Dual Career Ladders:
Individual Contributors in Modern Corporate Hierarchies*

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Abstract

Firms often maintain dual career ladders for managers and individual contributors (ICs). Using personnel records from 43 medium-sized and large firms, we reconstruct complete reporting chains and organizational layers to document how these tracks are structured and compensated. We show that ICs are prevalent throughout the hierarchy but earn substantially less than managers in comparable positions, with the pay gap increasing toward the top. To interpret these patterns, we develop and estimate a model of dual careers in which firms allocate workers across management and IC tracks subject to coordination and problem-solving frictions. The estimates reveal distinct firm types with respect to their hierarchy shape, degree of managerial specialization, and workforce composition that generate varying IC pay gaps and respond differently to organizational shocks. Motivated by the large pay gains associated with promotions from IC to manager roles, we then analyze the demographic composition of the IC workforce. While pay within each track does not significantly vary across demographic groups, women and minority workers are disproportionately represented on IC tracks, especially at higher ranks. Thus, assignment to IC and managerial tracks emerges as a key mechanism through which within-firm career inequality contributes to broader gender and racial pay gaps.

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1 Introduction

Career advancement inside firms is often framed as progression into management. At the same time, many firms also allow knowledge workers to rise as individual contributors (ICs), with higher rank and pay but no direct reports, even near the top of the hierarchy. These dual career ladders reflect an important organizational choice over how to divide work between supervision and specialized problem solving. Yet we know surprisingly little about how these tracks are structured, how they shape pay and careers, or why some firms rely on them more than others.

In this paper, we study dual career ladders as an organizational design margin. We ask how firms allocate workers, set pay, and structure career progression across managerial jobs, which involve supervision, and IC jobs, which do not. Using personnel records from 43 medium-sized and large firms, we reconstruct complete reporting chains and organizational layers and link them to worker demographics, compensation, and internal job moves.

Our paper uses these unique data to make three main contributions. First, we show that ICs are prevalent throughout the organizational hierarchy and earn systematically less than managers, with this IC pay gap widening at higher levels. The magnitude of these average patterns varies substantially across firms. Second, we develop and structurally estimate a model of firm organization that embeds both a vertical hierarchy and a within-level division of labor between supervision and problem solving, giving rise to dual career ladders. We then use the results to derive a typology of firms based on task specialization between ICs and managers that maps onto systematic differences in observed firm characteristics. We use counterfactuals to show that IC career ladders respond strongly to changes in supervision and problem-solving technologies. Third, we examine promotion practices into managerial roles by gender and race, and show that assignment to managerial versus IC jobs—rather than differential pay within these tracks—is an important driver of differences in career trajectories across these worker groups.

We start by building a harmonized, employee–month panel from de-identified administrative HR records covering the full workforce of firms in our sample. In addition to compensation and job titles, the data include direct reporting links, allowing us to map the organizational structures in detail. We define ICs as workers with zero direct reports and managers as workers with positive span of control, then construct a comparable hierarchy across firms with varying hierarchical depth by pooling layers into top, middle, and bottom tiers.

We document four core empirical facts about IC careers that motivate the subsequent analysis. First, ICs are prevalent throughout the hierarchy, representing 62 percent of workers in the middle and 36 percent at the top even after excluding administrative employees. Second, ICs earn substantially less than managers: on average, 0.31 log points less after controlling simultaneously for firm, month, hierarchical layer, and job function, as well as worker demographics. Moreover, they experience slower pay growth, lower promotion rates, and higher exit rates. This IC pay gap grows sharply toward the top of the hierarchy, almost doubling in magnitude. Third, while rare, transitions from IC to manager are consequential, leading to 0.25-log-points higher pay. Fourth, both the IC share and the IC pay gap vary widely across firms, pointing to systematic differences in how organizations structure dual career ladders.

To interpret these patterns, we extend the knowledge-hierarchy framework of Garicano (2000) to study how firms allocate high-level work between supervision and problem solving. In the baseline model, production workers generate problems and escalate those they cannot solve to higher-level workers with greater knowledge. We introduce supervision as a distinct task with convex time costs in the number of subordinates. Intuitively, supervision is useful because it addresses coordination frictions within the hierarchy by organizing communication and ensuring that problems are routed efficiently to workers with the relevant knowledge. Managers allocate time between supervision and problem solving, while ICs specialize in problem solving.

The firm optimally chooses at each level how many managers and ICs to employ and how to allocate their time. The model delivers closed-form expressions for optimal managerial span, IC share, and IC pay gap at each hierarchical level. Consistent with the motivating facts, the optimal allocation can generate a substantial share of IC workers throughout the hierarchy, including at the top, and IC pay gaps that widen at higher levels.

We take the model to the data by estimating a parsimoniously parameterized version for each firm. We formally show how observed hierarchy moments (spans, IC shares, IC pay gaps, and manager pay ratios across hierarchical tiers) identify the model's primitives. The estimates highlight a sharp distinction in supervision profiles across firms: about one quarter assign managers overwhelmingly to supervision tasks (corresponding to 90 percent or more of managers' time), while managers in the remaining firms split their time more equally between supervision and problem solving. This distinction is economically meaningful: firms in which managers are less specialized in supervision have more top-heavy hierarchies, flatter managerial career ladders and higher average IC pay, higher-skilled workforces, and are disproportionately concentrated in the tech sector.

Next, we use the estimated model for counterfactual simulations. Changes in supervision costs, problem-solving costs, and knowledge dispersion across hierarchical tiers have distinct effects on the career ladders of ICs. Lower problem solving costs reduce the pay gap between ICs and managers, but flatten the pay gradient of ICs. Lower variable supervision costs and less knowledge dispersion across levels steepen the pay gradient of ICs but widen the IC pay gap compared to managers and increase the risk of workers getting stuck in IC roles. These effects are more pronounced at more specialized firms, implying that differences between IC and manager careers in these organizations are particularly sensitive to changes in the production environment.

Finally, we use the worker-level panel to study how assignment to IC roles differs across demographic groups. We show that women and racial minority workers are significantly more likely to be employed as ICs. For example, women are 3 percentage points more likely to be ICs than male colleagues at the same hierarchical level and with the same age, tenure, and job function. This difference in IC status accounts for 13 percent of the gender pay gap (conditional on the same set of controls) and grows larger at higher hierarchical levels. At the same time, we find little evidence that the IC pay gap itself differs systematically by gender or race. These findings point to assignment to managerial or IC tracks, rather than differential pay within track, as a key driver of demographic differences in career trajectories.

Given the importance of this assignment margin, we next examine how firms select workers for transitions from IC to managerial roles across demographic groups. We first proxy for post-promotion managerial performance using the average pay of a manager's subordinates during her whole managerial spell, expressed as the within-firm percentile rank. Non-Asian minority and female managers lead teams with significantly lower average pay than White and male counterparts, while Asian managers show a positive, albeit insignificant, gap. Taken at face value, these results would suggest that firms promote less capable women and non-Asian minorities into management. However, the OLS estimates conflate differences in promotion decisions with differences in the composition of the candidate pool eligible for promotion.

To separate these channels, we follow the IV strategy of Benson et al. (2019), exploiting variation in the intensity of IC-to-manager transitions outside a worker's own team, measured at the firm-by-job-function level, to isolate the performance of marginally promoted managers. Therefore, the IV estimates capture whether firms apply different promotion thresholds across demographic groups, net of mean differences in the underlying candidate pools. Moving from OLS to IV substantially attenuates the gender gap, suggesting that factors preceding the promotion decision—such as self-selection, differential application rates, and earlier firm decisions over hiring, mentoring, and task assignment—account for much of the raw difference for women. The attenuation is proportionally similar for Asian employees, but from a positive starting point. For non-Asian minorities, by contrast, the gap persists largely unchanged at the margin, still pointing to differential treatment in the promotion decision itself.

Finally, the IV estimates still reflect the characteristics of the teams to which newly promoted managers are assigned. We address this by replacing average subordinate pay with manager value added estimated from a two-way fixed effects model, which isolates the manager's own contribution to subordinate outcomes. This step reveals that unfavorable team assignments account for a substantial share of the remaining gap for non-Asian minorities. At this stage, none of the average gaps between minority and majority groups are statistically significant, but firm-level estimations reveal meaningful heterogeneity, echoing the large cross-firm variation in hiring practices documented by Kline et al. (2022).

Our paper contributes to several strands of the literature in personnel and organizational economics. First, economic research has long tried to understand firms' tradeoffs in choosing their optimal hierarchical structure. One important strand of theoretical contributions considers hierarchies as a governance structure to provide monitoring and align incentives (Williamson, 1967; Calvo and Wellisz, 1978; Rosen, 1982). Important tradeoffs include limits to supervision as the managerial span of control increases and loss of control as the number of hierarchical layers increases. Another strand of the theoretical literature focuses on task assignments and communication to improve problem solving within the organization (Garicano, 2000; Garicano and Rossi-Hansberg, 2006). The key tradeoff compares gains from specialization to communication and coordination costs. A third strand emphasizes coordination and studies when organizations centralize decisions to align interdependent activities across units (Alonso et al., 2008; Dessein et al., 2022). Consistent with our theoretical approach, Roberts and Shaw (2022) argue in a recent review on managers and management practices that a key role of middle management is to coordinate people, projects, and information inside organizations. More broadly, Hoffman and Stanton (2025) highlight managers below the C-suite as an increasingly important object of study, emphasizing their effects on subordinate productivity. These theories of firm hierarchies, however, typically consider a single managerial ladder and abstract away from horizontal specialization within levels. We extend this literature by developing a model in which dual career tracks arise endogenously from the relative costs of coordination and problem solving, and in which the optimal mix of managers and ICs varies across hierarchy levels and firm types.

Second, in contrast to an established theoretical literature, empirical research on organizational structure has been scarcer, largely due to the difficulty of gathering detailed information about organizational structure across firms and over time. Influential work on how firms organize their workforce comes from a compensation survey on senior executives in publicly traded U.S. firms over 1986-1999 to study the structure of upper management (Raghuram G. Rajan and Julie Wulf, 2006; Maria Guadalupe and Julie Wulf, 2010). Garicano and Hubbard (2016) has quantified the productivity and earnings consequences of knowledge hierarchies in legal services, using data from the Census of Services. Additional work has used large administrative employer-employee data to analyze hierarchical organization across the entire workforce and compare hierarchical structures within and across industries (for example, Caliendo et al. (2015) for France, Caliendo et al. (2020) for Portugal, and Friedrich (2022) for Denmark). However, these studies based on administrative register data can only measure coarse hierarchies based on worker occupations and lack information on job ranks and reporting relationships within a particular firm. By contrast, the data used in this paper, provided by a private company specializing in people analytics services, contain detailed personnel records and reporting relationships for the entire workforce across firms and industries, allowing us to analyze organizational hierarchies and career ladders in much greater detail and to provide some of the first systematic cross-firm evidence on the structure and consequences of dual career ladders.

Third, our paper relates to the theoretical and empirical literature on careers within organizations. Classic work on internal labor markets emphasizes ports of entry and promotion incentives (Doeringer and Piore, 1970; Lazear and Rosen, 1981). Using detailed personnel records for a single firm, Baker et al. (1994) document an internal career ladder for managers, with substantial wage variation within levels, a close link between wage growth and promotions, and fast-track careers. Gibbons and Waldman (1999) provide a framework in which job assignment, learning, and human-capital accumulation jointly shape wage and promotion dynamics, while Ke et al. (2018) analyze how firms manage worker careers when promotion-based incentives are constrained by the organizational structure. We contribute to this literature by extending the focus from a single managerial ladder to dual career ladders and by studying how assignment across tracks shapes pay and career progression.

Fourth, we connect to the broader literature on gender and racial inequality in labor markets (for example, see the reviews by Blau and Kahn (2017) and Lang and Kahn-Lang Spitzer (2020)). Recent work points to hiring, job assignment, and promotions as key mechanisms behind remaining career achievement gaps. In particular, Kline et al. (2022) conduct correspondence experiments to show that racial discrimination in hiring remains persistent in the U.S., but varies substantially across firms. Using data for individual firms, Cullen and Perez-Truglia (2023) and Benson et al. (2026) respectively show that the gender gap in promotions can in part be explained by a lack of informal networks and lower subjective assessments of career "potential." We add to this literature by showing that differential sorting into IC and managerial roles is a quantitatively important margin behind gender and racial pay gaps, and by examining the promotion decisions that sustain this sorting.

