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Internal Versus Market Pay References in Knowledge-Intensive Firms

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Abstract. How do firms balance market competitiveness with internal cohesion when setting employee pay? We examine this question using confidential compensation data on 19 million U.S. employees across 479 firms varying in knowledge intensity. We construct precise pay reference groups: internal benchmarks based on skill-equivalent peers across functions and market benchmarks based on same occupation, skill level, and region at other firms. We find that in low knowledge-intensity firms, pay is equally sensitive to both internal and market benchmarks, whereas in high knowledge-intensity firms, pay becomes decoupled from market forces and aligns with internal benchmarks. Internal pay alignment also increases following chief executive officer transitions that prioritize innovation. These patterns are driven by high-skilled employees in roles requiring complex problem-solving and collaboration. Moreover, firms with greater internal pay alignment generate more patents, including breakthrough innovations. Altogether, our findings reveal that although some firms maintain close market alignment, knowledge-intensive firms appear to decouple pay from market forces. This is particularly the case for their skilled workers, consistent with firms prioritizing internal social dynamics in contexts where complex problem-solving and collaboration are important for value creation.

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1. Introduction

How do firms balance market and internal forces when setting employee pay? Research in the "theory of the firm" tradition has long recognized that firms operate simultaneously as economic actors competing in markets (e.g., Holmström 1999) and as social communities that coordinate production internally (Barnard 1938, Selznick 1948). Managing the firm as both a market actor and a social community creates a tension for leaders; competitive pressures demand market responsiveness, whereas effective internal cooperation requires trust and cohesion (Kogut and Zander 1992, 1996; Mahoney and Kor 2015). This tension has likely intensified in recent decades as firms increasingly rely on collaborative inputs involving knowledge and creativity (Wuchty et al. 2007, Groysberg et al. 2008, Deming 2022) while simultaneously facing pressure for more market-oriented employment relationships (Cappelli 1999, Bidwell et al. 2013). An important domain where this challenge manifests is compensation; firms must decide how much to align employee pay with external market rates while maintaining internal cohesion (Ethiraj and Garg 2012, Neckebrouck and Kryscynski 2024).

Prior research has highlighted the internal organizational challenges involved in setting compensation. External factors, such as labor market power, bargaining dynamics, and occupational pay norms, shape compensation (Coff 1997, 1999; Molloy and Barney 2015), yet strictly adhering to external rates can create disparities among employees within the firm. Studies find that greater internal pay disparities, particularly when they are perceived as unfair, lead to increased turnover, lower productivity and satisfaction, and unethical behavior (Carnahan et al. 2012, Obloj and Zenger 2017, Kacperczyk and Balachandran 2018). To mitigate these costs, firms compress pay differences among employees and mute incentives (Zenger 1992; Gartenberg and Wulf 2017, 2020), practices that prioritize internal equity over incentive provision (Larkin et al. 2012). Yet, we know little about how firms balance these drivers against market forces when setting pay. This is the aim of our study.

Our study examines how firms navigate this tension by analyzing how their relative reliance on internal versus market pay benchmarks varies with the nature of their work. We focus on variation in firm knowledge intensity and employee skill level as key

dimensions that shape the importance of internal cohesion relative to market alignment (Kogut and Zander 1992, 1996). Knowledge-intensive firms face a particular challenge in that value creation requires collaboration among diverse specialists, such as engineers, scientists, designers, and marketers, who operate in distinct labor markets with potentially divergent pay rates (Karim and Kaul 2015). If these firms strictly adhere to market benchmarks, they risk creating internal disparities that undermine the cooperation needed for innovation (Itoh 1991, Kretschmer and Puranam 2008). Conversely, firms whose work is more routine and modular may find it both feasible and efficient to maintain market alignment. By examining how pay sensitivity to internal versus market benchmarks varies these settings, we can understand how firms resolve the fundamental tension between market competitiveness and internal cohesion.

Understanding how firms resolve this tension requires data that permit construction of precise internal and market reference groups. To construct these benchmarks, we obtain confidential data from a leading compensation consultancy whose benchmarking services require detailed classification of jobs by skill level, occupation, and geographic region. The data are extensive, covering nearly 19 million employee records across 479 public and private companies within the United States. The public companies comprise 19.16% of total market capitalization of all public companies within the United States, whereas the private companies are also large. This combination of detailed job classifications with broad coverage allows us to construct reference groups specific to each employee. Our market pay benchmark is defined as the average pay of workers at other firms in the same occupation, skill level, and region. Our internal pay benchmark is defined as average compensation of employees within the same firm and same skill level but drawn from different functions. We construct these benchmarks for each focal employee data and then, measure the sensitivity of employee pay to these two benchmarks.

Our analysis yields three main findings. First, we find that internal pay sensitivity increases with both firm knowledge intensity and employee skill level. In low knowledge-intensive firms, pay is equally sensitive to internal and market benchmarks, whereas in high knowledge-intensive firms, pay is highly sensitive to internal pay and insensitive to market pay. A similar pattern holds for low- and high-skilled workers; among low-skilled workers, pay is equally sensitive to internal and market pay, whereas among high-skilled workers, pay is highly sensitive to internal pay and insensitive to market pay. This pattern is most pronounced at the intersection of high knowledge intensity and high skill levels.

To further identify the link between knowledge intensity and pay sensitivity, we study CEO transitions to examine how pay orientation changes when new leaders announce new strategic priorities. We find that when new CEOs prioritize innovation, firms shift toward internal pay orientation, particularly for skilled workers, and when CEOs prioritize other strategies, firms exhibit no such change. These patterns suggest that innovation and internal pay orientation are complementary strategic choices rather than merely reflections of other omitted factors.

Second, we explore why we observe the patterns above. Specifically, we test whether complex problem-solving and collaboration requirements account for differences in pay orientation. We do this by encoding the roles of our focal employees with estimates of their complex problem-solving intensity and collaboration intensity. We find that roles requiring complex problem-solving and particularly those combining intensive problem-solving with intensive collaboration exhibit the strongest internal pay orientation.

Third, we explore a key implication of this interpretation: that internal pay orientation should predict better innovation outcomes. We find this to be the case; firms with greater internal pay alignment generate more patents overall, more highly cited patents, and more breakthrough patents. Consistent with our proposed mechanism, we find that the relationship between internal pay orientation and innovation performance is particularly pronounced among complex problem-solving and collaborative jobs. These finds together suggest that internal pay orientation enables or at least is consistent with the type of crossfunctional, complex problem-solving required for successful innovation.

Our study makes several contributions. First, we contribute to central conversations on how to structure incentives to foster cooperation (e.g., Kretschmer and Puranam 2008). This challenge is particularly acute in innovative firms, where specialists must collaborate to solve complex problems in ways that defy formal contracts (Simon 1960, Arrow 1974, Kogut and Zander 1992, Nickerson and Zenger 2004, Kretschmer and Puranam 2008). Prior work on incentives in innovative firms has largely emphasized mechanisms that reward long-term success for individuals (Lerner and Wulf 2007, Azoulay et al. 2011, Manso 2011, Ederer and Manso 2013). We advance this research by showing that pay is not only a tool for individual motivation but also, a social mechanism for incentivizing collaboration. Harmonizing pay practices across functions to foster internal cooperation may be an important yet previously underexplored driver of innovative output.

Our study also contributes to active research that explores the relationship between economic and social factors within organizations, such as incentives, fairness, and social comparison (e.g., Nickerson and Zenger 2008, Larkin et al. 2012, Gartenberg and Zenger 2023). Prior research has shown that internal pay dispersion

has detrimental effects on performance and employee turnover (Pfeffer and Langton 1993, Siegel and Hambrick 2005, Carnahan et al. 2012, Obloj and Zenger 2017) and that firms compress pay differences and dampen incentive pay to mitigate negative effects of social comparison (Wade et al. 2006, Gartenberg and Wulf 2017). To the extent that our findings are explained by social factors, our paper shows that their influence is not uniform across settings but instead, concentrated in high-innovation, high-skilled environments.

Last, we contribute to the literature on the role of firms in labor markets. A long-standing question in this field is whether an individual's earnings are primarily determined by whom they work for or by market forces (Lazear and Oyer 2004, Bidwell 2011, Bidwell and Keller 2014, Card et al. 2018). Our findings reveal an interesting and unintuitive pattern in how knowledge-intensive firms manage talent markets. Conventional labor economics would predict that high-skilled workers with strong outside options would command market-aligned wages and that firms deviating from market rates would lose critical talent. Yet, we find the opposite; firms that are most reliant on knowledge capital are also those most decoupled from market pay. We find that firms with the highest internal pay orientation pay the largest premium over market rates to achieve this internal alignment. This suggests that knowledge-intensive firms are not simply compressing pay to avoid social comparison costs but rather, investing in a costly organizational strategy that prioritizes internal coherence over market efficiency. Our study, therefore, has implications for the ongoing discussion about the firm's role in increasing income inequality in the population (Barth et al. 2016, Cobb 2016, Song et al. 2019, Amis et al. 2020, Gartenberg and Wulf 2020, Wallskog et al. 2026). One potential mechanism driving wage disparities within and across firms is that within high-skill and knowledge-intensive settings, pay becomes effectively decoupled from market forces, whereas in other settings, it does not. Our findings support the intuition that as the economy becomes increasingly knowledge intensive, we will see a growing divergence in pay between innovative firms and their less innovative peers as well as between high- and low-skilled workers.

The remainder of our paper is structured as follows. Section 2 provides our research question. Section 3 describes the research design, including our overall approach, data, and benchmark construction. Section 4 provides the results. Section 5 presents a discussion of the implications of our findings, and Section 6 concludes.

2. Background

2.1. Complex Problems and Knowledge-Intensive Organizations

We begin by examining the nature of problems that organizations face and how this shapes their compensation strategies. Organizations have long been characterized as systems that integrate dispersed knowledge to solve problems (Simon 1960, Lawrence and Lorsch 1967, Arrow 1974, Kogut and Zander 1992, Kretschmer and Puranam 2008). They achieve this by differentiating knowledge into specialized domains and then, integrating across areas, generating solutions that neither individuals nor markets can easily reproduce.

The nature of these problems addressed by organizations varies along a continuum. At one end are routine problems with well-defined solutions and clear interfaces between functions. At the other end are complex problems requiring novel integration of diverse knowledge in ways that are difficult to specify ex ante (Simon 1960, Baldwin and Clark 2000, Nickerson and Zenger 2004). Although most organizations face a mix of both, knowledge-intensive firms more frequently encounter these complex problems that demand tight integration across domains (Iansiti and Clark 1994, Adler 1995, Ethiraj and Levinthal 2004, Karim and Kaul 2015). Consider Tesla's early electric vehicle development, which demanded an integrated solution involving battery design, thermal management, vehicle architecture, manufacturing processes, power electronics, software, and charging systems among others. For Tesla during this period, each domain's choices shaped solution spaces for others. Similarly, Apple's iPhone emerged not from isolated technical advances but architectural integration across chip design; camera technology; image processing; and other software, materials, and manufacturing (Podolny and Hansen 2020).

