustered by firm and calendar quarter are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Skills capital and Analyst Recommendations

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.: Analyst rec.	t	t+1	t+2	t+3	t+4	t+5
Skills capital/Assets$_t$	0.03***	0.02***	0.02***	0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log(MV)$_t$	0.16***	0.07***	0.04***	0.01	-0.03***	-0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Capex/Assets$_t$	0.01***	0.01***	0.01***	0.00	0.00	-0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Segments$_t$	0.00	0.00	0.00	0.00	0.01	0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ROA$_t$	0.30***	0.33***	0.19***	0.28***	0.20**	0.08
	(0.07)	(0.08)	(0.06)	(0.08)	(0.08)	(0.08)
ROA$_{t-1}$	-0.03	-0.04	0.07	0.00	-0.01	-0.02
	(0.07)	(0.06)	(0.07)	(0.07)	(0.08)	(0.08)
ROA$_{t-2}$	-0.17***	-0.09	-0.15**	-0.11	-0.14**	-0.02
	(0.06)	(0.06)	(0.06)	(0.07)	(0.06)	(0.08)
Observations	92,884	90,924	88,674	86,183	83,398	80,613
Adjusted R^2	0.14	0.13	0.12	0.12	0.12	0.12
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter × SIC2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter × State FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports panel regressions of analyst recommendations on firm-level Skills capital. The dependent variable is the consensus analyst recommendation score, where higher values indicate more favorable recommendations. Columns (1)–(6) report horizons t through t+5. All specifications include firm, quarter×SIC2, and quarter×state fixed effects. All continuous variables are winsorized at the 1st and 99th percentiles. Standard errors clustered by firm and calendar quarter are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Shift-Share Reduced-Form Evidence on Skills capital and Firm Outcomes

	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+4	(6) t+5
Dep. var.: Tobin's Q						
Shift-share IV_t	0.27***	0.23***	0.21***	0.19***	0.17***	0.15***
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Dep. var.: Sales growth						
Shift-share IV_t	0.60***	0.98***	1.28***	1.55***	1.49***	1.34***
	(0.17)	(0.16)	(0.16)	(0.19)	(0.20)	(0.20)
Dep. var.: ROA						
Shift-share IV_t	-0.01***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Dep. var.: R&D/Assets						
Shift-share IV_t	0.17***	0.13***	0.10***	0.08***	0.07***	0.06***
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Dep. var.: Patent/Assets						
Shift-share IV_t	0.01***	0.01***	0.01***	0.01***	0.01*	0.01*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Dep. var.: Patent value/Assets						
Shift-share IV_t	0.04*	0.03	0.01	0.01	−0.01	−0.02
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Dep. var.: SG&A/Assets						
Shift-share IV_t	0.72***	0.59***	0.52***	0.49***	0.45***	0.39***
	(0.06)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)
Dep. var.: Capex/Assets						
Shift-share IV_t	0.04***	0.03***	0.03***	0.03***	0.03***	0.03***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)
Dep. var.: Turnover						
Shift-share IV_t	−0.11***	−0.14***	−0.13***	−0.13***	−0.12***	−0.11***
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Dep. var.: Analyst rec.						
Shift-share IV_t	0.04***	0.03***	0.03***	0.03***	0.03***	0.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Notes. This table reports reduced-form regressions of firm outcomes on the shift-share IV. Each dependent-variable block reports a separate set of regressions across horizons t through $t+5$. All specifications include the control variables Log(MV), Capex/Assets, Segments, ROA, lagged ROA, and twice-lagged ROA, as well as firm, quarter×SIC2, and quarter×state fixed effects. All continuous variables are winsorized at the 1st and 99th percentiles. Standard errors clustered by firm and calendar quarter are reported in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Online Appendix

Table OA1: Skill Families — Distribution of Mean Wage Premiums

Skill Family	N skills	Mean	Median	Cross-skill SD
Finance	29	4,171	3,458	4,206
Energy and Utilities	12	3,567	2,560	3,184
Sales	12	3,483	2,237	3,523
Business	19	2,774	2,071	2,548
Transportation, Supply Chain, and Logistics	14	2,760	812	3,697
Engineering	30	2,651	2,181	2,970
Health Care	55	2,540	1,578	3,060
Information Technology	70	2,226	861	2,549
Property and Real Estate	3	2,215	391	3,504
Analysis	11	1,943	1,385	2,247
Design	9	1,688	727	2,128
Science and Research	16	1,524	67	2,470
Marketing and Public Relations	13	1,408	1,043	1,843
Architecture and Construction	15	1,297	332	2,654
Human Resources	7	945	776	898
Manufacturing and Production	17	915	37	1,409
Environment	11	871	377	1,283
Law, Regulation, and Compliance	11	773	369	1,146
Media and Communications	11	615	25	1,347
Economics, Policy, and Social Studies	4	536	600	174
Performing Arts, Sports, and Recreation	5	508	235	707
Public Safety and National Security	8	469	575	455
Agriculture, Horticulture, and Landscaping	7	457	81	969
Customer and Client Support	5	277	0	566
Personal Care and Services	4	250	55	429
Social and Human Services	4	230	252	209
Education and Training	11	214	50	463
Hospitality and Food Services	5	104	8	202
Maintenance, Repair, and Facility Services	13	55	0	174
Administration	6	0	0	0
Physical and Inherent Abilities	5	0	0	0

Notes: This table reports the distribution of mean estimated wage premiums by skill family. Premiums are estimated from a hedonic wage regression run each quarter separately and winsorized at the 1st and 99th percentiles prior to averaging across quarters. Skill taxonomy follows the data provider's classification.