2 Data

2.1 HR Data From Multiple Firms

Our main dataset consists of de-identified, employee-level administrative HR records drawn from multiple firms. These data are accessible through a collaboration with Visier, a leading workforce-analytics provider that aggregates and standardizes HR data from a large portfolio of firms. For each client, Visier processes raw HR data from disparate internal systems (for example, payroll, performance, and benefits) and maps them into a firm-specific panel dataset, enabling longitudinal tracking of workforce flows (hires, separations, internal moves) within firms and cross-firm comparability.

The sample covers 43 firms of varying workforce size: 47 percent have fewer than 2,000 employees, 30 percent have between 2,000 and 3,999 employees, and the remaining 23 percent have at least 4,000 employees (Table B1, Panel A). These firms operate across a range of industries, with the largest representation in manufacturing (28 percent of firms in the sample), high tech (30 percent), financial services (21 percent), and healthcare (9 percent). In all but one firm, the largest share of the workforce is located in the United States.

The data are organized at the employee–month level, with the average firm observed for 81 months. For each firm–month, we observe the full hierarchical reporting chain, which allows us to reconstruct the management structure within each firm, identify the team to which each worker belongs, and locate every employee's position in the broader organizational hierarchy. Alongside job-related information such as tenure and job function, classified into nine categories (for example, sales, admin, R&D), these datasets also contain demographic attributes including age, gender, and race, which allow us to study the representation of demographic groups across jobs and levels of the hierarchy.[1]

Access to the Visier Community data provides opportunities that are rarely available in organizational and personnel economics. First, the richness of the HR records makes it possible to analyze organizational hierarchies and career dynamics at a level of detail far beyond what is typically found in administrative data, where workers are often distinguished only by broad job categories. For example, we can observe exact reporting chains and team structures, which are necessary for studying the dual careers of managers and individual contributors. Second, by pooling information from many firms operating in different sectors, we can provide results that are more externally valid and examine heterogeneity across organizational contexts. Together, these features give us a uniquely powerful data source for understanding how modern firms structure their hierarchies and how individual careers evolve within them.

We discuss the summary statistics and the external validity of the sample in Appendix B. Specifically, we benchmark our sample against the U.S. Equal Employment Opportunity Commission's EEO-1 dataset. Overall, the sample is highly comparable in industry mix, gender and racial composition, and shows only small differences in the distribution of jobs across functions.

[1] In our data, Hispanic is coded as a mutually exclusive race category rather than a separate indicator of ethnicity.

2.2 Constructing the Key Variables

In this section, we describe how we construct the key variables for the analysis from the raw firm-month data.[2]

A central concept in our analysis is the distinction between individual contributors (ICs) and managers. We classify employees based on their span of control, defined as the number of direct reports assigned to them in the organizational hierarchy. Specifically, workers with a span of control of zero are defined as ICs. In our sample, the average share of ICs is 82 percent, with a standard deviation across firms of 8 percent (Table B1, Panel A). The average monthly transition rate from IC to manager is 0.5 percent, with a cross-firm standard deviation of 0.4 percent.

Next, the reporting chains in the data allow us to reconstruct the organizational layers within each firm. We define layers recursively: the C-suite occupies the top layer, their direct reports are assigned to layer 2, the direct reports of those employees are assigned to layer 3, and so on down the hierarchy. This procedure yields a detailed depiction of the vertical structure of each firm.

We then combine the first two layers of the hierarchy for confidentiality reasons because the number of employees observed at the very top of firms is often small. In practice, we relabel original layers 1 and 2 as layer 2.[3] We make analogous adjustments at the bottom of the hierarchy. In firms with up to nine layers, we merge the bottom two layers. In firms that originally had ten or more layers, we merge all layers from the ninth downward into a single layer, since these lower layers tend to be very small when considered in isolation. After these adjustments, we define the depth of a firm as the maximum organizational layer, with a maximum possible depth of nine. While firm depth varies across organizations, it is fairly concentrated toward the upper end of the distribution. The mean depth is 7.8 layers, and 94 percent of the firms in the sample have between seven and nine total layers.

For many analyses, we further aggregate organizational layers into top, middle, and bottom tiers (Figure A1). For example, we assign employees in layer 5 to the bottom tier if a firm has five total layers but to the middle tier if a firm has nine layers. This step creates a consistent framework for comparing organizational positions across firms of different depth. Across these three broad tiers, the average hierarchy is shaped as a narrow "pyramid," with employment shares falling rapidly from the bottom upward (Figure 1, Panel A).

In the first part of the analysis, one of our primary outcomes is annual direct compensation, which includes base salary, overtime pay, and bonuses paid in cash. We refer to this measure simply as pay throughout the analysis. In addition to pay, we consider three other outcomes that capture career dynamics within the firm: promotions, defined as moves to a higher hierarchical layer within the firm, monthly pay growth, and the probability of exit from the firm in the following month.

[2] We remove a small number of observations with incomplete reporting chains, which typically reflect workers who have just joined or left the firm. We also exclude employees with zero recorded pay, as these observations likely do not correspond to active employment relationships.

[3] Note that seven firms do not report C-suite level 1, so their highest level consists only of employees who were originally classified as belonging to level 2.

3 Core Empirical Facts

Panels B and C of Figure 1 provide a first look at how employment and pay vary across hierarchical tiers for ICs and managers. Two patterns stand out. First, ICs in lower tiers constitute the majority of total employment, whereas managerial employment is much lower and spread more evenly across tiers. Second, pay rises with tier for both roles, but the gradient is far steeper for managers. These findings point to fundamentally distinct career paths within firms. This section establishes four core facts about their properties across firms and industries.

Fact 1: ICs are prevalent throughout the hierarchy. Figure 2 presents the distribution of ICs across organizational tiers. At the bottom of the hierarchy, ICs make up 90 percent of employees. Their share declines to 64 percent in the middle tier. Strikingly, ICs continue to represent 44 percent of employees at the top of the hierarchy. Administrative employees account for higher-than-average IC shares at all tiers, but removing them does not alter the overall pattern.

Fact 2: ICs face a pay gap and experience slower career progression than managers. Next, we show that ICs earn substantially less than managers, even after accounting for detailed job information and employee characteristics (Table 1). In the most demanding specification, we compare pay between ICs and a managers in the same firm and month, working in the same hierarchical layer and job function, and with the same age, tenure, gender, and race. Even in this finely controlled setting, ICs earn on average 0.31 log points less than comparable managers, and this coefficient is statistically significant at the 1 percent level.

The pay gap for ICs is robust when we move beyond log pay and consider other measures of career success. Using promotion probability, monthly pay growth, and the likelihood of exit from the firm as dependent variables, ICs consistently fare worse than otherwise similar employees in the managerial track (Table A1). In the most saturated specifications, ICs are 0.2 percentage points less likely to be promoted each month, experience 0.1 percentage points lower monthly pay growth, and are 0.5 percentage points more likely to leave the firm in the following month. These results show that the disadvantages of IC roles extend beyond static pay levels and translate into slower career progression. These estimated disadvantages are economically meaningful and similar in relative size. Specifically, being an IC corresponds to an 18 percent decline relative to the mean monthly promotion rate of 1.15 percent, a 17 percent reduction relative to the mean monthly pay increase of 0.46 percent, and a 24 percent increase relative to the mean monthly exit rate of 1.9 percent.

Finally, we find that the IC pay gap is not uniform across the hierarchy but instead grows more severe toward the top (Table A2). In the bottom tier, ICs earn 0.28 log points less than managers in the same firm, month, organizational layer, and job function. At the top, ICs earn 0.49 log points less than comparable managers, a gap 75 percent larger than the one observed at the bottom.

Fact 3: IC-to-M transitions are rare and lucrative. Building on this evidence, we examine career transitions out of IC roles.[4] These transitions are rare, only 0.5 percent of employee-month observations involve a switch from IC to manager (Table B1), but consequential.

Across all outcomes, employees who remain ICs fare the worst (Table 2): they earn the lowest pay, experience the slowest pay growth, and face the highest probability of exit. By contrast, moving out of IC roles is associated with large gains. Relative to staying IC, IC-to-M transitions are linked to 0.25-log-points higher pay, 2 percentage points faster pay growth, and 1 percentage point lower turnover in the following month. Moreover, IC-to-M moves are associated with a 17-percentage-point higher probability of promotion, confirming that these transitions capture genuine career advancements rather than administrative relabeling.[5]

Fact 4: IC shares and penalties vary substantially across firms. Next, we leverage a distinctive aspect of our data by examining whether the IC share and IC pay gap vary across firms.

First, Panel A of Figure 3 plots the IC share across firms. We find substantial variation across firms, ranging from less than 70 percent to more than 95 percent. Second, the data indicate that negative IC pay gaps are common across firms in the sample. Panel B reports the estimated coefficients on the IC indicator from regressions run separately for each firm, where the dependent variable is log monthly pay and the controls match the most saturated specification in Table 1. In every firm, the IC coefficient is negative and statistically significant at the 5 percent level. The mean IC pay gap across firms is 0.34 log points, but individual firms deviate considerably from this mean. About 10 percent of firms have penalties larger than 0.47 log points, while another 10 percent have penalties smaller than 0.23 log points. The overall spread across firms is 0.58 log points, ranging from –0.64 in the most extreme case to –0.06 in the least.

4 A Model of Dual Careers

To interpret the empirical patterns, we develop a model in which firms choose how to allocate workers across managerial and individual-contributor roles within the organizational hierarchy. The model links observed differences in pay, career progression, and organizational structure to underlying features of production and coordination.

4.1 Setup

Overview. Closely following Garicano (2000), we model firm production as a process of handling problems of heterogeneous difficulty. Problems originate at the bottom of the hierarchy and can be solved locally if they fall within a worker's knowledge; otherwise, they are escalated to more knowledgeable workers at higher levels. A key departure from that benchmark model is that escalation and problem solving inside the firm are not frictionless: matching escalated tasks to experts and monitoring progress require supervision

[4] Specifically, we track employees across consecutive months and classify them by whether they stay in the same role type or switch between IC and manager (IC-to-M).

[5] M-to-IC moves are also associated with positive outcomes. These are not demotions but promotions into more senior IC tracks, as shown by the positive and significant coefficient of the M-to-IC dummy when the dependent variable is the promotion indicator.

and coordination time. We capture this additional task by introducing *managers* (M) whose defining role is to provide supervision and coordination for a team, while *individual contributors* (IC) specialize in problem solving without supervisory duties.

Firm organizational structure. Consider a firm with $L+1$ organizational levels, where level 0 is the lowest and level L the highest. There are N_0 production workers at level 0. Moreover, at each level $l > 0$, there are N_l workers split between managers and ICs. $N_l^M \geq 0$ and $N_l^{IC} \geq 0$ denote the numbers of managers and ICs at level l, respectively, such that $N_l = N_l^M + N_l^{IC}$.

Problem and knowledge distribution. Each production worker at level 0 receives one problem z per period, drawn from a distribution F_z in which problems are sorted from most to least common (so $f_z' < 0$).[6] Workers at level l have knowledge level Z_l: they can solve any problem $z \leq F_z^{-1}(Z_l)$ but have to escalate any problem $z > F_z^{-1}(Z_l)$ to the next level, as $Z_{l+1} > Z_l$.

Managers. Managers are both supervisors and problem solvers.

Each manager at level l supervises S_l subordinates at level $l-1$, facilitating their production and by extension the production of all workers below them in their reporting chains. The manager's time cost for supervising S_l subordinates is $F_l + c_l S_l^{\gamma}$, with $\gamma > 1$. The fixed component captures team- or firm-level costs, such as learning internal procedures and holding coordination meetings, while the variable component captures individual-level costs of supervision and monitoring. We assume convex variable costs to reflect, for example, limited managerial attention and increasing coordination frictions in larger teams.

Moreover, each manager can also directly handle problems escalated by K_l^M workers at level $l-1$. The manager's time cost for this problem-solving role is $t_l K_l^M$, where t_l represents the time required to either solve or further escalate problems received from one level-$(l-1)$ worker.

Individual contributors. ICs only handle problems escalated by workers at level $l-1$. Each IC helps K_l^{IC} workers at level $l-1$ at time cost $t_l K_l^{IC}$.

Manager and IC pay. Managers and ICs are paid in proportion to an "added value" index defined as the output loss from removing the worker, holding the rest of the organization fixed.[7] For managers, we assume that removing supervision reduces production throughout their reporting chain. For ICs, we assume that removing their expertise reduces the set of problems that can be solved relative to the level immediately below, so their added value is proportional to the incremental output of problem-solving from level $l-1$ to level l.