In contrast, organizations in more mature markets typically confront near-decomposable problems, where interdependencies are limited and well specified and the benefits often arise from scale, predictability, and efficiency. For example, large retailers optimize supply chains, consumer banks standardize lending decisions, and airlines maximize yield. These are challenging activities but ones that generally exist within established architectures with well-defined interfaces between functions (Baldwin and Clark 2000). For instance, a bank's loan underwriters can largely work independently from its mobile app team because the interdependencies between these groups are limited and well specified.

This variation in problem structure creates different organizational requirements, including distinct requirements for collaboration.

2.2. Collaboration, Complex Problems, and Innovation

The nature of the problem-solving drives the form of collaboration required within organizations. Knowledge-intensive work often requires crossfunctional collaboration that extends beyond traditional team production. In standard team production, workers jointly produce a single output, such as workers on assembly lines or in

garment production (Hamilton et al. 2003, Boning et al. 2007), where free riding is the central concern (Alchian and Demsetz 1972, Holmström 1982). In contrast, knowledge-intensive collaboration involves discretionary cooperation across specialists who maintain distinct goals and responsibilities but whose work benefits from knowledge-sharing and mutual adjustment (Iansiti 1995). This collaboration requires specialists to voluntarily share tacit knowledge, iterate on partially formed ideas, and adapt domain-specific solutions based on insights from other areas (Henderson and Cockburn 1994, Smith et al. 2005). Such contributions are inherently discretionary and difficult to specify in formal contracts (Holmström 1989). The need for this integration intensifies with specialization; as knowledge becomes more specialized, the interdependence among specialists typically increases, requiring greater coordination to achieve integrated solutions (Simon 1991).

Empirical research on innovation confirms the importance of such crossfunctional collaboration. Nickerson and Zenger (2004) argue that consensus-based (lateral) hierarchies are better matched to complex problem-solving than authority-based (vertical) hierarchies or market mechanisms because they allow for the unstructured knowledge exchange and mutual adjustment often required in these settings. Monteverde (1995) documents how "unstructured technical dialog" between design and manufacturing drives innovation in semiconductor firms. Podolny and Hansen (2020) attribute Apple's resurgence to deep collaboration across specialist functions rather than technical superiority in any single domain. Conversely, Henderson and Clark (1990) show that incumbent firms often fail at architectural innovation when established organizational structures and routines preempt the collaboration needed to reconceptualize how components work together.

These collaborative requirements create a particular challenge for compensation; the specialists who must work together often operate in distinct labor markets with different prevailing wage rates. As we discuss next, this creates tension between maintaining internal cohesion and responding to external market forces.

2.3. Compensation in Knowledge-Intensive Firms

The collaborative requirements identified above create a fundamental challenge for compensation design. To be effective, pay systems must balance the need for internal collaboration, which benefits from coherence, with external market forces, which demand competitive alignment. We review each competing force and then derive predictions for how firms resolve this tension.

2.3.1. Drivers of Internal Pay Orientation.

Firms, particularly those that are knowledge intensive, face the challenge of incentivizing crossfunctional collaboration. Empirical evidence shows that group incentives can align collective effort in traditional team production (Hamilton et al. 2003, Boning et al. 2007), and these settings assume specified outputs and clear team boundaries (Alchian and Demsetz 1972, Holmström 1982), conditions rarely met in the lateral hierarchies of innovative organizations (Nickerson and Zenger 2004).

Sustaining collaboration across specialists depends on employees' perceptions of fairness. Employees form reference groups within organizational boundaries, within which they compare pay (Festinger 1954, Nickerson and Zenger 2008, Gartenberg and Wulf 2017). Pay disparities, especially if they are perceived to arise from playing field differences across peers (e.g., Adams 1963), can undermine cooperation. Evidence from innovative settings supports this logic. Zenger (1992) finds pay compression among engineers in high-tech firms, and Yanadori and Cui (2013) find that higher pay dispersion negatively predicts innovation outcomes within research and development (R&D) teams. Although these studies focus on within-occupation compression, the logic extends to crossfunctional contexts that rely on cooperation. When engineers must work with designers, manufacturing specialists, and software developers, their reference group could broaden to encompass skill-equivalent peers across the organization (Nickerson and Zenger 2008). Consistent with this, Gartenberg and Wulf (2017, 2020) document pay compression across business units in multibusiness firms, even when they span diverse industries, that they attribute to fairness considerations inside the organization. Internal pay alignment can thus mitigate social comparison costs and sustain the voluntary collaboration on which knowledge-intensive work depends.

2.3.2. Drivers of Market Pay Orientation.

Despite these internal factors, external labor markets exert strong influence on wage setting (Card 2022). The employment relationship has become more market oriented (Bidwell et al. 2013), with firms and employees routinely benchmarking against market rates (Bizjak et al. 2008, Jäger et al. 2024). These market comparisons shape compensation in ways that reflect the relative bargaining positions of firms and employees (Coff 1997, 1999; Molloy and Barney 2015).[1] When employees possess scarce or valuable skills, competition can compel firms to align compensation upward with prevailing market rates to attract and retain talent (Gerhart and Milkovich 1990, Lazear and Oyer 2004), whereas more abundant and substitutable skills expose employees to downward pressure on wages (Acemoglu and Autor 2011). These market forces reflect supply and demand dynamics that vary substantially across occupations and skill levels (Card et al. 2018, Wallskog et al. 2026). Whichever their direction, these external pressures pull firms toward aligning pay toward market rates, even when this may complicate collaboration.

2.3.3. Internal-Market Tension and Predictions. This tension between internal alignment and market competitiveness is present in all firms but varies in salience. Knowledge-intensive firms depend more heavily on voluntary cooperation among specialists from different labor markets, making internal cohesion particularly valuable. Less knowledge-intensive firms, with more modular work and clearer boundaries between functions, may find market alignment both feasible and efficient. This leads to three predictions.

Prediction 1. Internal pay orientation will be stronger in knowledge-intensive firms (relative to other firms), reflecting their reliance on specialized knowledge and collaborative problem-solving.

Prediction 2. Internal pay orientation will be stronger for high-skill positions (relative to other positions), where specialized knowledge and collaborative problem-solving are most valuable.

Prediction 3. Internal pay orientation will be strongest among high-skill positions in knowledge-intensive firms, where demand for specialized knowledge and collaborative problem-solving is greatest.

3. Research Design

We now turn to our analysis, which aims to explore pay patterns based on these three predictions, the mechanisms underlying them, and implications for innovation performance.

3.1. Structure of Analysis

We employ a three-part analysis. Our first analysis reports patterns according to the three predictions at the end of Section 2 on the relationship between internal pay orientation, knowledge intensity, and skill level. Our second analysis tests the mechanism, exploring whether complex problem-solving and collaboration can account for the relationships reported in the first part. Our third analysis examines implications for innovation outcomes.

3.1.1. Pay Orientation, Knowledge Intensity, and Employee Skill. Our first analysis analyzes the relative sensitivity of pay to internal versus market benchmarks. We begin by measuring baseline sensitivities for the full sample. We then report how these sensitivities change with knowledge intensity and employee skill level along with the interaction between these two factors.

This preliminary analysis faces the identification challenge that unobserved characteristics may drive both firms' pay orientation and their knowledge intensity, making it difficult to interpret our findings as reflecting deliberate decisions rather than omitted factors. To address this challenge, we analyze chief executive officer (CEO) transitions to examine how pay orientation adjusts after new leaders announce different strategic priorities. We discuss the specifics of the analysis in Section 4 prior to presenting our results.

3.1.2. Mechanism Test: Complex Problem-Solving and Collaboration. Our second analysis explores whether our mechanism, the greater need by knowledge-intensive firms to incentivize complex problem-solving and collaboration, drives internal pay orientation. To test this mechanism, we conduct a two-step analysis. First, we examine whether jobs that demand complex problem-solving and intensive collaboration are more common in high-innovation firms and among high-skill employees. Second, we assess whether these types of jobs exhibit higher internal pay orientation. We discuss how we construct measures of complex problem-solving and collaboration in Section 4 prior to presenting results.

3.1.3. Innovation Outcomes Analysis. Our third analysis examines the association between internal pay orientation and innovation outcomes. We construct a panel of firm-year measures of internal pay sensitivity and market pay sensitivity, and we merge these with patent data to analyze how internal pay sensitivity predicts innovation quantity (patent and publication counts), quality (citations), and breakthrough innovations.

Additionally, we use our measures of complex problem-solving and collaboration intensity from our mechanism analysis to examine whether these relationships are driven by workers engaged in complex, collaborative work. Although this third analysis is not causal, we adopt the approach of earlier innovation studies and conduct the analyses by lagging explanatory variables (internal and market pay sensitivities) and controlling for factors known to influence innovation, including R&D spending and firm characteristics.

In summary, our research design explores evidence for the three predictions presented at the end of Section 2, whether these patterns are supported by our mechanism of complex problem-solving and collaboration shaping pay orientation, and their implications for innovation. We now turn to detailed discussion of our data (Section 3.2), measure construction (Sections 3.3 and 3.4), and model specification (Section 3.5).

3.2. Data

Our primary data set consists of compensation data provided by a leading compensation consultancy. The data set contains 18,974,767 compensation records of employees across 479 companies based in the United States from 2008 to 2020. The data cover a substantial proportion of companies across the United States, with the public companies in the sample accounting for 19% of the market capitalization of the publicly

traded companies in the United States. The consultancy provided us with all of their data for employees working at companies based in the United States.

The database was assembled to benchmark compensation for clients both against the market and within the organization. To this end, every employee in the data set is tagged with *Skill Level*, *Function*, *Occupation*, and *Region*, allowing us to construct detailed and precise measures of internal and market benchmarks. *Skill Level* is the central measure for benchmarking pay within and across firms, and it is a standardized cardinal measure of skill that ranges from level 1 to level 22.[2] Importantly, although the measure increases with job level within the organization, it is not equivalent to hierarchical level inside an organization. Instead, it varies within hierarchical levels and occupations with the tasks required, and it is intended as a reference level within which pay can be compared within and across firms. In fact, although we refer to it as *Skill Level* for generality within the paper, the consultancy refers to it as "reference level," reflecting its usage as the basis for comparisons. As such, this measure forms the core of the consultancy's ability to compare and benchmark the worth of different jobs across occupations, industries, regions, and firms, and we similarly use it for our analysis.[3]

Function includes 61 categories, such as "retail operations." *Occupation* is nested within *Function* and consists of 206 detailed categories. For example, the "retail operations" function includes occupations such as "retail operations sales staff," "store operations," "supervision and sales staff," and others (we provide examples of occupations by skill level in Table A.8 in the Online Appendix and examples of occupations nested within functions in Table A.2 in the Online Appendix). *Region* includes 10 categories, with 5 categories corresponding to metropolitan areas and 5 categories corresponding to nonmetro regions of the United States: the New York Metro Area, the Chicago Metro Area, the Texas Metro Dallas and Houston, Northern California (primarily the San Francisco Bay Area), Southern California (primarily the Greater Los Angeles Area), Western States, Southern States, Northeast States, Midwest States, and missing.