Table OA2: Robustness: Alternative Skills capital Estimation Methods

	(1)	(2)	(3)
	OLS	NNLS	Heckman
Dep. var.: Tobin's Q	t	t	t
Skills capital/Assets$_t$	0.432***	0.291***	0.410***
	(0.018)	(0.011)	(0.017)
ROA$_t$	-2.358***	-2.205***	-2.313***
	(0.159)	(0.156)	(0.158)
ROA$_{t-1}$	-1.324***	-1.248***	-1.297***
	(0.127)	(0.126)	(0.127)
ROA$_{t-2}$	-1.382***	-1.328***	-1.382***
	(0.127)	(0.126)	(0.126)
Log(MV)$_t$	0.950***	0.985***	0.970***
	(0.025)	(0.026)	(0.025)
Capex/Assets$_t$	0.029***	0.026***	0.030***
	(0.010)	(0.010)	(0.010)
Segments$_t$	-0.077***	-0.076***	-0.076***
	(0.009)	(0.009)	(0.009)
Observations	199,996	199,996	199,996
Adjusted R^2	0.781	0.786	0.783
Quarter × SIC2 FE	Yes	Yes	Yes
Quarter × State FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes

Notes: This table examines the robustness of the relation between Skills capital and firm value to alternative procedures for estimating Skills capital. The dependent variable is asset-based Tobin's Q. Columns (1)–(3) construct Skills capital using skill premiums estimated from OLS, NNLS, and Heckman selection specifications, respectively. The main specification reported elsewhere in the paper combines the Heckman correction with NNLS estimation. All regressions include firm, quarter×SIC2, and quarter×state fixed effects. All continuous variables are winsorized at the 1st and 99th percentiles. Standard errors clustered by firm and calendar quarter are reported in parentheses. Constants are omitted for brevity. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table OA3: Skills capital and Firm Value – Alternative Q Measures

	Equity-based Tobin's Q			Total-value Tobin's Q		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.	Equity Q	Equity Q	Equity Q	Total Q	Total Q	Total Q
Skills capital/Assets$_t$	0.288***	0.496***	0.514***	0.065***	0.135***	0.131***
	(0.030)	(0.035)	(0.034)	(0.012)	(0.015)	(0.014)
Log(MV)$_t$	0.896***	1.833***	1.855***	0.394***	0.964***	0.970***
	(0.049)	(0.074)	(0.078)	(0.028)	(0.055)	(0.056)
Capex/Assets$_t$	0.213***	0.066**	0.094***	-0.019	-0.019	-0.006
	(0.041)	(0.029)	(0.029)	(0.020)	(0.013)	(0.014)
Segments$_t$	-0.394***	-0.171***	-0.179***	-0.241***	-0.079***	-0.084***
	(0.037)	(0.041)	(0.040)	(0.028)	(0.015)	(0.016)
ROA$_t$	-9.407***	-7.697***	-7.730***	-1.022***	0.184	0.130
	(0.852)	(0.798)	(0.779)	(0.326)	(0.231)	(0.224)
ROA$_{t-1}$	-5.785***	-4.116***	-3.992***	-1.422***	-0.264	-0.222
	(0.712)	(0.588)	(0.581)	(0.258)	(0.201)	(0.188)
ROA$_{t-2}$	-6.258***	-3.421***	-3.187***	-2.471***	-0.855***	-0.764***
	(0.712)	(0.572)	(0.560)	(0.336)	(0.242)	(0.224)
Observations	185,346	185,228	184,866	158,835	158,728	158,308
Adjusted R^2	0.153	0.541	0.545	0.220	0.768	0.778
Quarter FE	Yes	Yes		Yes	Yes	
SIC2 FE	Yes			Yes		
Firm FE		Yes	Yes		Yes	Yes
Quarter × SIC2 FE			Yes			Yes
Quarter × State FE			Yes			Yes

Notes: This table reports panel regressions of alternative Tobin's Q measures on firm-level Skills capital. Columns (1)–(3) use an equity-based Tobin's Q measure, and columns (4)–(6) use a total-value Tobin's Q measure. Columns (1) and (4) include quarter and SIC2 fixed effects; columns (2) and (5) include firm and quarter fixed effects; columns (3) and (6) include firm, quarter×SIC2, and quarter×state fixed effects. All continuous variables are winsorized at the 1st and 99th percentiles. Standard errors clustered by firm and calendar quarter are reported in parentheses. Constants are omitted for brevity. *** p<0.01, ** p<0.05, * p<0.1.