The combined output of the full reporting chain of a manager at level l totals $Z_l \rho_{l-1} S_l$, where ρ_{l-1} captures the scale of activity generated by a level-$(l-1)$ worker.[8] Without the manager, this combined

[6] An alternative interpretation is that problems are sorted by level of difficulty, as discussed in Garicano (2000).

[7] The implicit assumption is that managers and ICs have the same bargaining power vis-a-vis the firm.

[8] Alternatively, ρ_{l-1} can be interpreted as the expected output generated by the whole reporting chain of a level-$(l-1)$ worker without further escalations to level l.

output is only $(1-\kappa)Z_l\rho_{l-1}S_l$, where $\kappa > 0$ denotes the proportion of incremental output made possible by the manager through her supervision activities. It follows that the added value of managers at level l is

$$\begin{aligned} & \kappa Z_l\rho_{l-1}S_l + (1-\kappa)(Z_l - Z_{l-1})\rho_{l-1}K_l^M \\ = & \underbrace{\kappa Z_{l-1}\rho_{l-1}S_l}_{\text{subordinates' output}} + \underbrace{\kappa(Z_l - Z_{l-1})\rho_{l-1}(S_l - K_l^M)}_{\text{escalated prob. solved by others}} + \underbrace{(Z_l - Z_{l-1})\rho_{l-1}K_l^M}_{\text{escalated prob. solved by manager}} . \end{aligned} \tag{1}$$

Managers' added value can be decomposed into three components: (i) the output generated by their level-$(l-1)$ subordinates thanks to supervision, $\kappa Z_{l-1}\rho_{l-1}S_l$, (ii) the output from the problems escalated by their subordinates thanks to supervision and solved at level-l by other managers and ICs, $\kappa(Z_l - Z_{l-1})\rho_{l-1}(S_l - K_l^M)$, and (iii) the output from the problem-solving directly undertaken by the manager, $(Z_l - Z_{l-1})\rho_{l-1}K_l^M$.

For an IC at level l, the added value is $(Z_l - Z_{l-1})\rho_{l-1}K_l^{IC}$. Because supervision and problem-solving are complementary inputs and reporting chains overlap, added values need not sum to total firm output; we use them only to characterize relative pay.

Equilibrium conditions. First, we require that no workers be left unsupervised. Accordingly, the number of workers supervised by level-l managers must equal the number of workers at level $l-1$, since any excess supervisory capacity at level l would be suboptimal. That is, $N_l^M S_l = N_{l-1}$.

Second, following Garicano (2000), we require that all problems escalated by level-$(l-1)$ workers be handled by some level-l manager or IC, such that $N_l^M K_l^M + N_l^{IC}K_l^{IC} \geq N_{l-1}$. However, since any excess problem solving capacity at level l would also be suboptimal, the equilibrium conditions imply $N_l^M K_l^M + N_l^{IC}K_l^{IC} = N_{l-1} = N_l^M S_l$.

4.2 The Optimization Problem Across Levels

Given a fixed number of organizational levels $L+1$, firm size N ($N = \Sigma_{l=0}^{L} N_l$), problem distribution F_z, and knowledge distribution Z_l, the firm chooses the allocation of production workers, managers, and individual contributors across organizational levels to maximize total output. Intuitively, this is equivalent to maximizing the number of level-0 production workers N_0, subject to having a sufficient number of managers and ICs at each higher level to manage and support production. We formally show this by induction below.

As it follows from Section 4.1, the mean total output of a level-l worker is $Z_l\rho_l$. Thus, the combined output of all workers at level l and below is $Z_l\rho_l N_l$. Separately by worker type, this combined output is $N_l^M[Z_{l-1}\rho_{l-1}S_l + (Z_l - Z_{l-1})\rho_{l-1}K_l^M] + N_l^{IC}(Z_l - Z_{l-1})\rho_{l-1}K_l^{IC}$, where the first half represents the combined output of N_l^M level-l managers and their reporting chains and the second half represents the output of N_l^{IC} level-l ICs.

It follows that:

$$\begin{aligned} Z_l \rho_l N_l &= N_l^M [Z_{l-1}\rho_{l-1} S_l + (Z_l - Z_{l-1})\rho_{l-1} K_l^M] + N_l^{IC}(Z_l - Z_{l-1})\rho_{l-1} K_l^{IC} \\ &= Z_{l-1}\rho_{l-1}(N_l^M S_l) + (Z_l - Z_{l-1})\rho_{l-1}(N_l^M K_l^M + N_l^{IC} K_l^{IC}) \\ &= Z_{l-1}\rho_{l-1} N_{l-1} + (Z_l - Z_{l-1})\rho_{l-1} N_{l-1} \\ &= Z_l \rho_{l-1} N_{l-1}. \end{aligned} \tag{2}$$

As $\rho_l N_l = \rho_{l-1} N_{l-1} \forall\, l \in \{1, L\}$, it follows that $\rho_l N_l = N_0 \;\forall\, l \in \{1, L\}$.[9]

The firm's total output, which is the combined output of all workers at level L and below, is $Z_L \rho_L N_L = Z_L N_0$. Maximizing total output is therefore equivalent to maximizing N_0, the number of production workers. For a given firm size N, this is the same as minimizing $\Sigma_{l=1}^{L} N_l$, the total number of managers and ICs. This problem is equivalent to minimizing $\Sigma_{l=1}^{L} N_l$ for a given number of production workers N_0.

Finally, we show in Appendix C.1 that this is equivalent to recursively minimizing N_l, the number of level-l managers and ICs, given N_{l-1}, the number of level-$(l-1)$ workers, starting from level 1 up to level L. We study this level-by-level minimization problem in the next subsection.

4.3 The Optimization Problem at Each Level l

At each level l, the firm chooses the number of managers N_l^M and individual contributors N_l^{IC}, together with their spans S_l, K_l^M, and K_l^{IC} to minimize $N_l^M + N_l^{IC}$, given the number of level-$(l-1)$ workers N_{l-1}, the two equilibrium conditions in Section 4.1, managers' and ICs' time constraints, and feasibility constraints. This optimization problem is:

$$\min_{\{N_l^M, N_l^{IC}, S_l, K_l^M, K_l^{IC}\}} \quad N_l^M + N_l^{IC} \tag{3}$$

$$s.t.$$

$$N_l^M S_l = N_{l-1} \tag{4}$$

$$N_l^M K_l^M + N_l^{IC} K_l^{IC} = N_{l-1} \tag{5}$$

$$F_l + c_l S_l^{\gamma} + t_l K_l^M \leq 1 \tag{6}$$

$$t_l K_l^{IC} \leq 1 \tag{7}$$

$$N_l^M \geq 0, N_l^{IC} \geq 0, \qquad S_l \geq 0, K_l^M \geq 0, K_l^{IC} \geq 0 \tag{8}$$

where Equations (4) and (5) are the equilibrium conditions discussed in Section 4.1, Inequalities (6) and (7) represent managers' and ICs' time constraints, respectively, and the inequalities in (8) form a set of feasibility constraints. Observe that $N_l^M + N_l^{IC}$ is minimized when the time constraints hold with equality.

Proposition 1. *Suppose $F_l \leq (\gamma - 1)/\gamma$. For layer l, the cost-minimizing allocation is given by optimal*

[9] Without loss of generality, we normalize $\rho_0 = 1$.

spans $S_l{}^*$, K_l^{IC*}, K_l^{M*} *with*

$$
\begin{aligned}
S_l{}^* &= \left(\frac{F_l}{(\gamma-1)c_l}\right)^{1/\gamma} && (9)\\
K_l^{IC*} &= \frac{1}{t_l} && (10)\\
K_l^{M*} &= \frac{1-\frac{\gamma}{\gamma-1}F_l}{t_l}. && (11)
\end{aligned}
$$

Managers and ICs coexist at level l *if and only if*

$$D_l \equiv S_l{}^* - K_l^{M*} > 0.$$

This result illustrates how the optimal span for managerial supervision $S_l{}^*$ *increases in the fixed cost of supervision* F_l *and decreases in the variable supervision cost* c_l. *The spans for problem solving,* K_l^{IC*} *and* K_l^{M*}, *are inversely related to the time cost of problem solving* t_l. *Managers only spend time on problem solving if their time constraint does not yet bind after their supervision tasks, which require* $\frac{\gamma}{\gamma-1}F_l$ *units of time. Here, the assumption* $F_l \leq (\gamma-1)/\gamma$ *ensures that* K_l^{M*} is weakly positive. *At the upper bound on* F_l, *managers are fully specialized in supervision tasks.* See Appendix C.2 for proof.

The condition $D_l > 0$ indicates that managers cannot provide problem solving for all employees that they supervise in the level below. This, in turn, ensures that some ICs exist at level l to provide the remaining problem solving capacity. The condition $D_l > 0$ holds when F_l is sufficiently large, c_l is sufficiently small, and/or t_l is sufficiently large. Intuitively, larger F_l promotes specialization in supervision due to larger fixed cost of managing, and smaller c_l and/or larger t_l imply lower management cost relative to problem-solving cost. Both mechanisms increase $S_l{}^*$ relative to K_l^{M*}, thereby inducing the need for ICs. We will focus on this case going forward.

Proposition 2. *Suppose managers and ICs coexist at level* l $(D_l > 0)$.
1. The IC share at level l,ξ_l, *can be expressed by*

$$\xi_l \equiv \frac{N_l^{IC*}}{N_l^{M*}+N_l^{IC*}} = \frac{S_l{}^* - K_l^{M*}}{K_l^{IC*}+S_l{}^*-K_l^{M*}} \tag{12}$$

and is increasing in F_l *and* t_l, *and decreasing in* c_l.
2. The IC pay gap at level l, π_l, *defined as the difference between IC pay and manager pay, can be expressed by the log difference in their added value,*

$$
\begin{aligned}
\pi_l &\equiv \ln\left((Z_l - Z_{l-1})\rho_{l-1}K_l^{IC*}\right) - \ln\left(\kappa Z_l \rho_{l-1} S_l{}^* + (1-\kappa)(Z_l - Z_{l-1})\rho_{l-1}K_l^{M*}\right)\\
&= -\ln\left(\kappa\frac{1}{q_l}t_l S_l{}^* + (1-\kappa)(1-\frac{\gamma}{\gamma-1}F_l)\right), && (13)
\end{aligned}
$$

where $q_l \equiv (Z_l - Z_{l-1})/Z_l$. *This (negative) IC pay gap widens as* t_l *and* κ *increase, and as* c_l *and the knowledge gap* q_l *decrease.* See Appendix C.3 for proof.

4.4 Model Implications

Section 3 documents that (i) the IC share declines toward the top of firms' hierarchies, (ii) the IC pay gap rises toward the top, and (iii) hierarchies display a pyramidal shape. The next proposition characterizes when the model can generate these empirical patterns jointly.

Proposition 3. *Assume $D_l > 0 \; \forall \; l \in \{1, L\}$, so that managers and ICs coexist at every level, and let $\gamma = 2$. Then:*

1. *The IC share declines toward the top of the hierarchy, $\xi_{l+1} < \xi_l$, if $t_l \sqrt{F_l/c_l} + 2F_l$ is decreasing in l.*
2. *The (negative) IC pay gap widens toward the top, $\pi_{l+1} < \pi_l$, if $\kappa t_l \sqrt{F_l/c_l}/q_l - 2(1-\kappa)F_l$ is increasing in l.*
3. *Employment declines toward the top of the hierarchy, $N_l < N_{l-1}$, if $t_l + 2\sqrt{F_l c_l} < 1 \; \forall \; l \in \{1, L\}$.*

See Appendix C.4 for proof.

Proposition 3 illustrates that under a broad range of parameter combinations, the model can generate the core patterns observed in the data. We assume $\gamma = 2$ for simplicity, reflecting quadratic supervision costs. One sufficient condition for the model to match the patterns in the data is that problem solving costs t decline toward the top ($t_{l+1} < t_l$, because support is needed less frequently), whereas supervision costs remain stable ($F_{l+1} = F_l$ and $c_{l+1} = c_l$). This ensures falling IC shares. In addition, fixed supervision costs imply a stable span $S = \sqrt{F/c}$. Hence, the incremental knowledge q must fall faster than the costs of problem solving to guarantee widening IC pay gaps. Finally, with sufficiently small cost parameters, pyramidal employment holds.

While this example illustrates one sufficient condition that generates the empirical regularities, a specific firm's joint choice of managerial span of control, IC shares, and IC pay gaps is a complex function of its underlying costs and knowledge parameters (see Appendix D for further discussion). We therefore turn to firm-level structural estimation, using observed choices to recover structural parameters and derive a typology of firms.