3.3. Benchmark Construction

We create two benchmarks for our study, which we refer to as *Internal Pay* and *Market Pay*. To create these benchmarks, we employ a two-step approach that avoids the problem of mechanical correlation between the dependent variable and the explanatory variables.

In the first step, we partition our data set into two parts: one part that we set aside to be used for the dependent variable and the second part that we use to construct *Internal Pay* and *Market Pay*. To do this, we assign the 18,974,767 employee records in our data set into 177,540 groups, reflecting unique combinations of "firm-*Occupation-Skill Level-Region-Year*." From each combination, we select the median-paid employee as our dependent variable. This subset of data, therefore, includes 177,540 employees that we refer to as *Focal Employee*.

In the second step, we use the remaining 18,797,227 employees (18,974,767 minus 177,540 *Focal Employees*) to construct our benchmarks of *Internal Pay* and *Market Pay*. For a focal employee, the *Internal Pay* benchmark is calculated as the log of average cash compensation (the sum of the base salary and cash bonuses) of her internal reference group. There is no definitive way to designate an internal reference group, and research has shown that people use multiple reference groups against which to compare themselves (e.g., Festinger 1954). For this study, we define the internal reference group as all employees who (i) work at the same firm as the focal employee and (ii) are at the same skill level (iii) in the same year but critically, (iv) are outside the focal employee's functional area. Consider the example of an employee in 2017 who works for a large retailer ("large retailer A") at skill level 3 and in the occupation "retail operations sales staff" within the "retail operations" function ("large retailer A-skill level 3-retail operations sales staff-2017"). This focal employee's internal reference group, therefore, consists of employees who also work for "large retailer A" in 2017 at skill level 3 but *outside* the "retail operations" function (drawn from functions such as "administration/support/service" and "loss prevention"). This definition is a research design choice that we make to limit, to the extent possible, the degree to which team production is driving internal pay comovement. For example, those in "retail operations"—even if outside the sales staff—may obtain similar pay because they work together to improve sales across stores.[4] Although this may still occur across functions, it is less likely to be the case that those falling within our definition of internal reference groups engage in traditional team production.[5]

For our market benchmark, we construct *Market Pay* as the log of average cash compensation of the market reference group for each focal employee. Specifically, our market reference group includes all employees in our data set who meet the following criteria: (i) work at the same skill level as the focal employee and (ii) are employed in the same occupation (iii) in the same region (iv) in the same year (v) at firms other than the focal employee's employer. To illustrate, consider our previous example of a focal employee ("large retailer A-skill level 3-retail operations sales staff-New York Metro-2017"). The market reference group for this employee consists of all individuals at skill level 3 working in the "retail operations sales staff" occupation in the "New York Metro Area" in 2017 at any other firm except for "large retailer A." This definition of the market reference

group allows us to capture the most relevant external market comparisons for each focal employee.

Once we construct these benchmarks for each "firm-*Occupation-Skill Level-Region-Year*" combination, we merge them with our individual *Focal Employee* subsample to create an analysis data set with 177,540 employee-level observations, their *Market Pay* and *Internal Pay* benchmarks, and relevant controls.

3.4. Dependent Variable

Our dependent variable is *Employee Pay*, a log of cash compensation (the sum of the base salary and cash bonuses) of the focal employee. We use cash compensation as our primary measure rather than total compensation (cash compensation plus long-term incentives (LTIs)) to avoid concerns that LTI valuation may induce mechanical correlations between our internal pay benchmark and the focal employee pay. In Tables A.3 and A.4 in the Online Appendix, we replicate our analysis with LTI included in our pay measure, with the unchanged results.

3.5. Model

We estimate our main model as follows:

$$\begin{aligned} EmployeePay_{iosrt} = \alpha + \beta_1 InternalPay_{iosrt} \\ + \beta_2 MarketPay_{iosrt} + \eta_{iosr} + \nu_t \\ + F_{it} + \epsilon_{iosrt}, \end{aligned} \quad (1)$$

where the subscript i denotes a firm, o denotes an occupation, s denotes a skill level, r denotes a region, and t denotes a year. *EmployeePay* is our dependent variable, a log-transformed cash compensation of the *Focal Employee*. *InternalPay* and *MarketPay* are the main explanatory variables. η represents "firm-*Occupation-Skill Level-Region*" four-way interacted fixed effects. ν represents *Year* fixed effects. With these fixed effects, the estimates of the model can be interpreted as the sensitivity of changes in pay and to changes in the two pay benchmarks over time. To absorb performance shocks, we also include two measures of firm performance: *Return on Assets* and log *Sale* represented by F_{it}. The coefficient on *InternalPay* estimates the sensitivity of employee pay to the internal pay benchmark. The coefficient on *MarketPay* estimates the sensitivity of employee pay to the market pay benchmark. Standard errors are clustered at a firm level because compensation policies and benchmarking practices are set at the firm, not the firm-year, level (Abadie et al. 2023).

Lastly, we weight each observation by the log of the number of employees in each "firm-*Occupation-Skill Level-Region-Year*" cell from which the focal employee is drawn. This approach prevents our findings from being skewed either by the thousands of specialized roles with few employees or by a handful of low-skilled "megaroles" representing massive employee populations. Our results are robust to this choice and remain consistent across alternative weighting schemes. Table 1 presents summary statistics on the data and the main variables, and correlations are provided in Table A.5 in the Online Appendix.

4. Results

4.1. Pay Orientation, Knowledge Intensity, and Skill Level

4.1.1. Main Analysis. Table 2 presents our baseline analysis of pay sensitivity to internal and market benchmarks. All models include "firm-*Occupation-Skill Level-Region*" fixed effects and year fixed effects, which remove persistent differences across firms, occupations, skills, and regions and allow for comparisons within narrowly defined employee groups.

Column (1) in Table 2 shows that a 10% increase in the internal reference group's pay is associated with a 1.2% increase in the focal employee's pay ($p < 0.01$), whereas column (2) in Table 2 shows that a 10% increase in the market reference group's pay is associated with a 0.4% increase in focal employee pay ($p < 0.01$). When both benchmarks are included simultaneously in column (3) in Table 2, the coefficients remain virtually unchanged at 0.124 for *Internal Pay* and 0.043 for *Market Pay* (both $p < 0.01$). Column (4) in Table 2 additionally includes performance controls, reflecting the main specification from Equation (1). The coefficients remain nearly identical at 0.123 for *Internal Pay* and 0.044 for *Market Pay* (both $p < 0.01$).

To assess whether these findings are sensitive to modeling choices, we also estimate a range of alternative models and different sets of fixed effects. Figure A.1 in the Online Appendix plots the coefficients across these models. Although the magnitude of the coefficients shifts depending on the specification, the internal pay benchmark emerges as the stronger predictor of pay across nearly all specifications.

Next, we explore how pay sensitivity varies with knowledge intensity. Following Peters and Taylor (2017), we calculate the industry-average knowledge capital intensity, defined as the accumulated sum of past spending on research and development.[6] We then split the 18 industries in our sample (as defined by our data provider) into terciles, yielding low-, moderate-, and high-knowledge categories of 6 industries each. Firms falling withing low-knowledge industries (e.g., retailers and restaurants) have an average of less than 1% knowledge capital intensity, those within moderate knowledge-industries (e.g., construction and insurance) range from 1% to 4%, and those within high-knowledge industries (e.g., chemicals and high technology) exceed 4% (see Table A.6 in the Online Appendix for a detailed breakdown of industries and sample sizes by industry type).

Table 1. Summary Statistics of All Employee Records

Panel A: Compensation data statistics

Variable	Count
Employee	18,974,767
Focal Employee[a]	177,540
Benchmark Employee	18,797,227
Firm	479
Public Firm	257
Public Firm with New CEO (2008–2020)	113
Public Firm with Patent (2008–2020)	94
Year	13 (2008–2020)
Skill Level	22
Function	61
Occupation	206
Region	10
"*Firm-Year-Skill Level-Occupation-Region*" unit	177,540

Panel B: Control variable statistics

Variable	Mean	St. dev.	25th	50th	75th
Compensation data statistics					
Skill	11.23	3.08	9	12	13
Employee pay ($)	85,912	42,159	54,000	76,894	108,577
Internal pay benchmark ($)[b]	87,890	45,455	56,329	79,127	109,527
Market pay benchmark ($)[c]	86,574	44,628	55,053	77,702	109,214
Number of employees per internal pay-benchmark group	1,332.51	12,161.55	36	124	445
Number of employees per market pay-benchmark group	2,328.61	15,973.66	38	148	567
Number of firms per market pay-benchmark group	18.86	18.32	6	13	26
Number of employees per "firm-year-skill-occupation-region" unit	725.23	7,058.33	6	19	84
Control variable statistics					
Return on assets	0.105	0.073	0.067	0.102	0.127
Sale (in million $)	41,611.67	90,234.17	4,222.9	11,145.9	36,595.9

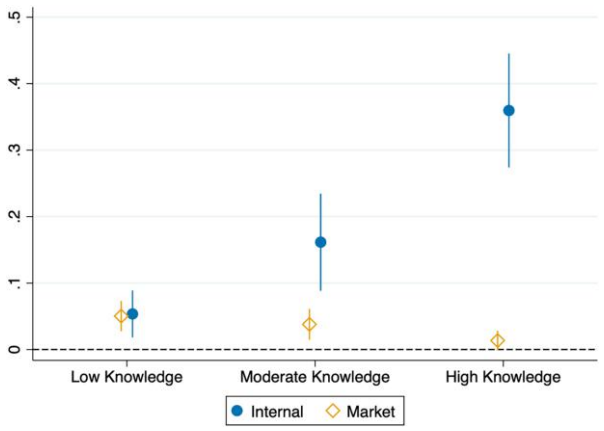
Note. St. dev., standard deviation.
[a]Each focal employee represents a median-paid employee of a unique "firm-*Year-Skill Level-Occupation-Region*" unit.
[b]Cash compensation of the internal reference group consists of employees with the same "firm-*Year-Skill Level*" as the focal employee but working in different functions. To create the pay-benchmark group, we use 18,797,227 benchmark employees (18,974,767 employees minus 177,540 focal employees).
[c]Cash compensation of the market reference group consists of employees with the same "*Year-Skill Level-Occupation-Region*" as the focal employee but working at different firms.

Table 2. Relationship Between Employee Pay and Internal and Market Pay Benchmarks

	Dependent variable: *Employee pay*			
	(1)	(2)	(3)	(4)
Internal Pay	0.123***		0.124***	0.123***
	(0.019)		(0.019)	(0.019)
Market Pay		0.043***	0.043***	0.044***
		(0.007)	(0.007)	(0.007)
ROA				−0.019
				(0.047)
Log *Sale*				0.005
				(0.006)
Constant	9.778***	10.678***	9.291***	9.241***
	(0.214)	(0.077)	(0.218)	(0.226)
Firm-occupation-skill level-region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	177,540	177,540	177,540	177,540
Adjusted R^2	0.965	0.965	0.965	0.965

Note. FE, fixed effect; ROA, return on assets.
***Significant at 1%.

Figure 1. (Color online) Pay-Benchmark Sensitivity by Firm Knowledge Intensity



Notes. Each marker represents a coefficient on an internal or market pay benchmark using the fully specified regression model in Equation (1) within given subsamples of firms split by knowledge intensity. Lines represent 95% confidence intervals. Red diamond markers represent coefficients on the internal pay benchmark, and black circular markers represent coefficients on the market pay benchmark.

Figure 1 presents the coefficients from estimating Equation (1) separately for each knowledge intensity group (see Table A.7 in the Online Appendix for underlying regression results). In low-knowledge industries, internal pay sensitivity (0.054, $p < 0.01$) and market pay sensitivity (0.050, $p < 0.01$) are statistically indistinguishable. However, in high-knowledge industries, internal pay sensitivity is 0.31 ($p < 0.01$), whereas market pay sensitivity is 0.02 ($p < 0.01$). This pattern indicates that in more innovative settings, firms orient pay primarily toward internal benchmarks, consistent with Prediction 1.

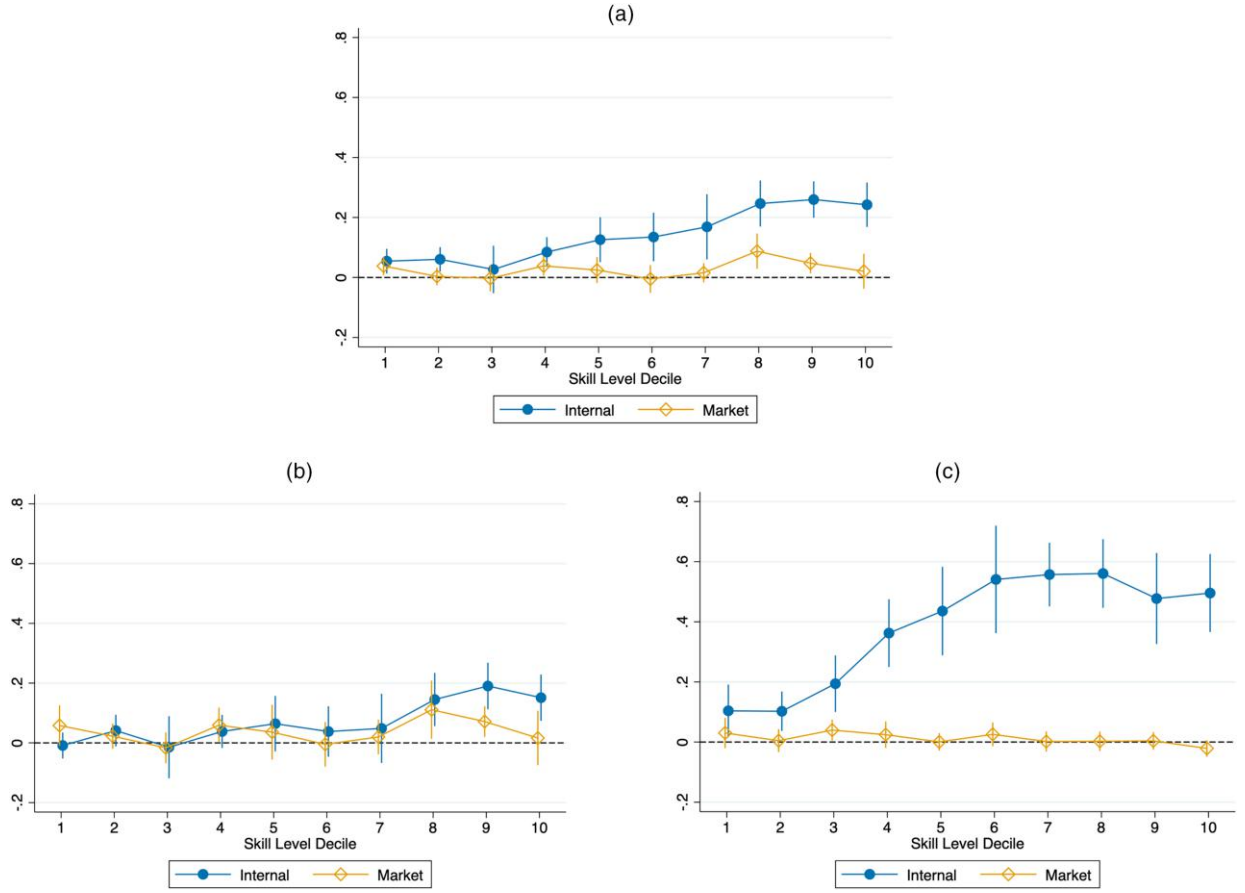
Next, we analyze pay sensitivity by employee skill level. We divide employees into deciles by *Skill Level* and apply our specification in Equation (1) to each decile. Panel (a) of Figure 2 presents estimates of pay sensitivity across employee skill deciles for each of these 10 regressions.[7] For employees in the lowest skill decile, internal and market pay sensitivities converge. However, as skill level increases, internal pay sensitivity rises, whereas market pay sensitivity remains largely flat. This divergence is most pronounced among the three highest deciles of skilled workers. Figure 2 indicates that firms rely more heavily on internal benchmarking for their most skilled employees, consistent with Prediction 2.

Finally, panels (b) and (c) of Figure 2 explore the relationship between knowledge intensity, skill level, and pay sensitivity. Within low-knowledge firms (panel (b) of Figure 2), internal pay sensitivity in the lowest decile is −0.01 ($p = 0.69$) compared with market pay sensitivity of 0.06 (standard error: 0.03, $p < 0.10$). Market pay sensitivity and internal pay sensitivity are statistically the same for all workers except for the highest three skill deciles. In the top decile, internal pay sensitivity reaches 0.15 ($p < 0.01$) compared with market pay sensitivity of 0.02 ($p = 0.72$). In contrast, high-knowledge firms (panel (c) of Figure 2) show statistically higher internal pay sensitivity across all skill levels, starting at 0.10 ($p < 0.05$) for internal pay sensitivity versus 0.03 ($p = 0.24$) for market pay sensitivity in the lowest decile and reaching 0.50 ($p < 0.01$) for internal pay sensitivity versus −0.02 ($p = 0.13$) for market pay sensitivity in the highest decile. These results suggest that both knowledge intensity and skill level independently and jointly relate to firms' relative emphasis on internal benchmarks versus market benchmarks in setting pay, consistent with Prediction 3.

4.1.2. CEO Transition Analysis. Our results thus far suggest that innovation focus and internal pay orientation are linked, but this relationship could reflect unobserved firm characteristics simultaneously driving both. To better understand this relationship, we use CEO transitions to examine whether shifts in strategic focus drive corresponding changes in pay orientation. CEO changes provide a useful setting because they often mark significant shifts in firm strategy, and new CEOs typically articulate their strategic vision clearly in their first interactions with investors. If innovation focus drives internal pay orientation, we would expect to see shifts toward internal benchmarking specifically when new CEOs emphasize innovation but not when they announce other strategic priorities. Among 257 public firms in our sample, we identify 113 CEO transitions during our sample period. To classify these transitions, we analyze the new CEOs' first earnings call transcripts to score their strategic focus along three dimensions: innovation, market growth, and cost efficiency (see Online Appendix A for details). We classify them based on which dimension receives the highest score, resulting in 20 firms with innovation-focused CEOs, 47 firms with market-growth-focused CEOs, and 46 firms with cost-efficiency-focused CEOs (for summary statistics, see Tables A.11 and A.12 in the Online Appendix).

To analyze how pay orientation changes following CEO transitions, we employ a differences-in-differences (DiD) framework that compares changes in pay sensitivity before and after a new CEO arrival with changes in firms without CEO turnover. Because CEO transitions occur at different times, we use a stacked DiD approach (Cengiz et al. 2019, Deshpande and Li 2019) that groups treated units by transition year and ensures that treated units are only compared with control units from the same "stack." Our goal is to observe whether shifts in strategic focus and pay orientation occur in conjunction and therefore, whether an innovation focus and internal pay orientation are complementary choices by leaders.

Figure 2. (Color online) Pay-Benchmark Sensitivity by Employee Skill Level and Firm Knowledge Intensity



Notes. The *x* axes represent *Skill Level* split into deciles (e.g., decile 1 includes employees whose skill level is lower than the 10th percentile of *Skill Level*). Each marker represents a coefficient on an internal or market pay benchmark using the fully specified regression model in Equation (1) within given subsamples of employees (split by skill level) and firms (split by knowledge intensity). Lines represent 95% confidence intervals. Red diamond markers represent coefficients on the internal pay benchmark, and black circular markers represent coefficients on the market pay benchmark. (a) All. (b). Low knowledge. (c) High knowledge.

Table 3 presents the results of this analysis. Column (1) in Table 3 shows that, on average, firms with new CEOs do not exhibit significant changes in internal or market pay sensitivities relative to control firms. Columns (2) and (3) in Table 3 further show that firms whose new CEOs emphasize cost efficiency or market growth similarly experience no significant shifts in pay orientation. However, column (4) in Table 3 provides suggestive evidence that firms whose new CEOs emphasize innovation do exhibit changes. Specifically, the coefficient on *CEO Change* × *Post* × *Internal Pay* is positive and moderately significant (0.08, $p < 0.10$). Next, we examine whether the complementarity of innovation focus and internal pay orientation is strongest among high-skilled employees. In columns (5) and (6) in Table 3, we restrict the sample to firms with innovation-focused new CEOs and split employees by skill level. Column (5) in Table 3 shows no significant change in pay orientation among low-skilled employees. However, column (6) in Table 3 reveals that pay becomes more internally oriented for high-skilled employees. The coefficient on *CEO Change* × *Post* × *Internal Pay* is positive and significant (0.14, $p < 0.01$), whereas the coefficient on *CEO Change* × *Post* × *Market Pay* is negative and significant (−0.21, $p < 0.01$). These results indicate that following an innovation-focused CEO change, the shift toward internal pay orientation is driven by high-skilled workers. Figure A.2 in the Online Appendix presents event study plots corresponding to this analysis. Across panels (a)–(d) of Figure A.2 in the Online Appendix, there is no evidence of pretrends in pay-benchmark sensitivities, supporting the interpretation that observed shifts occur around the CEO transition.

Altogether, these results suggest that when firms shift toward innovation-focused strategies, they increase internal pay orientation, particularly for high-skilled employees.