5 A Typology of Firms and Heterogeneous Adjustments in Career Ladders

The model in Section 4 delivers sharp predictions about how IC and manager careers coexist inside organizations, and how their relative attractiveness changes across the hierarchy. The empirical patterns in Section 3 align with the basic predictions of the model and show substantial heterogeneity in IC career ladders, as evidenced by wide dispersion in the IC pay gap and IC shares across firms. We now take the model to the data and derive a typology of firms based on firm-specific primitives: the supervision technology, the cost of problem solving, and the slope of the knowledge ladder.We then map the resulting firm types to observable firm characteristics and use the model estimates for counterfactual analysis to understand how changes in supervision technology, problem-solving costs, or knowledge dispersion would reshape the task allocation and pay structure within firms.

5.1 Estimation Strategy

Parameterization. To estimate the model, we adopt a parsimonious parameterization that maps the rich hierarchy observed in the data into three broad layers—bottom (b), middle (m), and top (t)—plus an initial layer indexed by 0. We assume quadratic supervision costs, $\gamma = 2$ and normalize employment at the initial layer to one, $N_0 = 1$. We normalize top-layer knowledge to one, $Z_t = 1$, representing the maximum problem-solving level of the organization, and interpret knowledge in lower levels as a fraction of this total knowledge stock.

We impose three restrictions on the layer-specific primitives for $\ell \in \{b, m, t\}$. First, the fixed component of supervision follows a two-parameter logistic profile:

$$F_\ell = \frac{1}{2} \cdot \frac{\exp(F_0 + \alpha_F \ell)}{1 + \exp(F_0 + \alpha_F \ell)}. \tag{14}$$

This function imposes $F_\ell \leq \frac{1}{2}$: based on equation (11) above and $\gamma = 2$, the maximum level of fixed costs implies that managers are fully specialized in supervision, and any $F_\ell < \frac{1}{2}$ ensures $K^M > 0$. The unconstrained parameter α_F governs the profile of fixed supervision costs across the hierarchy, with $\alpha_F < 0$ reflecting decreasing costs, for example. Second, variable supervision costs and problem-solving (or escalation) time costs follow log-linear profiles across layers:

$$c_\ell = \exp(c_0 + \alpha_c \ell), \qquad t_\ell = \exp(t_0 + \alpha_t \ell), \tag{15}$$

where ℓ is interpreted as a numeric index ($b = 1$, $m = 2$, $t = 3$). Third, in the baseline implementation, we impose a minimum gap of $Z_\ell - Z_{\ell-1} \geq 0.05$ in the knowledge ladder across adjacent layers.

Overall, the structural parameter vector is

$$\theta = \{F_0, c_0, t_0, \alpha_F, \alpha_c, \alpha_t, \kappa, Z_0, Z_b, Z_m\}. \tag{16}$$

Estimator and targeted moments. We estimate the model separately for each firm by choosing θ to match a set of layer-by-layer moments. Specifically, we target layer-specific spans of control (S_b, S_m, S_t), IC pay gaps (π_b, π_m, π_t), IC shares (ξ_b, ξ_m, ξ_t), and manager pay ratios across layers (denoted by wr^M_{tb} and wr^M_{tm}).[10] Together, these 11 measures constitute the vector of targeted moments for each firm. As illustrated in Section 4, these moments have closed forms under the maintained assumptions (see also Appendix D.1). Hence, estimation can be carried out by the method of moments:

$$\hat{\theta} = \arg\min_{\theta \in \Theta} \big(\widehat{m} - m(\theta)\big)' W \big(\widehat{m} - m(\theta)\big), \tag{17}$$

where $\widehat{m}$ is the vector of empirical moments with elements $\hat{m}_k$ (for moments $k = 1, \ldots, 11$), $m(\theta)$ denotes their model-implied counterparts. W is a weighting matrix which we set to a diagonal matrix with elements $(1/\hat{m}_k)^2$ to minimize percentage deviations from the targeted moments. We use untargeted moments implied

[10] Note that wr^M_{mb} is implied by the ratio of wr^M_{tm} and wr^M_{tb} and as such does not add additional identifying variation.

by the model, such as the IC pay ratios or average pay ratios across layers, or employment shares, to evaluate the goodness of fit.

5.2 Identification

This subsection sketches the identification argument; Appendix D.2 provides the full proof. The key insight is that, under Equations (14)–(15), the model maps a set of targeted moments into primitives in a triangular way.

Step 1: recover employment at b and m. Using the IC-share expression together with the employment recursion, the model implies an inversion of the form $N_\ell = \frac{N_{\ell-1}}{S_\ell(1-\xi_\ell)}$. Given $N_0 = 1$, this implies that relative employment levels N_b, N_m are point-identified from empirical spans and IC shares.

Step 2: recover the knowledge ladder at b and m. Given (N_b, N_m) and observed spans, manager pay ratios can be inverted to identify Z_b and Z_m: $Z_b = \frac{S_t}{S_b N_m wr^M_{tb}}$, $\qquad Z_m = Z_b \cdot wr^M_{mb} N_b \cdot \frac{S_b}{S_m} = Z_b \cdot \frac{wr^M_{tm}}{wr^M_{tb}} N_b \cdot \frac{S_b}{S_m}$.

Step 3: identify the supervision profile parameters (F_0, α_F). The log-linear restrictions on c_ℓ and t_ℓ imply that $\log c_\ell$ and $\log t_\ell$ must lie on straight lines in ℓ. Using the closed-form solutions for optimal spans and IC shares implied by the model to substitute out c_ℓ and t_ℓ respectively, we obtain two restrictions (one from the c_ℓ profile and one from the t_ℓ profile) that depend only on observable moments and on fixed supervision costs (F_0, α_F). These two restrictions jointly pin down (F_0, α_F) under a standard local rank condition.

Steps 4–5: recover (c_0, α_c), (t_0, α_t), κ, and Z_0. Given (F_0, α_F), we recover (c_0, α_c) from $\log c_\ell = \log(F_\ell / S_\ell^2)$ and log-linearity across layers, and we recover (t_0, α_t) from the IC-share inversion for t_ℓ and log-linearity. Finally, the top-layer IC pay gap π_t identifies κ (using $Z_t = 1$ and Z_m from Step 2), and the bottom-layer IC pay gap π_b identifies Z_0. The remaining IC pay gap π_m provides an additional overidentifying restriction.

5.3 Estimated Parameters and Model Fit

Figure 4 plots the distribution of fixed supervision costs F, averaged across levels at each firm. We focus on this parameter because it drives the degree of specialization of managers as discussed in Section 4.3. Overall, we find a wide range of supervision costs across firms, which motivates the firm typology below. Specifically, we find a substantial share (25 percent) of firms, highlighted in the red bar, where managers are highly specialized, spending on average at least 90 percent of their time on supervision tasks, as a result of high fixed supervision costs F. We distinguish these specialized firms from others with lower F, indicating that managers spend more time on problem solving and less on supervision.

Appendix Table D1 reports the full parameter estimates and shows that problem-solving costs t_ℓ decline toward the top, indicating that each expert can support a larger number of subordinates. However, this decline is much more pronounced among less specialized firms. Variable supervision costs c_ℓ are uniformly lower in less specialized firms and rise mildly toward the top in both groups. Finally, the implied knowledge ladder is similar across firm types. Importantly, both the average estimates across all firms and the results by group satisfy the sufficient conditions in Proposition 3 to match the core empirical facts.

Appendix Table D2 shows that the model matches the targeted moments closely for all firm groups. In addition, the model performs well in capturing untargeted pyramidal employment structures and pay ratios for IC and all workers. Yet, the model assigns a higher employment share to the top of the firm than observed in the data. This discrepancy likely reflects the limitations of our parsimonious three-layer model.

5.4 Interpreting the Firm Types

The estimates suggest a typology of firms based on supervision costs F_ℓ, which maps directly into the optimal share of managers' time spent on supervision tasks. We now connect these structural types to observable firm characteristics and show that these types are economically meaningful: they correlate with observable characteristics such as industry affiliation (in particular, high-tech concentration), skill composition, job-function mix, and hierarchy shape.

Table 3 reports differences in firm characteristics across groups using a set of univariate regressions.[11] Each row reports the coefficient from a separate regression of the given firm characteristic on an indicator for being a firm with highly specialized managers. The regression evidence indicates three takeaways. First, differences in manager specialization relate to systematic differences in hierarchy shape. Although hierarchy depth is similar across firm groups, the top-to-bottom span ratio for fully specialized firms is 29 percent lower than average. In addition, these firms are more bottom-heavy, whereas less specialized firms have a 30-percent higher share of employment at the top and middle of the hierarchy.

Second, the pay structure across the hierarchy and across roles systematically differs across firms with more or less specialized managers. Firms with highly specialized managers have a 41 percent higher manager pay ratio top-to-bottom and they systematically pay ICs less.

Third, firm types differ in skill and job composition. The share of skilled workers is 13.3 percentage points lower in highly specialized firms, and this difference is mostly driven by ICs.[12] These patterns reflect in part a lower share of computer/math and R&D positions and a higher share of admin jobs in highly specialized firms, in which higher fixed supervision costs are likely to generate a greater need for administrative support of managers. Overall, this is consistent with a stronger emphasis on revenue-generating and high-skill technical roles in firms where managers engage in a mix of supervision and problem-solving tasks (Garicano and Hubbard, 2007). Moreover, firms with less specialized managers are significantly more likely to be in the high-tech sector, as evidenced by the fact that all tech firms in our sample fall into this group (Table D3).[13]

[11] Table D3 complements these regression results using sample averages of firm characteristics by group.

[12] Skilled job functions include business, finance, and legal; computer and math; research and development; and top management.

[13] This pattern is consistent with the way many technology firms describe their internal career systems, which often emphasize technical expertise, autonomy, and advancement outside management. Shopify, for instance, has introduced a dual-track promotion system that explicitly recognizes and rewards technical "crafters" alongside managerial "people leaders" (https://www.worklife.news/leadership/dual-track-promotion/). More recently, large technology firms such as Amazon (https://www.businessinsider.com/amazon-fewer-managers-leaked-document-2024-9) and Google (https://www.businessinsider.com/google-ceo-company-cut-manager-vp-roles-2024-12) have announced initiatives to reduce the number of managerial layers, increasing the ratio of individual contributors to managers as part of broader efforts to raise pro-

Finally, we estimate multivariate regressions (Table D4) to evaluate the relative importance of these sets of firm characteristics in explaining which firms feature full specialization of managers. Notably, firm size and hierarchy depth alone only explain a small share of the variation across firms (columns 1–2), whereas the R-squared increases substantially after controlling for measures of hierarchy shape, skill levels, and job composition (columns 3–5).

Taken together, the evidence indicates that the groups with high or low specialization of managers represent distinct organizational types that go beyond reflecting scale differences and are strongly linked to task composition and hierarchy shape.

5.5 Counterfactual Analysis

Using our firm-level estimates, we conduct counterfactual experiments that perturb key primitives and recompute the model's implied organizational outcomes. Results are summarized in Table 4. We focus on three scenarios, each representing a 1 percent change in one primitive. For each scenario, we ask how the shock changes the career ladders for ICs and managers.

A. Lower variable supervision costs c. Reducing variable supervision costs mainly operates through the span-of-control margin. Average spans rise by about 0.5%. As a result, manager pay increases and manager pay dispersion rises modestly. Because managers can supervise more workers, their value added rises relative to that of ICs , especially at the top of the hierarchy.[14] The IC pay gap therefore widens within each level of the organization: this increase is stronger at the bottom of the firm, as evidenced by a decrease in the top-to-bottom IC-penalty ratio.[15] At the same time, a higher span reduces the number of managers needed for supervision, increasing the IC employment share, especially at the top. Together, IC jobs become more prevalent but relatively less attractive than at baseline, increasing the risk that workers remain on the IC ladder.

B. Lower problem-solving costs t. Since lower t increases IC productivity in problem solving, the average IC pay gap becomes substantially less negative (by 2.16%). The effect is strongest at the bottom where ICs' relative knowledge contribution is larger. Manager pay dispersion also increases: fewer problem solvers are required at each level, so the hierarchy narrows more sharply toward the top and top managers' reporting chains expand.[16] Due to an increase in problem-solving efficiency, the share of ICs declines slightly in this scenario, especially at the top. Together, lower problem-solving costs steepen the manager pay schedule,

ductivity and speed up decision-making.

[14] The consequences of this counterfactual are closely related to Garicano and Hubbard (2018), which shows that changes in coordination costs altered hierarchical leverage and earnings inequality among lawyers.

[15] This pattern indicates that the manager-to-IC value-added ratio at lower levels is more sensitive to span increases. Specifically, in Equation (13), this occurs when the supervision term $\kappa t_l S_l / q_l$is large relative to the remaining problem-solving term $(1-\kappa)(1-\gamma F_l/(\gamma-1))$. Indeed, the ratio t_l/q_l is larger at the bottom (Table D1) and acts as a multiplier for the effect of the increasing span on the widening IC pay gap.

[16] The productivity boost in problem solving does increase manager pay as well, but the relative time spent on supervision tends to increase towards the top, mitigating the increase in managerial pay dispersion.

raise the level of the IC pay schedule, and flatten its slope, making IC positions overall more attractive but resulting in less frequent promotions along the IC ladder with smaller pay raises.

C. Compress the knowledge ladder (slope of Z). Compressing productivity differentials across layers worsens IC pay gaps, especially at the bottom and reduces manager pay dispersion.[17] The reason is that the productivity gain for lower-level workers scales with managers' reach, so it raises managerial value added more than IC value added. Managerial spans and IC shares are unaffected by this scenario because we hold problem solving and supervision costs constant.

Effects across firm types. Comparing the effects of these different scenarios across firm types shows that changes are often more pronounced in firms with higher managerial specialization in supervision at baseline. Although average IC shares and manager pay respond similarly across firm types, the slope of the IC pay scale changes more in highly specialized firms. Intuitively, making managers more productive by lowering variable supervision costs increases their pay more relative to ICs if they spend more time on supervision to begin with. Similarly, reducing the cost of problem solving helps ICs to catch up more if managers do not spend much time on problem solving. Changing the knowledge ladder also exacerbates the IC pay gap more at highly specialized firms because the knowledge boost especially benefits managers for whom supervision constitutes a larger share of their compensation. This heterogeneity is important when assessing the differential impact of real-world policies or technological shocks on workers across firms.

Summary. Taken together, the counterfactual exercises imply that different organizational shocks have distinct effects on the careers of ICs and managers. Supervision-cost reductions primarily move the span of control, while problem-solving cost reductions or changes to the knowledge ladder more strongly reshape pay gradients. Lower problem-solving costs lift but flatten IC pay schedules, while lower variable supervision costs or less knowledge dispersion lead to a steeper IC pay schedule with higher risk of getting stuck in low-paying IC roles at the bottom of the hierarchy.

These counterfactual scenarios complement the analysis of technological change and firm organization in Garicano and Rossi-Hansberg (2006) and further relate to recent evidence in Espinosa and Stanton (2026) who show that training front-line workers relaxes managerial time constraints and thereby generates substantial spillovers to higher layers of the hierarchy. Together, our results quantify the channels emphasized in Section 4 and provide a disciplined basis for evaluating organizational changes that shift the balance between IC and manager careers. These counterfactuals also suggest that differences in who is assigned to IC versus managerial tracks may be an important source of inequality within the firm, a question we examine next.

[17] We implement this scenario by reducing the gap between each knowledge level Z_l and the top, Z_t, by 1 percent, thus reducing the slope of the Z schedule. Specifically, we impose $Z_l^c = Z_l + 0.01(Z_t - Z_l)$.

6 The Demographic Composition of the IC Workforce

Section 3 shows that the distinction between IC and managerial tracks is a central determinant of pay and career progression inside firms. IC roles are associated with lower pay, slower wage growth, and lower promotion rates, and transitions from IC roles to manager positions come with large monetary gains. The estimation and counterfactual analysis in Section 5 highlight that the magnitude of this IC pay gap varies systematically with firm characteristics and the shape of firms' dual career ladders is sensitive to technological shocks. To understand the distributional consequences of these alternative careers within firms, we now analyze whether workers are sorted into these tracks differently by gender and race. Section 6.1 documents that women and racial minorities are significantly more likely to hold IC roles and that these gaps widen toward the top of the hierarchy. Section 6.2 examines how firms choose workers of different race and gender for transitions from IC roles to managerial jobs.

6.1 Key Facts About the Demographic Characteristics of ICs

This subsection establishes three facts about the demographic composition of IC roles: (i) women and racial minorities are more likely to be ICs, (ii) these gaps widen sharply toward the top of the hierarchy, and (iii) the IC pay gap does not differ systematically across demographic groups. Together, these facts point to assignment across tracks, rather than group-specific pay setting within tracks, as a key margin of gender and racial inequality.

The first finding is that women and racial minorities are more likely to hold IC roles (Table 5).[18] Our preferred and most saturated specification, in which we control for a quadratic function of age and tenure and a full set of firm-by-month–by–layer–by–job fixed effects, indicates that women are 3 percentage points more likely than men to be ICs, and that racial minority employees are about 2 percentage points more likely than White employees. The minority gap ranges from 1.96 percentage points for Asian employees to 2.33 percentage points for Black employees.

As a simple descriptive benchmark, we approximate how much these differences in IC incidence could contribute to observed pay disparities. Using the mean conditional IC pay gap of 0.31 log points (Table 1, column 5) and the mean conditional gender pay gap of 0.07 log points, women's higher likelihood of being ICs can account for roughly 13 percent ($(0.03 * 0.31)/0.07$) of the gender pay gap in our sample. Applying the same calculation to racial groups suggests that differences in IC incidence explain about 5 to 12 percent of their respective pay gaps.

The second finding is that demographic differences in the likelihood of being an IC widen toward the top of the hierarchy (Table A3). For women, the IC gap relative to men within the same job function and organizational layer rises from 1.76 percentage points at the bottom to 7.27 points at the middle and 7.62 points at the top of the organization. The racial gaps follow a similar patterns, although their magnitudes differ across groups. At the bottom of the hierarchy, minority groups display similarly small IC differentials of 1.2 to 1.7 percentage points compared to White employees. At the top, Black, Hispanic, and other minority employees exhibit gaps between 6.0 and 6.8 percentage points, whereas Asian employees reach only 3.77

[18] For brevity, we refer to racial groups throughout, though our categorization includes both race and ethnicity.

points.

These magnitudes are large. For example, the 7.62-percentage-point gender gap in IC status at the top equals 17 percent of the mean IC share in the upper layers (Figure 2). It is also comparable to the change in IC probability associated with reducing tenure by roughly eight years for an employee with ten years of experience, holding gender and race fixed.[19] The widening of these gaps toward the top is difficult to reconcile with pure statistical discrimination, which would predict convergence in later career stages when firms are supposed to observe individual ability more accurately.

The third finding is that the IC pay gap does not vary systematically across gender and racial groups (Table 6). We regress log pay on IC status and interact it with gender and race indicators, while controlling for the same rich set of fixed effects and demographic variables used in the previous analyses. The estimated interaction terms are usually small and statistically insignificant. Compared with men and White employees, respectively, women and Asian employees exhibit smaller IC pay gaps, but these differences are either small and insignificant in the case of women or large but imprecisely estimated in the case of Asian employees. The coefficients for Black and Hispanic employees are both negative, indicating larger gaps relative to the majority group, but they are close to zero and insignificant.

6.2 Transitions Into Managerial Roles across Demographic Groups

Section 6.1 shows that assignment to IC versus managerial jobs appears to be the primary channel through which these dual career tracks contribute to pay gaps between minority and majority groups. This finding motivates studying how firms select employees of different race and gender for transitions from IC jobs into managerial roles.

Specifically, we ask whether promoted workers differ in post-promotion managerial performance by gender and race. We start from the simplest possible approach, OLS regressions of post-promotion managerial performance on demographic indicators, and argue that these estimates conflate several potential mechanisms for cross-group differences. We then progressively refine both the estimation strategy and the outcome variable, with each refinement removing a distinct class of explanations.

We start by building a monthly panel of IC workers. Workers who remain ICs contribute observations in each month in which they are observed in IC roles. Workers who transition from IC to manager contribute observations during their IC spell and one additional observation in the month of promotion, when we measure their subsequent managerial performance.

Our initial measure of managerial performance is the mean log pay of a manager's subordinates, averaged across all months in which the employee served as a manager and expressed as a percentile rank within the firm-specific pay distribution.[20] The outcome is assigned to the worker in the promotion month and is zero otherwise.

[19] In Table 5, the estimated coefficients for tenure (measured in months) and tenure squared are -0.11 and 0.0002, respectively.

[20] Prior work has measured managerial performance using the output of subordinates: for example, transactions per hour in Lazear et al. (2015)and sales in Benson et al. (2019). These studies focus on settings with homogeneous job functions where a common productivity metric is available. Our data span many firms with heterogeneous workforces, so we use pay as the most broadly comparable indicator of productivity.

OLS regressions. We estimate the following equation separately for each demographic group g:

$$Y^g_{if} \cdot \text{IC-to-M}^g_{ift} = \alpha_g + \beta^{OLS}_g \text{IC-to-M}^g_{ift} + \gamma_g X^g_{ift} + \delta^g_f + \lambda^g_t + \varepsilon^g_{ift}, \tag{18}$$

where Y^g_{if} is the managerial performance of employee i at firm f, IC-to-M$^g_{ift}$ is an indicator for a transition from IC to manager, and X^g_{ift} includes age, tenure, and their squares, along with a gender indicator when estimating within racial groups and race indicators when estimating within gender groups. In the baseline analysis, the minority groups are Asian employees, other racial minorities, and women, while the majority groups are White employees and men. We include firm fixed effects δ^g_f and month-year fixed effects λ^g_t, and cluster the standard errors at the firm level.

The coefficient β^{OLS}_g captures the average post-promotion performance of newly promoted managers in demographic group g. Our object of interest is the difference in β^{OLS}_g between minority and majority groups: women versus men and each racial minority versus White workers. The baseline sample is restricted to firms with at least fifteen managerial promotions for each of our six main demographic groups, leaving twelve firms in the sample.[21]

The OLS estimates show that non-Asian minority and female managers lead teams with significantly lower average pay (Table 7, Panel A). Subordinates of non-Asian minority managers rank 8.7 percentiles lower in the pay distribution than those supervised by White managers ($p < 0.01$). For women, the pattern is qualitatively similar but smaller in magnitude: subordinates of female managers rank about 6 percentiles lower than those supervised by male managers ($p < 0.01$). Asian managers show no such penalty: the point estimate is positive (3.2 percentiles) but insignificant. Formal tests confirm that the $\Delta\beta^{OLS}_g$ coefficient for Asian managers is significantly larger than that for other minority managers and for women (Table A4).

These OLS estimates conflate three channels: (i) differences in promotion decisions at the margin, (ii) differences in the pool of candidates eligible for promotion, and (iii) differences in the teams to which newly promoted managers are assigned.

First, if firms apply different promotion thresholds to different demographic groups, otherwise similar racial minority or female candidates must clear a different bar than White or male employees. A growing body of evidence documents such differential thresholds in practice for women (Huang et al., 2024; Benson et al., 2026) and minority workers (Rim et al., 2024).

Second, the pool of candidates eligible for promotion may itself differ across groups for reasons that precede the promotion decision. Women and racial minorities may be less likely to put themselves forward for managerial roles (Hospido et al., 2022; Haegele, 2025), to negotiate over working conditions (Caldwell et al., 2026), or to engage with competitive working environments (Niederle and Vesterlund, 2007). Women may also have weaker average preferences for management jobs if these roles carry less flexibility (Bertrand et al., 2010; Mas and Pallais, 2017; Wiswall and Zafar, 2018). Beyond self-selection, the composition of the candidate pool may reflect cumulative differences along the career pipeline, such as discriminatory hiring practices (Bertrand and Mullainathan, 2004; Kline et al., 2022), differential access to informal networks (Cullen and Perez-Truglia, 2023), unequal recognition for collaborative work (Sarsons et al., 2021), and

[21] The six demographic groups are White employees, Asian employees, Hispanic employees, Black employees, women, and men. One of the robustness checks at the end of this section replicates the results using the full sample of firms.

differential task assignment (Bircan et al., 2025).

Third, mean subordinate pay may reflect not only the manager's effect on subordinates' outcomes but also the baseline characteristics of the team to which the manager is assigned. For example, women and minorities may be systematically placed in charge of weaker teams upon promotion (Ryan and Haslam, 2005, 2007).

IV Regressions. Our first refinement addresses the fact that the OLS coefficient β_g^{OLS} reflects the performance of the *average* worker promoted to a managerial position within each demographic group. As such, it captures how firms set promotion thresholds for each demographic group, as well as the composition of the underlying candidate pool.