Table 3. New CEO's Strategic Focus and Change in Pay-Benchmark Orientation

	Dependent variable: *Employee pay*					
	New CEO strategic focus					
	All (1)	Cost efficiency (2)	Market growth (3)	Innovation (4)	Innovation (5) Employee skill level: Below median	Innovation (6) Employee skill level: Above median
Post × *CEO Change* × *Internal Pay*	0.024 (0.026)	0.006 (0.045)	0.008 (0.023)	0.084* (0.049)	0.015 (0.039)	0.142*** (0.042)
Post × *CEO Change* × *Market Pay*	−0.007 (0.029)	−0.015 (0.045)	0.015 (0.026)	−0.031 (0.059)	0.055 (0.064)	−0.213*** (0.065)
Post × *Internal Pay*	−0.012 (0.011)	−0.009 (0.010)	−0.010 (0.010)	−0.009 (0.010)	0.007 (0.010)	−0.007 (0.018)
Post × *Market Pay*	0.019* (0.011)	0.019* (0.011)	0.019* (0.011)	0.019* (0.011)	0.025*** (0.010)	0.032 (0.023)
CEO Change × *Internal Pay*	−0.039 (0.030)	−0.041 (0.034)	0.000 (0.036)	−0.111 (0.070)	−0.016 (0.041)	−0.259** (0.103)
CEO Change × *Market Pay*	−0.008 (0.021)	0.023 (0.038)	−0.033 (0.021)	0.000 (0.028)	−0.075* (0.038)	0.177*** (0.055)
Internal Pay	0.095*** (0.014)	0.090*** (0.013)	0.095*** (0.013)	0.090*** (0.013)	0.000 (0.012)	0.242*** (0.015)
Market Pay	0.026** (0.011)	0.022** (0.011)	0.026** (0.011)	0.022** (0.011)	0.020*** (0.007)	−0.031* (0.019)
Post × *CEO Change*	−0.191 (0.161)	0.121 (0.170)	−0.236* (0.125)	−0.604 (0.408)	−0.798 (0.559)	0.839 (0.576)
Constant	9.848*** (0.134)	9.799*** (0.127)	9.743*** (0.121)	9.873*** (0.139)	10.493*** (0.135)	9.071*** (0.214)
Stack firm-occupation-skill level-region FE	Yes	Yes	Yes	Yes	Yes	Yes
Stack year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	202,917	169,068	170,598	159,235	93,334	59,533
Treated observations	54,925	21,076	22,606	11,243	5,832	4,975
Control observations	147,992	147,992	147,992	147,992	87,502	54,558
Adjusted R^2	0.969	0.970	0.971	0.970	0.957	0.916

Notes. See Online Appendix A for details on the construction of the new CEO's strategic focus measures. Tables A.11 and A.12 in the Online Appendix report the summary statistics for these measures. FE, fixed effect.

*Significant at 10%; **significant at 5%; ***significant at 1%.

4.2. Mechanism Test: Complex Problem-Solving and Collaboration

Our core finding thus far is that internal pay orientation increases with firm knowledge intensity, employee skill level, and their interaction, consistent with Predictions 1 and 2. We now turn to the mechanism behind this pattern as discussed in Section 2 that knowledge-intensive firms and high-skill jobs demand more complex problem-solving and intensive collaboration across specialists. If this mechanism holds, we should observe two patterns; (i) complex problem-solving and collaboration demands are more prevalent in high-innovation, high-skill settings, and (ii) roles that require these capabilities exhibit greater internal pay sensitivity.

4.2.1. Distribution of Jobs That Require Complex Problem-Solving and Collaboration. We construct measures of complex problem-solving and collaboration by adapting the Hay Group's published framework of nine job components as a measurement guide.[8] The Hay Group is an established compensation consultancy that performs services equivalent to those of our data provider. We rely on the publicly available component descriptions to estimate each occupation-skill-level combination's position on these nine job dimensions.

From these estimated scores, we then construct indices of complex problem-solving and collaboration. We prompt ChatGPT-4.0 to map each occupation to the nine components using the definitions in Hay's job evaluation public documentation, yielding an occupation-level base profile across the nine components. From these profiles, we estimate an index of complex problem-solving intensity as the average of scores across the following three components: (i) practical/technical know-how, (ii) problem-solving thinking environment, and (iii) problem-solving thinking challenge (for more details,

see Online Appendix B). We then construct a binary indicator, *Complex Problem-Solving*, which equals one if the combined score is above the median ("*Complex Problem-Solving (High)*") and zero otherwise ("*Complex Problem-Solving (Low)*"). We also construct a collaboration index that includes the average of scores for (i) communicating know-how, (ii) planning know-how, (iii) account freedom, and (iv) account area, and we construct a similar binary indicator of *Collaboration*.[9]

Table 4 provides the number of units and illustrative occupations by category. *Complex Problem-Solving (Low)* occupations include those that are more routine, such as clerical services, whereas *Complex Problem-Solving (High)* occupations include those that require more cognitive and analytical skills, such as general engineers. We then create several subsamples consistent with our mechanism. First, we split high-complex problem-solving roles by collaboration demand (*Complex Problem-Solving (High) & Collaboration (Low)* versus *Complex Problem-Solving (High) & Collaboration (High)*). Second, we further subdivide our above-median *Complex Problem-Solving (High)* subsample into two halves: *Complex Problem-Solving (Medium-High, Q3)* and *Complex Problem-Solving (Highest, Q4)*. These two subsampling approaches are not mutually exclusive. Instead, they offer different approaches to explore our mechanism; based on our discussion in Section 2, we would expect our effects to be more pronounced within *Complex Problem-Solving (High) & Collaboration (High)* subsamples (compared with *Complex Problem-Solving (High) & Collaboration (Low)*) and within *Complex Problem-Solving (Highest, Q4)* (compared with *Complex Problem-Solving (Medium-High, Q3)*).

We next use these measures to examine whether jobs that demand complex problem-solving and collaboration are concentrated in high-innovation firms and among high-skill workers. Panel (a) of Figure 3 shows that the prevalence of complex problem-solving jobs rises with both firm knowledge intensity and employee skill level. Panel (b) of Figure 3 shows that jobs combining complex problem-solving and collaboration are more common in knowledge-intensive firms and among high-skill workers. Finally, panel (c) of Figure 3 indicates that the most demanding complex problem-solving jobs (Q4) exhibit a similar pattern. These results, consistent with our proposed mechanism, indicate that jobs demanding complex problem-solving and collaboration are more prevalent in high-innovation, high-skill contexts.

4.2.2. Complex Problem-Solving, Collaboration, and Internal Pay Orientation.

We next examine whether roles that require complex problem-solving and collaboration exhibit higher internal pay orientation. To explore this, we repeat our main analysis and CEO switching analyses within subsamples defined by problem-solving and collaboration intensities.

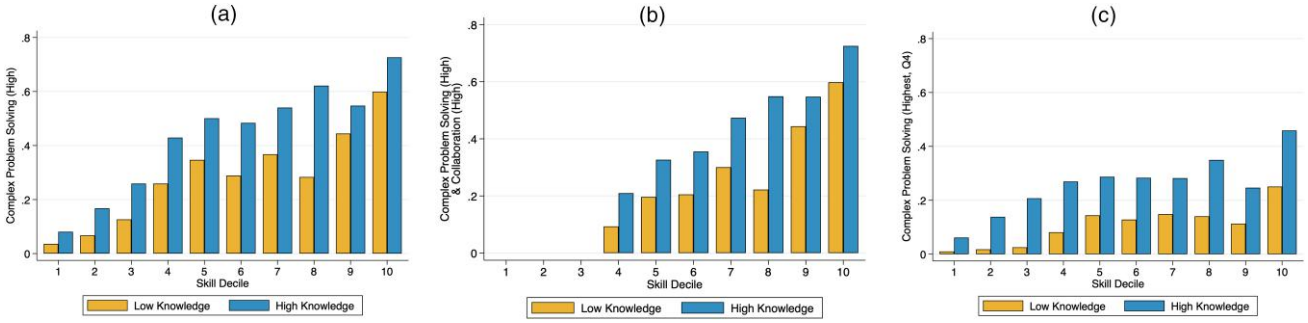
Table 5 reports internal and market pay sensitivities across job types. Columns (1) and (2) in Table 5 show that internal pay sensitivity is significantly higher for complex problem-solving jobs (0.191, $p < 0.01$) than for other jobs (0.096, $p < 0.01$), whereas market pay sensitivity is lower for complex problem-solving jobs (0.033, $p < 0.01$) than others (0.045, $p < 0.01$). Columns (3) and (4) in Table 5 split the complex problem-solving sample

Table 4. Summary Statistics of Job Type

Job type	No. of units	Representative occupations
Complex Problem-Solving (Low)	117,370	Retail operations store management, production, territory sales, clerical services, customer service-nontechnical
Complex Problem-Solving (High)	55,432	General engineers, financial planning, research and development, marketing-brand/product management, information technology-application development
Complex Problem-Solving (High) & Collaboration (Low)	16,489	Quality assurance, production-maintenance/skilled manual, merchandise operations-buying, secretarial, technical operations and end user support
Complex Problem-Solving (High) & Collaboration (High)	38,943	General engineers, financial planning, research and development, marketing-brand/product management, project management
Complex Problem-Solving (Medium-High, Q3)	29,405	Financial planning, marketing-brand/product management, purchasing/procurement, accounting, technical operations and end user support
Complex Problem-Solving (Highest, Q4)	26,027	General engineers, research and development, design, information technology-application development, software/application development and implementation
Nonclassifiable occupations	4,738	Unclassified, general/other

Notes. See Online Appendix B for details on the construction of the complex problem-solving and collaboration measures. Tables A.11 and A.12 in the Online Appendix report the summary statistics for these measures.

Figure 3. (Color online) Distribution of Job Type by Employee Skill Level and Firm Knowledge Intensity



Notes. The *x* axes represent *Skill Level* split into deciles (e.g., decile 1 includes employees whose skill level is lower than the 10th percentile of *Skill Level*). Each bar represents the percentage of jobs within given subsamples of firms split by knowledge intensity. Blue bars represent the percentage of jobs in low-knowledge firms, and red bars represent the percentage of jobs in high-knowledge firms. (a) Complex problem-solving jobs. (b) Complex problem-solving and collaboration jobs. (c) Complex problem-solving (highest, Q4) jobs.

by collaboration intensity. Among complex problem-solving jobs, those with high collaboration demands show an even stronger internal pay sensitivity (0.220, $p < 0.01$) than those with low collaboration demands (0.121, $p < 0.01$). Columns (5) and (6) in Table 5 further split the complex problem-solving sample to highest (Q4) and medium-high (Q3) problem-solving jobs. Again, jobs in Q4 show greater internal pay sensitivity (0.217 relative to 0.170 in Q3, both $p < 0.01$). These results indicate that jobs with greater demands for complex problem-solving and collaboration drive internal pay orientation.[10]

We next rerun our CEO switching analysis on our complex problem-solving and collaboration subsamples, with the results reported in Table 6 (for firms whose new CEOs emphasized innovation) and Table 7 (for firms whose new CEOs emphasized other strategies). As Table 6 reports, following the innovation-focused CEO transition, internal pay sensitivity increases and market pay sensitivity decreases *only* among complex problem-solving jobs. In contrast, no such effects are observed in other jobs. Moreover, even within complex problem-solving jobs, these effects are even more pronounced for those that also require collaboration (column (4) in Table 6) or the most intense problem-solving capabilities (column (6) in Table 6).