To separate these channels, we follow an instrumental-variable strategy inspired by Benson et al. (2019) and Benson et al. (2026). We instrument individual IC-to-M transitions with the share of IC-to-M transitions occurring in the same firm, month, and job function but outside the focal worker's team. Workers whose promotion is induced by this variation are compliers: they move into management when their firm faces an unusually high need to fill managerial positions in their function, and would not have transitioned otherwise.

The coefficient β_g^{IV} measures the managerial performance of workers at group g's promotion margin, averaged across all firms in our sample. Therefore, evaluating β_g^{IV} across demographic groups compares the standard each group must meet to be promoted, once differences in the candidate pool away from the margin are set aside. This comparison recovers the gap in promotion standards when the instrument draws compliers from the same region of each group's candidate distribution.

The first stage is as follows:

$$\text{IC-to-M}_{ift}^{g} = \pi_0^g + \pi_1^g Z_{ift} + \pi_2^g X_{ift}^g + \delta_f^g + \lambda_t^g + u_{ift}^g. \tag{19}$$

For each employee i in firm f, month-year t, and job function j, we define the instrument Z_{ift} as the number of IC-to-M transitions among workers in the same firm, month-year, and job function who do not share i's direct manager in month-year t divided by the total number of employees in firm f, month-year t, and job function j (and multiplied by 100).

The second stage replaces the actual transition indicator with its fitted value:

$$Y_{if}^{g} \cdot \text{IC-to-M}_{ift}^{g} = \alpha_g + \beta_g^{IV} \widehat{\text{IC-to-M}}_{ift}^{g} + \gamma_g X_{ift}^g + \delta_f^g + \lambda_t^g + \varepsilon_{ift}^g. \tag{20}$$

As before, we estimate this specification separately for each demographic group g and compare β_g^{IV} across minority and majority groups. Standard errors are clustered at the firm level.

The first stage is positive and highly significant for all groups (Table A5). A one-standard-deviation increase in the promotion share at the firm-job level raises an individual's promotion probability by 0.25 to 0.39 percentage points, relative to mean baseline promotion rates of 0.2 percent to 0.3 percent per employee and month. Similar first-stage coefficients and baseline promotion rates across groups suggest that the instrument shifts promotion timing and intensity similarly for all demographic groups, making it less likely that marginally promoted workers across groups are promoted into systematically different circumstances.

In this setting, the exclusion restriction requires the instrument to affect post-promotion managerial performance only through individual promotion decisions. Because our object of interest is the cross-group difference in β_g^{IV}, rather than its group-specific levels, violations common to all groups, such as periods of firm growth that raise both promotion rates and subordinate pay equally for all groups, do not affect the comparison. Violations that differ across groups remain possible, but the empirical design mitigates this concern: we absorb aggregate time-series variation with month-year fixed effects and smooth out transitory conditions at the time of promotion by averaging subordinate pay over the full managerial spell. Moreover, the leave-out construction of the instrument severs the mechanical link between an individual worker's promotion and the instrument, precluding reverse causality.

The IV estimates are smaller in magnitude than the OLS estimates and less precise (Table 7, Panel A). For women, the gap in IV coefficients falls by about 40 percent, suggesting that much of the OLS gap reflects differences in the candidate pool rather than different promotion thresholds for otherwise comparable workers. The Asian coefficient attenuates by a similar proportion (35 percent) but starts from a positive value. For other minorities, the coefficient declines by only 11 percent, indicating that most of the gap persists even after accounting for candidate-pool composition. Despite the overall attenuation, the difference between Asian employees and other minorities remains statistically significant, while the gap between Asian employees and women is no longer significant (Table A4).

Manager value added. Mean subordinate pay may reflect both the manager's influence on her subordinates' career progression and the preexisting characteristics of the assigned team. To isolate the manager's contribution, we estimate a two-way fixed effects model (Abowd et al., 1999; Lazear et al., 2015) that decomposes worker pay into a time-invariant worker component and a time-invariant manager value-added component.

Specifically, we estimate the following model separately within each firm (notation f for firms omitted below):[22]

$$Y_{imt} = \alpha_i + \psi_m + \beta X_{it} + \lambda_t + \varepsilon_{imt}, \tag{21}$$

where Y_{imt} is the log pay of worker i under manager m in month-year t, α_i is a time-invariant worker fixed effect, ψ_m is a time-invariant manager fixed effect, X_{it} includes time-varying worker controls (age, tenure, their squares, hierarchical level, and job function), and λ_t is a set of month-year fixed effects. The manager fixed effect ψ_m is our object of interest: it measures the component of subordinate pay attributable to the manager, net of both the subordinate's own permanent and time-varying characteristics, as well as aggregate time variation. Identification of ψ_m relies on workers who switch managers within the same firm during the sample period. The key identifying assumption is that these transitions are uncorrelated with time-varying unobservables: conditional on α_i, X_{it}, and λ_t, the timing and direction of subordinate mobility across managers must not systematically correlate with transitory shocks to pay.

The estimated manager fixed effect ψ_m, expressed as a percentile rank within the firm, replaces mean

[22] We implement the model separately within each firm using the PyTwoWay package (Bonhomme et al., 2023), restrict estimation to the largest connected set of workers and managers, and apply the standard limited-mobility bias correction (Andrews et al., 2008).

subordinate pay as the dependent variable in Equation (20). Unlike the baseline outcome, ψ_m is by construction orthogonal to the composition of the manager's team. The resulting estimates shift in different directions across groups (Table 7, Panel B, IV columns). For women, the gap widens to -4.9 percentiles, suggesting that female managers were assigned to teams with higher non-manager-driven pay. For other minorities, the gap narrows substantially to -5.6 percentiles, indicating that unfavorable team assignments account for much of the remaining difference. For Asian employees, the estimate shifts from positive to slightly negative at -1.8 percentiles; after removing team composition, marginally promoted Asian managers no longer outperform White managers. Moreover, we now fail to reject the hypothesis that the difference in $\Delta\beta_g^{IV}$ between Asian employees and all other minority groups is zero (Table A4).

Firm-level estimations. We next estimate the OLS and IV regressions separately by firm.

The firm-level estimates reveal substantial heterogeneity (Figure 5). Across all specifications, each demographic comparison includes firms with positive, near-zero, and negative estimates, and this dispersion is economically meaningful (Table A6). For example, in the IV specification with mean subordinate pay, the interquartile range of firm-level estimates is 25.9 percentiles for Asian employees: a firm at the 75th percentile of the distribution of $\Delta\beta_{asian}^{IV}$ promotes marginal Asian managers whose subordinates rank 14.6 percentiles higher than those of marginal White managers, while a firm at the 25th percentile promotes marginal Asian managers whose subordinates rank 11.3 percentile points lower. In light of such heterogeneity, pooled estimates can differ sharply from the experience of workers in any individual firm, echoing the findings in Kline et al. (2022) on cross-firm variation in hiring practices.

The firm-level estimates also help summarize the role of the three broad categories of explanations for differences in post-promotion performance across demographic groups (Table A6, columns 7-8). In the OLS specification, large shares of firms show significant gaps: 83.3 percent for women, 66.7 percent for other minorities, and 41.7 percent for Asian employees. Moving to IV cuts these shares substantially as differences in the candidate pool are removed. Replacing mean subordinate pay with manager value-added produces a further, albeit smaller, decline, reflecting the role of team formation. For women, the total share of firms with significant estimates falls from 83.3 percent in OLS to 33.3 percent in IV, and then to 16.6 percent with manager value added. After both refinements, the share of firms with significant estimates is small but nonzero, with significant positive and negative gaps still present across firms, indicating some residual role for differential promotion thresholds that operate in opposite directions depending on the firm.

Finally, within-firm promotion gaps are positively correlated across racial minority groups but not between racial minorities and women (Figure A2). Firms that appear to set higher thresholds for one racial minority group tend to do so for other racial minority groups, but not systematically for women.

Limitations, robustness checks, and additional results. Appendix E discusses the limitations of our empirical strategy and reports robustness checks using alternative instruments, specifications, samples, group definitions, team-assignment measures, and managerial-performance outcomes based on retention rates and performance ratings. The main conclusions are qualitatively unchanged.

7 Conclusion

Using personnel records from 43 firms, we find that individual contributors (ICs) are prevalent throughout corporate hierarchies but earn less than managers in comparable roles, with the penalty widening toward the top. We develop a parsimonious model of dual career ladders that rationalizes these patterns and use it to show that differences in career ladders map into observable firm characteristics. We then establish that shocks to the production environment can reshape IC and manager careers in different ways across firms. Finally, we document that assignment to IC versus managerial career ladders is a key source of within-firm inequality, with women and racial minority workers disproportionately sorted into IC roles.

We highlight two implications based on our findings. First, the framework is well suited for analyzing organizational change and the career consequences of new technologies, making it especially relevant as firms adopt AI. Across sectors, firms, and job functions, AI may differentially change knowledge dispersion and the costs of problem solving and supervision. The model offers a disciplined way to generate and test hypotheses about restructuring, promotions, and worker outcomes in response to these innovations.

Second, consistent with the existing literature, our analysis emphasizes that transitions into management are a key mechanism shaping inequality. However, the demographic gaps we document appear to originate early in the pipeline that determines who becomes a viable candidate for management, rather than at the time of promotion. Hence, firms seeking to narrow career gaps across demographic groups should pay particular attention to those early-career decisions that can shape access to management-track pathways.

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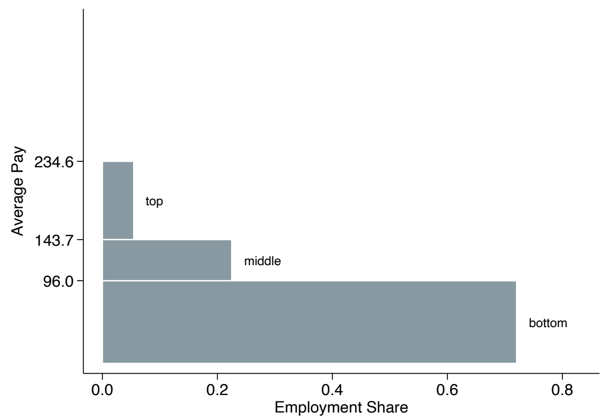
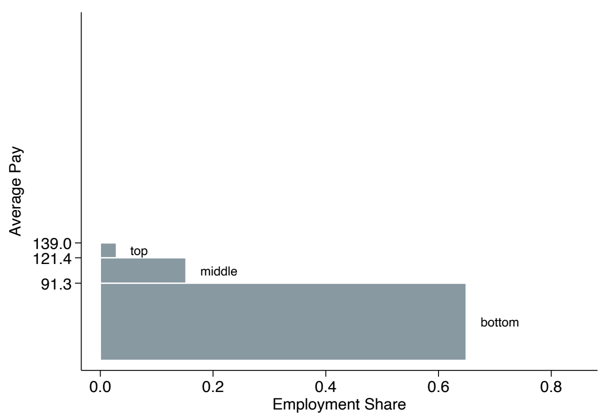
Figures and Tables

Figure 1: Summary of the Organizational Structures

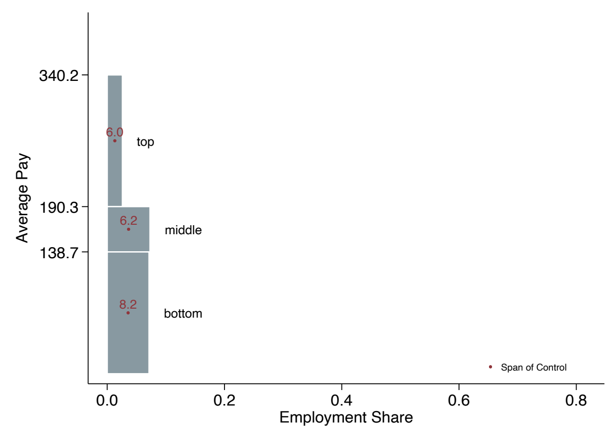
Panel A: All workers



Panel B: ICs

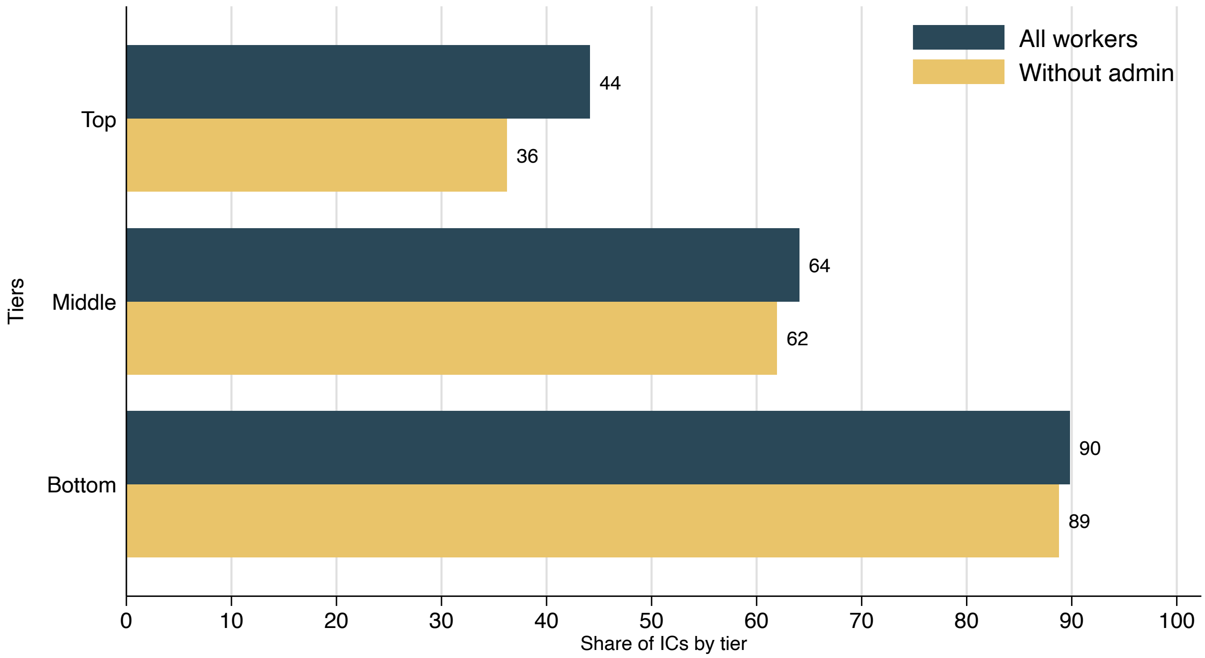


Panel C: Managers



Notes: This figure summarizes three aspects of firm organizational structure by hierarchical position (top, middle, bottom) and role (individual contributors ICs vs. managers). For each group, the horizontal bars report the group's employment share, and the vertical height of the bars reports average pay. For managers, red markers report the average span of control in the corresponding top/middle/bottom tier. We construct the figure by first computing these group-level moments within each firm over the months observed for that firm, and then averaging the resulting firm-specific values across the 43 firms in the sample.
Source: Authors' calculations from de-identified employee-level administrative internal HR records from 43 firms, accessed through a collaboration with Visier.

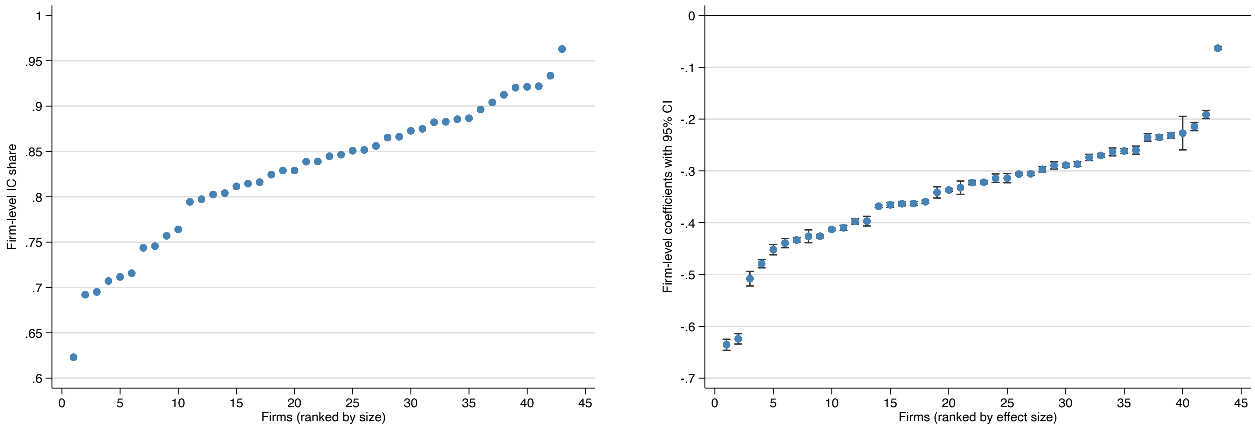
Figure 2: IC Share by Hierarchical Tier



Notes: The figure reports, by hierarchical tier, the share of workers who are individual contributors (ICs), shown separately for (i) all workers and (ii) workers who do not hold an administrative job. We compute IC shares within each firm-tier-month, average them over the months observed for each firm, and then report the average of these firm-layer values across the 43 firms in the sample.
Source: Authors' calculations from de-identified employee-level administrative internal HR records from 43 firms, accessed through a collaboration with Visier.

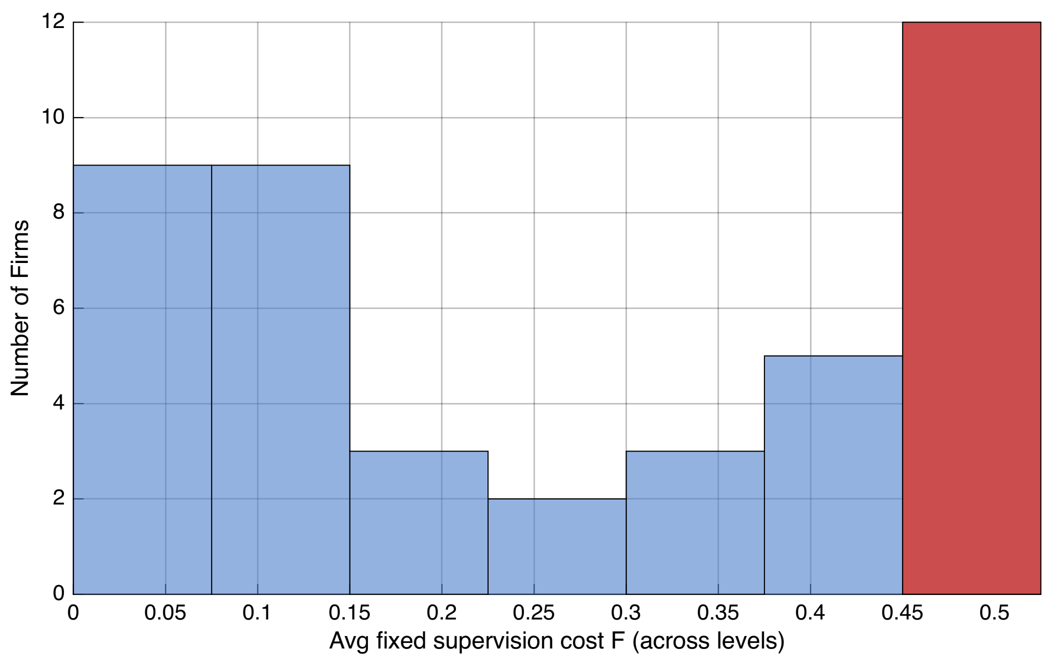
Figure 3: IC Share and IC Penalty Across Firms

Panel A: IC share | **Panel B**: IC penalty



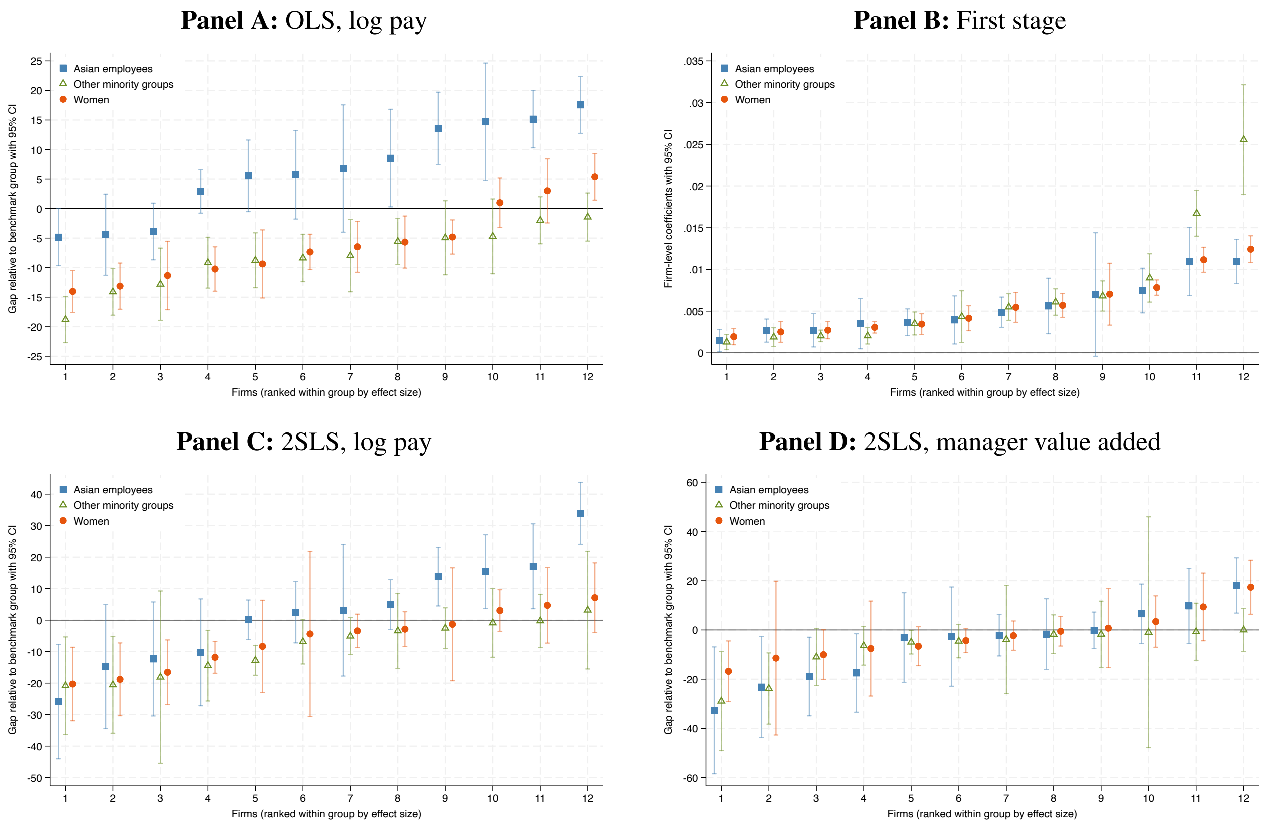
Notes: Panel A plots the share of ICs across the different firms in the sample. Panel B plots firm-specific estimates of the association between IC status and pay. Each point is the coefficient on an IC indicator from a separate firm-level regression of log pay on IC status, controlling for firm by month by hierarchical layer by job function fixed effects, age, tenure, gender, and race. Bars show 95% confidence intervals based on standard errors clustered by firm. Firms are ordered in ascending order of the estimated IC coefficient.
Source: Authors' calculations from de-identified employee-level administrative internal HR records from 43 firms, accessed through a collaboration with Visier.

Figure 4: Estimation Results: Average Fixed Supervision Costs Across Firms



Notes: The figure reports the distribution of estimated fixed supervision costs F across firms, using the average estimated F across hierarchy levels at each firm. The red bar denotes firms with average estimated $F = 0.5$, which corresponds to the upper bound on this cost parameter and maps to full manager specialization on supervision tasks.
Source: Authors' calculations from de-identified employee-level administrative internal HR records from 43 firms, accessed through a collaboration with Visier.

Figure 5: Firm-Level IV Estimations



Notes: This figure presents firm-level OLS and IV estimates of demographic differences in post-promotion managerial performance. In the 2SLS, the endogenous variable is a dummy equal to 1 for transitions from IC to managerial roles (IC-to-M). The instrument is the share of IC-to-M transitions in the same firm, month, and job function, excluding the focal employee's team. Panels A reports OLS estimates of the mean gaps between minority and majority groups. Panel B reports first-stage coefficients from the 2SLS specification, separately by minority group. Panels B and C report the second-stage gaps: the difference between each group's 2SLS coefficient and the benchmark group (White employees for race groups, men for women). In Panel B, the dependent variable is the rank of average subordinate log pay averaged across all periods as manager (zero for ICs). In Panel C, the dependent variable is the manager value added in pay percentile, defined as the manager fixed effect from an AKM decomposition of subordinate pay rank (zero for ICs). Each point represents a single firm; bars show 95% confidence intervals. Within each demographic group, firms are ranked in ascending order of the estimated coefficient, so points at the same position on the horizontal axis do not necessarily correspond to the same firm. The sample includes the 12 firms with at least 15 IC-to-M transitions in each demographic subgroup and is not restricted to employees who eventually become managers. All regressions include firm fixed effects and control for age, tenure, their squares, and demographic fixed effects (a gender dummy in race-specific regressions; racial dummies in gender-specific regressions).