Table 7 focuses on firms whose new CEOs emphasized other noninnovation goals, such as market growth or cost efficiency. Among these firms, we observe no changes in internal or market pay sensitivity, regardless

Table 5. Relationship Between Employee Pay and Internal and Market Pay Benchmarks by Employee Type

	Dependent variable: *Employee pay*					
			Complex Problem-Solving (High)			
Job type	*Complex Problem-Solving (Low)* (1)	*Complex Problem-Solving (High)* (2)	*Low Collab* (3)	*High Collab* (4)	*Medium High (Q3)* (5)	*Highest (Q4)* (6)
Internal Pay	0.096***	0.191***	0.121***	0.220***	0.170***	0.217***
	(0.019)	(0.024)	(0.022)	(0.026)	(0.020)	(0.034)
Market Pay	0.045***	0.033***	0.018	0.043***	−0.002	0.068***
	(0.008)	(0.011)	(0.013)	(0.014)	(0.011)	(0.016)
ROA	−0.069	0.138***	0.147**	0.132***	0.091*	0.190***
	(0.054)	(0.052)	(0.069)	(0.050)	(0.054)	(0.071)
Log *Sale*	0.005	0.006	0.011	0.004	0.005	0.010
	(0.007)	(0.007)	(0.009)	(0.007)	(0.008)	(0.011)
Constant	9.417***	8.849***	9.58***	8.503***	9.471***	8.154***
	(0.242)	(0.253)	(0.276)	(0.287)	(0.251)	(0.368)
Firm-occupation-skill level-region FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	117,370	55,432	16,489	38,943	29,405	26,027
Adjusted R^2	0.958	0.954	0.944	0.943	0.951	0.956

Note. FE, fixed effect; ROA, return on assets.
*Significant at 10%; **significant at 5%; ***significant at 1%.

Table 6. Innovation-Focused CEOs and Change in Pay-Benchmark Orientation by Job Type

	Dependent variable: *Employee pay*					
			Complex Problem-Solving (High)			
Job type	*Complex Problem-Solving (Low)* (1)	*Complex Problem-Solving (High)* (2)	*Low Collab* (3)	*High Collab* (4)	*Medium High (Q3)* (5)	*Highest (Q4)* (6)
Post × CEO Change × Internal Pay	0.063	0.143***	0.148**	0.193***	0.094***	0.218***
	(0.054)	(0.038)	(0.059)	(0.060)	(0.025)	(0.071)
Post × CEO Change × Market Pay	0.009	−0.149***	−0.091	−0.172***	−0.084***	−0.240***
	(0.056)	(0.040)	(0.069)	(0.049)	(0.031)	(0.082)
Post × Internal Pay	0.005	−0.029**	−0.022	−0.043**	−0.052***	0.010
	(0.011)	(0.013)	(0.017)	(0.017)	(0.012)	(0.021)
Post × Market Pay	−0.002	0.034**	0.008	0.042***	0.062***	−0.010
	(0.011)	(0.014)	(0.023)	(0.015)	(0.012)	(0.026)
CEO Change × Internal Pay	−0.087	−0.130	−0.221**	−0.086	−0.084	−0.172
	(0.067)	(0.097)	(0.093)	(0.105)	(0.075)	(0.105)
CEO Change × Market Pay	−0.050*	0.142***	0.060	0.165***	0.073**	0.251***
	(0.029)	(0.046)	(0.049)	(0.058)	(0.033)	(0.080)
Internal Pay	0.037***	0.207***	0.111***	0.226***	0.242***	0.152***
	(0.014)	(0.014)	(0.023)	(0.016)	(0.014)	(0.024)
Market Pay	0.049***	−0.023	−0.010	0.014	−0.076***	0.027
	(0.012)	(0.015)	(0.012)	(0.018)	(0.012)	(0.024)
Post × CEO Change	−0.815*	0.071	−0.643	−0.256	−0.104	0.253
	(0.492)	(0.261)	(0.593)	(0.396)	(0.268)	(0.402)
Constant	10.112***	9.303***	10.234***	8.697***	9.424***	9.411***
	(0.151)	(0.219)	(0.261)	(0.275)	(0.191)	(0.356)
Stack firm-occupation-skill level-region FE	Yes	Yes	Yes	Yes	Yes	Yes
Stack year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	109,508	45,179	10,205	31,047	24,672	20,507
Treated observations	7,971	2,956	891	2,065	1,742	1,214
Control observations	101,537	42,223	13,241	28,982	22,930	19,293
Adjusted R^2	0.966	0.955	0.937	0.950	0.951	0.955

Note. FE, fixed effect.
*Significant at 10%; **significant at 5%; ***significant at 1%.

of job type. Figure A.3 in the Online Appendix shows the event study plots, which are consistent with the regression results.

Finally, we explore whether our results are driven by unobservable task characteristics rather than collaboration. Because we cannot explore these other potential tasks directly, we use occupation colocation as a proxy for collaboration; when workers at the same skill level span different occupations within a location, this suggests greater interdependence requiring collaboration. Importantly, although occupation colocation plausibly affects collaboration intensity, it is less likely to correlate with other unobservable factors, such as autonomy, managerial responsibility, or tenure-based firm-specific human capital. We measure this using one minus the occupation Herfindahl–Hirschman Index (HHI) within each firm-year-skill level-region unit, where higher values indicate more diverse colocated occupations. We predict that internal pay sensitivity will be higher when occupation colocation is greater, particularly among workers engaged in complex problem-solving. Tables A.13 and A.14 in the Online Appendix confirm this prediction.

In summary, these findings offer consistent support for our proposed mechanism. Internal pay orientation is most pronounced in jobs that demand complex problem-solving and collaboration. These demands help explain why internal pay benchmarks are heightened in knowledge-intensive, high-skill settings.

4.3. Innovation Outcomes Analysis

Our analyses thus far suggest that firms orient pay internally in knowledge-intensive settings for skilled workers and that this orientation is explained at least partly by the demands for complex problem-solving and collaboration. These findings raise a natural question. Does stronger internal pay orientation predict better innovation outcomes?

Table 7. Noninnovation-Focused CEOs and Change in Pay-Benchmark Orientation by Job Type

			Dependent variable: *Employee pay*			
			Complex Problem-Solving (High)			
Job type	*Complex Problem-Solving (Low)* (1)	*Complex Problem-Solving (High)* (2)	*Low Collab* (3)	*High Collab* (4)	*Medium High (Q3)* (5)	*Highest (Q4)* (6)
Post × CEO Change × Internal Pay	−0.004	0.021	0.023	0.024	0.037	0.008
	(0.034)	(0.023)	(0.038)	(0.028)	(0.023)	(0.037)
Post × CEO Change × Market Pay	0.015	−0.013	0.046	−0.022	−0.026	−0.007
	(0.031)	(0.025)	(0.048)	(0.029)	(0.028)	(0.041)
Post × Internal Pay	0.003	−0.028**	−0.023	−0.041**	−0.053***	0.017
	(0.011)	(0.013)	(0.017)	(0.017)	(0.012)	(0.020)
Post × Market Pay	−0.001	0.033**	0.012	0.041***	0.063***	−0.015
	(0.011)	(0.015)	(0.024)	(0.015)	(0.012)	(0.026)
CEO Change × Internal Pay	0.003	−0.051	−0.030	−0.040	−0.122***	0.039
	(0.027)	(0.037)	(0.046)	(0.042)	(0.030)	(0.056)
CEO Change × Market Pay	−0.031	0.036	0.033	−0.004	0.058**	0.025
	(0.028)	(0.025)	(0.031)	(0.028)	(0.023)	(0.039)
Internal Pay	0.041***	0.210***	0.116***	0.228***	0.247***	0.153***
	(0.014)	(0.014)	(0.024)	(0.016)	(0.014)	(0.025)
Market Pay	0.053***	−0.020	−0.016	0.018	−0.073***	0.035
	(0.012)	(0.015)	(0.013)	(0.018)	(0.012)	(0.024)
Post × CEO change	−0.108	−0.077	−0.753	−0.012	−0.119	−0.007
	(0.168)	(0.162)	(0.484)	(0.200)	(0.227)	(0.213)
Constant	9.993***	9.287***	10.115***	8.84***	9.523***	9.151***
	(0.129)	(0.196)	(0.235)	(0.251)	(0.169)	(0.312)
Stack firm-occupation-skill level-region FE	Yes	Yes	Yes	Yes	Yes	Yes
Stack year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	130,082	56,379	12,127	39,134	30,352	26,027
Treated observations	28,545	14,156	4,004	10,152	7,422	6,734
Control observations	101,537	42,223	13,241	28,982	22,930	19,293
Adjusted R^2	0.965	0.956	0.937	0.950	0.954	0.957

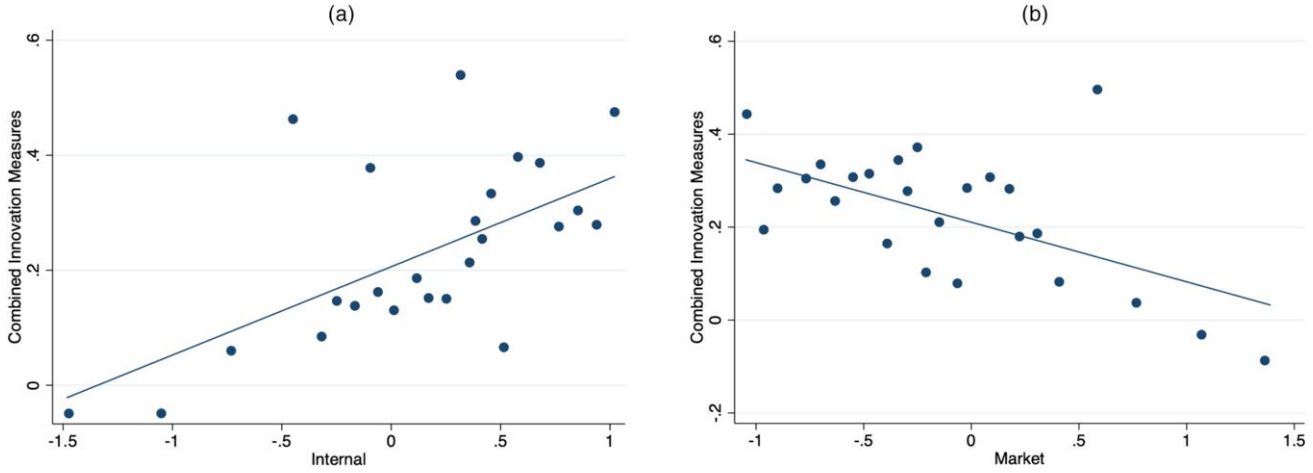
Note. FE, fixed effect.
**Significant at 5%; ***significant at 1%.

To examine this, we construct firm-year measures of internal and market pay sensitivity for the 94 public firms in our sample that filed at least one patent during the sample period.[11] For each firm-year, we estimate the sensitivity of employee pay to internal and market benchmarks using a three-year rolling window ($t-3$ to $t-1$) estimated relative to nonpatenting firms. *Internal Pay Sensitivity* is the coefficient on *Internal Pay* for each firm-year relative to nonpatenting firms. *Market Pay Sensitivity* is the corresponding measure for *Market Pay*. Because we pool nonpatenting firms to form the base group, the estimated coefficients on patenting firms' firm-year variables represent the three-year average firm-year pay sensitivities *relative to* nonpatenting firms. A positive (negative) coefficient denotes higher (lower) sensitivity to that benchmark relative to the average nonpatenting firm.

We merge these measures with patent and publication data from the Duke Innovation & SCientific Enterprises Research Network (DISCERN) database, which provides comprehensive coverage of patents, publications, and citations while accounting for changes in firm ownership structure (Arora et al. 2021). We identify 94 firms of 257 public firms in our data set as having filed at least one patent or publication from 2008 (the start of our compensation data) to 2015 (the last year available in DISCERN). We also merge our data with the breakthrough innovation (Consolidation-Disruption (CD) index) database (Funk and Owen-Smith 2017). Lastly, we include Compustat data to create control variables that may simultaneously influence pay orientation and innovation outcomes, such as knowledge capital intensity, sales, and leverage. Summary statistics for all variables in this analysis appear in Table A.15 in the Online Appendix.

Figure 4 plots the average of z-scored innovation outcomes—which include the number and stock of patents and publications, forward citations by the most cited patent, and the breakthrough index of most breakthrough innovation—against a z-scored

Figure 4. (Color online) Relationship Between Pay-Benchmark Sensitivity and Innovation Outcome



Notes. The *y* axes are the sum of *z*-scored innovation measures (the number and stock of patents and publications, forward citations by the most cited patent, and the breakthrough index of the most breakthrough innovation). The *x* axes are *z*-scored pay sensitivity measures. (a) Internal pay sensitivity. (b) Market pay sensitivity.

measure of pay orientation in each firm-year. Panel (a) of Figure 4 shows a positive correlation between innovation and *Internal Pay Sensitivity*, whereas panel (b) of Figure 4 shows a negative correlation with *Market Pay Sensitivity*, suggesting that higher internal pay sensitivity predicts stronger innovation performance.

Table 8 formally examines these relationships. Across all columns in Table 8, we regress the average of *z*-scored innovation outcomes on *z*-scored internal pay sensitivity. Each column in Table 8 represents a job type. Following prior work, we include year and industry fixed effects and control for knowledge intensity, revenues, and leverage (e.g., Lerner and Wulf 2007, Yanadori and Cui 2013). Column (1) in Table 8 presents results for all employees. The estimate on *Internal Pay Sensitivity* is positive and significant, indicating that a 1-standard-deviation increase in internal pay sensitivity is associated with a 0.155-standard-deviation increase in innovation

Table 8. Internal Pay Sensitivity and Innovation Outcome

				Dependent variable: *Innovation outcome*			
				Complex Problem-Solving (High)			
Job type	*All* (1)	*Complex Problem-Solving (Low)* (2)	*Complex Problem-Solving (High)* (3)	*Low Collab* (4)	*High Collab* (5)	*Medium High (Q3)* (6)	*Highest (Q4)* (7)
Internal Pay Sensitivity$_{t-1}$	0.155**	0.083	0.111*	0.160	0.298**	0.140*	0.291
	(0.059)	(0.069)	(0.065)	(0.117)	(0.138)	(0.075)	(0.229)
Knowledge Intensity$_{t-1}$	2.177***	2.224***	2.060***	2.583***	2.062***	2.092***	2.451***
	(0.442)	(0.434)	(0.473)	(0.635)	(0.466)	(0.483)	(0.607)
Revenues (logged)$_{t-1}$	0.328***	0.327***	0.310***	0.321***	0.304***	0.320***	0.330***
	(0.036)	(0.037)	(0.041)	(0.043)	(0.040)	(0.040)	(0.040)
Leverage$_{t-1}$	−0.592*	−0.510	−0.589	−0.763*	−0.572	−0.557	−0.701
	(0.353)	(0.366)	(0.363)	(0.410)	(0.349)	(0.362)	(0.428)
Constant	−2.843***	−2.860***	−2.655***	−2.734***	−2.624***	−2.739***	−2.799***
	(0.297)	(0.302)	(0.350)	(0.350)	(0.331)	(0.330)	(0.349)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry[a] FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	229	229	219	202	214	218	206
Adjusted R^2	0.676	0.664	0.670	0.662	0.677	0.639	0.680

Notes. The unit of analysis is "firm-year." The dependent variable is the sum of *z*-scored innovation measures (the number and stock of patents and publications, forward citations by the most cited patent, and the breakthrough index of the most breakthrough innovation). The independent variable, *Internal Pay Sensitivity*, is also *z* scored for interpretability. FE, fixed effect.

[a]Industry is classified according to the Standard Industrial Classification one-digit industry classification.

*Significant at 10%; **significant at 5%; ***significant at 1%.

outcomes ($p < 0.05$). Columns (2) and (3) in Table 8 split the sample by problem-solving intensity. The coefficient is statistically significant for complex problem-solving jobs (0.111, $p < 0.10$), but it is insignificant for other jobs. Columns (4) and (5) in Table 8 further divide complex problem-solving jobs based on collaboration intensity. The coefficient is only significant for high problem-solving jobs that also require high collaboration, and economic magnitude is larger than for the full sample; a 1-standard-deviation increase in internal pay sensitivity is associated with a 0.298-standard-deviation increase in innovation outcomes ($p < 0.05$). Columns (6) and (7) in Table 8 split complex problem-solving jobs into those that require the highest level of complex problem-solving (Q4) and others (Q3). The coefficient is lower in the Q3 subsample (0.140, $p < 0.10$) than in the Q4 subsample, although the latter is not statistically significant (0.291, $p = 0.210$).[12]

These results suggest that firms with stronger internal pay orientation, particularly among complex problem-solving and collaborative roles, tend to produce more and better innovation. Although we cannot definitively establish causality, the observed pattern is consistent with the idea that internal pay orientation supports the collaboration and knowledge-sharing needed for innovation.

Taken together, our empirical analyses reveal the following pattern; innovative firms prioritize internal pay benchmarks over market pay benchmarks, particularly among jobs that require complex problem-solving and collaboration, and this internal pay orientation is positively associated with better innovation outcomes.

5. Discussion

Our analysis reveals that the relative sensitivity of pay to internal over market benchmarks increases with both firm knowledge intensity and employee skill level, with the strongest effects at their intersection. This internal pay sensitivity is strongest for jobs requiring complex problem-solving and collaboration, consistent with these job demands driving the relationship between internal pay sensitivity in high-innovation, high-skill settings. Our analysis of innovation outcomes indicates that these choices matter; firms with more internally oriented pay generate superior innovation outcomes, producing higher quantities and quality of patents, including more breakthrough innovations.

The discussion begins with methodological considerations concerning our data and sample. We then consider alternative mechanisms and definitions of the reference group.

5.1. Why Would Employees Agree to Internally Aligned Pay?

Our core finding is that knowledge-intensive firms, particularly for their high-skilled workers, decouple pay from external market rates. This raises an important question regarding employees' participation constraint. Why would they accept compensation that is unrelated to their market value? Although firms may desire internal alignment for strategic reasons, they are not unilateral setters of wages and must offer pay that is sufficiently attractive for employees to join and remain with the firm.

The most plausible explanation is that these firms do not ignore market rates but rather, use them as a compensation floor. In other words, firms achieve internal alignment not by ignoring the market value of their employees but by paying a premium when needed to achieve internal alignment. To test this possibility, we conduct an additional analysis in which we split our sample into two groups: firms that, on average, pay a premium over the market wage for a given role and those that pay a discount. We then rerun our main specification separately for each subsample.

The results, presented in Table A.18 in the Online Appendix, strongly support this explanation. For the group of firms paying a premium, the sensitivity of employee pay to the internal benchmark is substantial and highly significant (coefficient = 0.132). For firms paying a discount, the sensitivity to the internal benchmark is much smaller (coefficient = 0.043). This suggests that the emphasis on internal alignment is a practice engaged in by firms that pay a premium to their workers. Employees, in turn, may therefore be willing to have their pay determined by internal benchmarks because their overall compensation exceeds their outside options. Consistent with this, in supplemental analyses in the Online Appendix, we also find that firms with higher internal pay orientation also have lower horizontal pay dispersion and pay skewness among workers in the same role.

5.2. Sample and Other Methodological Considerations

Our use of data from a compensation consultancy raises questions of sample selection. Tables A.19 and A.20 in the Online Appendix compare the public firms in our sample with those in Compustat. The comparison reveals that our sample includes larger and more profitable companies than the average Compustat firm, alongside over- and underrepresentation across industries. Another potential selection effect may relate to firm performance in that that the choice to engage with the consultancy in any given year is driven either by strong performance that provides resources to cover the engagement or by underperformance that motivates the client to engage a consultancy to identify labor efficiencies. A related concern is that the consultancy's work, benchmarking and advising on pay, may itself influence compensation levels within client firms.

Several aspects of our research design mitigate these concerns. Most importantly, for sample bias to explain our results, the direction of the effect would need to explain not only inclusion in our sample but also, the patterns that we report across our three analyses in Section 4. In other words, the different pay sensitivities that we observe across various subsamples by innovation, skill level, complex problem-solving, and collaboration would need to reflect differential selection of these firms and employees into our sample along these same dimensions for reasons that are unrelated to our paper. Our view is that this is a substantial hurdle to meet.

In addition, empirically, it does not appear that performance or firm size is influencing our results. We control for performance differences across our specifications, and our results are not sensitive to their inclusion. In Figure A.4 in the Online Appendix, we reproduce Figure 2, excluding firms with the highest return on assets (above 90th percentile), and in Figure A.5 in the Online Appendix, we exclude extremely large firms (more than 25,000 employees). We find that the patterns are consistent with our main findings.

Therefore, although observational studies cannot completely eliminate sample concerns, any sample bias would need to account for more than just the average pay sensitivities reported. Whether arising from which client firms enter the sample, when they enter, or the consultancy's service itself, such bias would have to explain the specific patterns of pay sensitivities that we observe across innovation and skill settings, a more demanding standard that mitigates this concern.

5.3. Alternative Explanations

Our proposed mechanism is not the only factor that can influence market and internal pay sensitivity. We now consider whether plausible alternatives could explain our reported patterns.

5.3.1. Labor Market Power. One possibility is that differences in pay sensitivity reflects differences in bargaining processes between firms and employees. If employer monopsony power or conversely, employee bargaining power varies systematically across the same subsamples that we explore above, this could provide a different explanation for the patterns that we report.

To test whether relative power is driving our results, we examine labor market tightness as a moderator of our effects. We construct several measures of labor market tightness using the Bureau of Labor Statistics occupational and regional unemployment rates. If monopsony power was driving the empirical patterns, we would observe stronger reliance on market pay in occupations and regions with lower unemployment, where outside options are more readily available and talent competition is greater. Our results, which are reported in Tables A.21 and A.22 in the Online Appendix, indicate that market pay sensitivity does not consistently change with unemployment rates. This, in turn, suggests that labor market tightness is unlikely to be the primary driver of firms' reliance on market benchmarks.

We further test this using a direct measure of labor market concentration. Following Azar et al. (2020, 2022), we construct a labor market HHI that captures concentration in occupation-region-year markets based on firms' shares of job vacancies using the publicly available Choi and Marinescu (2024) measure. If labor market power drove our findings, we would expect a positive interaction between internal pay and labor market HHI. Instead, Table A.23 in the Online Appendix shows that this interaction is insignificant. Together, these results indicate that firms' pay orientation reflects strategic choices beyond simply responding to competitive labor market pressures.

5.3.2. Firm-Specific Human Capital. The accumulation of firm-specific human capital is another potential explanation for our findings. As employees spend more time at a firm, they acquire knowledge and skills that are not easily transferable to other employers, which may weaken the link between their pay and market rates. If this mechanism was at play, we would expect longer-tenured employees to show lower pay sensitivity to market benchmarks. To test this, we use the limited tenure data available from the consultancy. The results, presented in Table A.24 in the Online Appendix, show some evidence that longer-tenured employees are less responsive to market benchmarks, consistent with this explanation. However, there is no evidence that longer-tenured employees' pay is more sensitive to internal benchmark. Moreover, although it is theoretically clear why greater firm-specific human capital would lead to lower market pay sensitivity, it is less clear why it would lead to greater internal pay sensitivity rather than simply more idiosyncratic pay.

5.3.3. Common Profit Shocks and Rent-Sharing Practices. Another possible explanation is that internal pay sensitivity reflects the distribution of firm surplus, which manifests particularly in high-performing firms with more rents to share and among high-skill workers who are better positioned to capture it. In this view, high internal pay sensitivity may not reflect a deliberate emphasis on internal collaboration but rather, a redistribution of rents among profitable firms and skilled talent. Indeed, firms might maintain stable rent-sharing formulas over time for procedural clarity and administrative simplicity.

We address this possibility in two steps. First, our main specification incorporates firm performance controls to account for profit shocks. Because our design includes firm fixed effects, these controls absorb within-firm changes in profitability over time. As shown in Table 2, including these controls does not alter the estimates on internal or market benchmarks, nor does it affect the model's explanatory power. In other words, if internal pay sensitivity was driven by rent sharing, we would expect it to be explained by profitability fluctuations over time, yet it remains stable even after controlling for performance changes. This provides some confidence that profit shocks are not driving internal pay sensitivity, at least not in full.

Next, we conduct two additional tests to further test the rent-sharing explanation. We first interact profitability with our pay sensitivities to explore whether a greater surplus leads directly to more correlated internal pay. The results, which are reported in Table A.25 in the Online Appendix, show no evidence of this relationship. We also report whether knowledge intensity continues to moderate internal pay sensitivity even after accounting for profitability and its interaction effects. Table A.26 in the Online Appendix shows that the moderating role of knowledge intensity persists and is not explained away by profitability.

Taken together, although surplus distribution plausibly contributes to pay levels, we find limited empirical support that profitability itself drives changes in internal pay sensitivity. Although rent-sharing dynamics are likely present and may account for the variation in pay-setting practices, they do not appear to be the main force behind the patterns that we observe.

5.3.4. Upward Comparison by Laggard Firms.

An alternative possibility is that market pay sensitivity reflects upward adjustment by firms that underperform financially. Because firms rarely cut wages and have incentives to keep pay low (to capture the greatest delta between wages and revenue), alignment with market benchmarks may result primarily from upward adjustments by these "laggard" firms.

We evaluate this possibility by identifying laggard firms as firms with lower financial performance using return on assets as a proxy. If performance shapes compensation, these firms should be more likely to adjust employee pay in response to market rates. However, as shown in Table A.27 in the Online Appendix, we find no evidence that lower-performing firms are more responsive to market wages.

5.4. Robustness to Benchmark Definitions

A potential concern is that the nature of the external market may vary across occupation, potentially influencing our results. For instance, labor markets for high-skilled workers may be national or industry specific rather than regional, whereas those for lower-skilled workers may be more local. Furthermore, industry is a well-known determinant of pay that is not in our primary market definition. To ensure that our findings are not an artifact of a specific benchmark definition, we conducted two key robustness tests using alternative, nonregional market benchmarks.

First, we create a national, region-agnostic market benchmark and repeat our main analysis using this definition (Figure A.6 in the Online Appendix), which yields patterns consistent with our main findings; the relative emphasis on internal pay increases with skill and knowledge intensity. We note that the pay estimates for lower-skilled workers are noisier, which supports the intuition that their labor markets are indeed more local but that the overall pattern was unchanged.

Second, we create an industry-specific benchmark, replacing the region criterion with an industry one. This is important as many high-skilled labor markets may be national but bounded by industry. Again, our core findings regarding the increasing importance of internal pay with skill and innovation continued to hold (Figure A.7 in the Online Appendix).

Together, the consistency of our results across these different operationalizations strengthens our confidence that the observed shifts in pay orientation are a real phenomenon and not an artifact of our research design choices.

6. Conclusion

This study examines how firms navigate the tension between market and internal forces when setting employee compensation. Using nearly 19 million confidential U.S. employee records across 479 firms, we construct employee-specific internal and market pay benchmarks to measure the relative sensitivity of pay to these competing reference points.

Our analysis reveals that high knowledge-intensive firms exhibit strong internal pay sensitivity and minimal market pay sensitivity, whereas low knowledge-intensive firms show roughly equal sensitivity to both. Internal pay sensitivity increases with employee skill level, whereas market pay sensitivity remains flat. We interpret these patterns as reflecting innovation's collaborative demands; when complex problems require specialists from different domains to cooperate and share tacit knowledge, market-based pay disparities become obstacles to collaboration. Software engineers, product designers, and manufacturing specialists must work as partners despite importing different pay rates from their respective labor markets. Firms resolve this tension by prioritizing internal alignment where it matters most: in roles requiring complex problem-solving and intensive collaboration. This strategy appears effective;

internally aligned firms produce more patents and breakthrough innovations. CEO transition analysis confirms that these are deliberate choices. Firms with new CEOs who announce a renewed focus on innovation increase internal pay alignment particularly among their skilled workers, whereas firms with CEOs who announce other priorities exhibit no such change.

Our results provide a new perspective on incentives in innovative firms by highlighting their social dimension. Prior research has emphasized mechanisms that motivate individuals to pursue long-term, risky innovation, such as long-term incentive pay for heads of centralized R&D departments (Lerner and Wulf 2007) or reward schemes that tolerate early failure (Azoulay et al. 2011, Manso 2011, Ederer and Manso 2013). Our study shows that pay is not only a tool for motivating individual effort but also, a social phenomenon for aligning employees with one another. This is particularly important in innovative firms, where interdependencies require specialists to collaborate on complex problems that defy simple contracts. This study suggests that internal pay orientation itself can foster the horizontal cooperation needed for innovative outcomes.

Future work should explore the implications of these findings for corporate strategy; firms pursuing mergers and acquisitions may face integration challenges when units differ in pay philosophy, particularly when combining innovative and noninnovative businesses (Larsson and Finkelstein 1999, Zollo and Singh 2004). Pay orientation may, therefore, shape not only cooperation within firms but also, target selection, postacquisition integration, and the design of diversified firms. Additionally, governance likely matters as well; innovation-experienced CEOs and long-horizon owners may tolerate external misalignment to preserve internal coherence, whereas cost- and market-focused owners may not.

In conclusion, our findings reveal fundamental differences in how firms structure employment in innovative versus traditional contexts. As the economy shifts toward knowledge-intensive activities, successful innovation appears to require prioritizing internal communities over market relationships. Where talent is most valued, in innovative firms employing skilled workers, pay is least tied to market forces. This decoupling serves a strategic purpose, creating the collaborative environments necessary for innovation. These patterns suggest growing divergence in employment practices between innovative and traditional firms, with implications for wage inequality, labor mobility, and economic organization.

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Endnotes

[1] These bargaining dynamics are most salient in the hiring process, where firms compete directly for talent and market benchmarks shape entry wages and offers to new employees.

[2] The consultancy developed a proprietary system to construct the measure, which it has been using for more than 60 years to provide benchmarking services to thousands of client firms around the world. It sends out extensive surveys and deploys consultants to client firms to gather detailed data on job requirements and salary. They then compute a score for each job along four dimensions of (i) knowledge (which further breaks down to technical, managerial, and communicative knowledge), (ii) problem-solving capabilities, (iii) discretionary power, and (iv) impact to an organization. Finally, the scores are combined to compute *Skill Level*, which they provide to us (they do not provide the component measures).

[3] One assumption is that employees know their reference level (or at least those setting compensation assume that the employees do). This is relatively common in labor market practices in large firms; firms publish salary bands and promotion criteria by reference level, and employees know who else occupies their band.

[4] The "retail operations" function includes this example focal employee's occupation ("retail operations sales staff") as well as other occupations, such as "store operations" and "supervision and sales staff."

[5] In alternative specifications where we have included more proximate occupations to the internal reference group, overall internal pay sensitivity (unsurprisingly) increases, whereas our main results are effectively unchanged.

[6] Peters and Taylor (2017) explain their measure as follows: "A firm develops knowledge capital by spending on R&D. We estimate a firm's knowledge capital by accumulating past R&D spending using the perpetual inventory method: $G_{it} = (1 - \delta_{R\&D})G_{i,t-1} + R\&D_{it}$ where G_{it} is the end-of-period stock of knowledge capital, $\delta_{R\&D}$ is its depreciation rate, and $R\&D_{it}$ is real expenditures on R&D during the year" (Peters and Taylor 2017, p. 256).

[7] Tables A.8–A.10 in the Online Appendix correspond to these plots.

[8] See "Hay job evaluation: Foundations and applications" at https://segoslavia.wordpress.com/wp-content/uploads/2011/10/method-of-job-evaluation-2.pdf (accessed August 20, 2025).

[9] Prior research uses task content to develop similar measures. For example, Deming and Kahn (2018) measure cognitive skills in job postings by identifying keywords, such as "problem-solving," "research," and "analytical," guided by the Autor et al. (2003) description of "nonroutine analytical" tasks. They also measure social skills using keywords, such as "communication," "teamwork," and "collaboration." Deming (2017) constructs occupation-level measures of social skill intensity using Occupational Information Network variables: (i) coordination,

(ii) negotiation, (iii) persuasion, and (iv) social perceptiveness. Our approach is conceptually similar but enhances precision by incorporating proprietary skill-level measures and detailed Hay Group component descriptions. This enables us to capture within-occupation variation in both problem-solving intensity and collaborative intensity.

[10] In Tables A.28 and A.29 in the Online Appendix, we show that our main finding (the shift toward internal pay alignment) is driven by the presence of these complex problem-solving roles, regardless of the firm's overall knowledge intensity. In other words, our mechanism is broader than innovation and industry effects alone.

[11] Our compensation data, although available at the individual level, do not include employee identifier (e.g., name), and we are unable to match these data to an individual inventor or scientist.

[12] In Table A.16 in the Online Appendix, we report the estimates from regressing each innovation measure on *Internal Pay Sensitivity* separately; we find generally consistent results across measures rather than any single innovation outcome driving the patterns reported in Table 8. In Table A.17 in the Online Appendix, we report results from regressing innovation outcomes on *z*-scored *Market Pay Sensitivity*. The results are reversed relative to Table 8, with a negative relationship between *Market Pay Sensitivity* and innovation performance, particularly among the complex problem-solving (high) subsamples.

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