Source: Authors' calculations from de-identified employee-level administrative internal HR records from 43 firms, accessed through a collaboration with Visier.

Table 1: Pay and IC Status

Dependent variable:	Log Pay (1)	Log Pay (2)	Log Pay (3)	Log Pay (4)	Log Pay (5)
IC	-0.537***	-0.433***	-0.405***	-0.350***	-0.308***
	(0.040)	(0.023)	(0.022)	(0.011)	(0.014)
Female			-0.139***	-0.072***	-0.067**
			(0.030)	(0.026)	(0.026)
Asian			-0.085	-0.100	-0.099
			(0.173)	(0.171)	(0.167)
Black			-0.203***	-0.132***	-0.115***
			(0.022)	(0.016)	(0.016)
Hispanic			-0.147***	-0.098***	-0.091***
			(0.030)	(0.030)	(0.029)
Other minorities			-0.083***	-0.051***	-0.051***
			(0.015)	(0.012)	(0.013)
Observations	9,629,781	9,629,781	9,629,781	9,629,781	9,629,781
Mean of dep. var.	11.272	11.272	11.272	11.272	11.272
Age and tenure	X	X	X	X	X
Firm-Month FE	X				
Firm-Month-TMB FE		X	X		
Firm-Month-TMB-Job FE				X	
Firm-Month-Layer-Job FE					X

Notes: This table reports OLS regressions of individual log pay on worker characteristics, pooling all employees across the firms and months in the sample. The key regressor is IC, a dummy equal to one if the worker is an individual contributor in month t. Columns add progressively richer controls. "Firm-Month-TMB FE" include fixed effects for three-way interactions of firm identifiers, months, and dummies for either the top, middle, or bottom organizational layers. "Firm-Month-TMB-Job FE" further interacts these fixed effects with dummies for the different job functions. "Firm-Month-Layer-Job FE" absorb the full interaction of firm, month, organizational layer (where a refers to the worker's exact layer rather than the coarser top/middle/bottom grouping), and job function. Standard errors are clustered by firm. Statistical significance: $***$, $p < 0.01$; $**$, $p < 0.05$; $*$, $p < 0.1$.
Source: Authors' calculations from de-identified employee-level administrative internal HR records from 43 firms, accessed through a collaboration with Visier.

Table 2: Pay and Promotions to IC

Dependent Variable:	Log Pay (1)	Log Pay (2)	Promotion (3)	Promotion (4)	Pay Increase (5)	Pay Increase (6)	Last Month (7)	Last Month (8)
IC-to-M	0.420***	0.251***	17.552***	17.454***	2.226***	2.210***	-1.039***	-1.062***
	(0.037)	(0.015)	(2.634)	(2.670)	(0.300)	(0.302)	(0.123)	(0.113)
M-to-M	0.541***	0.312***	-0.060	-0.197***	0.052***	0.024**	-0.235***	-0.361***
	(0.040)	(0.014)	(0.079)	(0.068)	(0.016)	(0.010)	(0.084)	(0.061)
M-to-IC	0.424***	0.225***	5.955***	5.694***	0.692***	0.649***	7.657***	7.453***
	(0.048)	(0.019)	(1.002)	(1.013)	(0.113)	(0.115)	(1.041)	(1.032)
Female		-0.067**		0.096***		0.022***		-0.089***
		(0.026)		(0.022)		(0.003)		(0.031)
Asian		-0.099		-0.129***		-0.031***		0.059
		(0.167)		(0.028)		(0.007)		(0.056)
Black		-0.115***		0.015		-0.003		0.284***
		(0.016)		(0.044)		(0.006)		(0.045)
Hispanic		-0.091***		-0.022		-0.006		-0.050
		(0.029)		(0.029)		(0.005)		(0.046)
Other minorities		-0.051***		-0.029		-0.003		0.244***
		(0.013)		(0.025)		(0.004)		(0.063)
Observations	9,629,781	9,629,781	9,629,781	9,629,781	9,629,781	9,629,781	9,629,781	9,629,781
Mean of dep. var.	11.272	11.272	1.153	1.153	0.459	0.459	1.927	1.927
Age and tenure	X	X	X	X	X	X	X	X
Firm-Month FE	X		X		X		X	
Firm-Month-Layer-Job FE		X		X		X		X

Notes: This table reports regressions of workers' career outcomes on indicators for transitions in managerial status from month $t-1$ to month t. The key regressors are three mutually exclusive indicators: (i) moving from IC to a manager position (IC-to-M), (ii) remaining manager (M-to-M), and (iii) moving from manager to IC (M-to-IC). The omitted category is remaining IC (IC-to-IC). The dependent variables are log pay (columns 1 and 2); promotion in month t, which is an indicator equal to one if the worker is promoted (multiplied by 100 to make coefficients easier to interpret) (columns 3 and 4); monthly pay growth from month $t-1$ to month t (multiplied by 100) (columns 5 and 6); and an indicator equal to one if month t is the worker's final observed month with the firm (columns 7 and 8). All specifications include additional worker and firm controls. "Firm-Month-Layer-Job FE" absorb the full interaction of firm, month, organizational layer (where a refers to the worker's exact layer rather than the coarser top/middle/bottom grouping), and job function. Standard errors are clustered by firm. Statistical significance: $***$, $p < 0.01$; $**$, $p < 0.05$; $*$, $p < 0.1$.
Source: Authors' calculations from de-identified employee-level administrative internal HR records from 43 firms, accessed through a collaboration with Visier.

Table 3: Estimated Firm Types and Observed Firm Characteristics

Variable	$\hat{\beta}$ (highF)	SE	p-value	Mean
High-tech sector	-0.419***	0.091	0.000	0.302
Manufacturing sector	0.075	0.161	0.642	0.279
Firms with less than 2000 employees	-0.067	0.172	0.699	0.465
Firm depth	0.059	0.287	0.838	7.791
Span of control (bottom)	1.058	1.195	0.381	8.424
Span of control (top)	-1.060	0.675	0.124	6.268
Span ratio (top/bottom)	-0.242**	0.106	0.028	0.848
Estimated IC penalty	-0.062*	0.035	0.086	-0.341
Estimated IC-to-M pay raise	0.065*	0.034	0.065	0.286
Average IC pay	-0.418***	0.104	0.000	11.452
IC pay ratio (top/bottom)	0.298	0.191	0.125	1.575
M pay ratio (top/bottom)	1.051***	0.372	0.007	2.564
Pay ratio (top/bottom)	1.148**	0.535	0.038	2.819
Skilled worker share	-0.133**	0.058	0.027	0.457
Cond. share of skilled at bottom layer	-0.159**	0.060	0.012	0.437
Share of top-mid workers	-0.083*	0.043	0.058	0.276
Firm share of skilled IC	-0.106**	0.047	0.028	0.358
IC share (bottom)	0.019	0.018	0.290	0.898
IC share (middle)	-0.005	0.036	0.902	0.639
IC share (top)	0.094	0.063	0.147	0.441
Admin	0.102**	0.048	0.041	0.145
Business, Finance & Legal	-0.009	0.047	0.841	0.178
Computer & Math	-0.084***	0.028	0.005	0.166
Other occupation share	0.017	0.059	0.777	0.113
Production	0.099	0.069	0.160	0.130
R&D	-0.043*	0.021	0.054	0.073
Sales	-0.084***	0.030	0.008	0.154
Top management	0.002	0.015	0.877	0.039
F (average)	0.321***	0.026	0.000	0.264

Notes: This table presents results from univariate regressions of a set of observed firm characteristics (listed in the rows) on an indicator variable for firms with estimated supervision costs F corresponding to full specialization of managers on supervision tasks, whereas managers in the second group of firms spend less time on supervision. For each regression model, we present the coefficient estimate, standard error, and p-value. Standard errors are heteroskedasticity robust. Statistical significance: $***$, $p < 0.01$; $**$, $p < 0.05$; $*$, $p < 0.1$.
Source: Authors' calculations based on de-identified employee-level administrative internal HR records from 43 firms, accessed through a collaboration with Visier.

Table 4: Counterfactual Analysis: Adjusting Career Ladders

%Change	Average Span	IC Penalty	IC Penalty Ratio	M Pay Ratio	IC Share	IC Share Ratio	Top+Mid Empl. Share
Panel A. Reduce variable supervision costs ($0.99 \times c$)							
All Firms	0.51	-1.01	-0.52	0.18	0.16	0.46	-0.08
highF	0.52	-1.26	-0.71	0.27	0.15	0.17	-0.15
lowF	0.51	-0.92	-0.44	0.15	0.17	0.57	-0.05
Panel B. Reduce problem solving costs ($0.99 \times t$)							
All Firms	0.03	2.16	1.19	1.66	-0.23	-0.93	-0.59
highF	0.05	2.66	1.49	1.47	-0.20	-0.34	-0.47
lowF	0.02	1.97	1.07	1.73	-0.24	-1.15	-0.64
Panel C. Reduce slope of the knowledge ladder ($0.99 \times Z$ *slope*)							
All Firms	0.00	-2.88	-2.66	-0.30	0.00	0.00	0.00
highF	0.00	-3.53	-3.05	-0.56	0.00	0.00	0.00
lowF	0.00	-2.63	-2.51	-0.19	0.00	0.00	0.00

Notes: This table presents results from counterfactual simulations based on the model estimates from Table D1. For each firm separately, we simulate optimal organizational restructuring in response to changes in structural parameters. We consider four different scenarios, reported in Panels A–D, each affecting the value of one specific primitive (variable supervision costs, fixed supervision costs, problem-solving costs, knowledge ladder) and perturbing it by 1% of its baseline value. We focus on several organizational outcomes in the columns and compute their averages across firms under the counterfactual scenario. We report the implied percent change compared to the baseline for each outcome. Full results on levels are in Table D5. We split the firm sample into two groups based on the estimated profile of supervision fixed costs *F*. The first group has high fixed costs, corresponding to full specialization of managers on supervision tasks, whereas managers in the second group of firms spend less time on supervision. *Source*: Authors' calculations based on model estimates using de-identified employee-level administrative internal HR records from 43 firms, accessed through a collaboration with Visier.

Table 5: IC Status and Demographics

Dependent Variable:	IC (1)	IC (2)	IC (3)	IC (4)
Female	5.046***	5.530***	2.976***	3.002***
	(1.022)	(0.598)	(0.350)	(0.295)
Asian	3.317***	2.731***	2.233***	1.960***
	(0.627)	(0.515)	(0.541)	(0.538)
Black	7.493***	5.077***	3.603***	2.333***
	(0.825)	(0.694)	(0.440)	(0.411)
Hispanic	5.443***	3.855***	2.841***	2.086***
	(0.473)	(0.493)	(0.296)	(0.262)
Other minorities	4.649***	3.120***	2.669***	2.076***
	(0.461)	(0.388)	(0.401)	(0.383)
Observations	9,629,781	9,629,781	9,629,781	9,629,781
Mean of dep. var.	83.474	83.474	83.474	83.474
Age and tenure	X	X	X	X
Firm-Month FE	X			
Firm-Month-TMB FE		X		
Firm-Month-TMB-Job FE			X	
Firm-Month-Layer-Job FE				X

Notes: This table reports individual-level regressions of an indicator for being an individual contributor (IC) on demographic characteristics (gender and ethnicity), pooling workers across all firms and months in the sample. Specifications always include controls for age and tenure and increasingly detailed fixed effects. "Firm-Month-TMB FE" include fixed effects for three-way interactions of firm identifiers, months, and dummies for either the top, middle, or bottom organizational layers. "Firm-Month-TMB-Job FE" further interacts these fixed effects with dummies for the different job functions. "Firm-Month-Layer-Job FE" absorb the full interaction of firm, month, organizational layer (where a refers to the worker's exact layer rather than the coarser top/middle/bottom grouping), and job function. Standard errors are clustered by firm. Statistical significance: $***$, $p < 0.01$; $**$, $p < 0.05$; $*$, $p < 0.1$.
Source: Authors' calculations from de-identified employee-level administrative internal HR records from 43 firms, accessed through a collaboration with Visier.

Table 6: IC Penalty and Demographics

Dependent variable:	Log Pay (1)	Log Pay (2)	Log Pay (3)	Log Pay (4)
IC	-0.515***	-0.400***	-0.373***	-0.333***
	(0.031)	(0.023)	(0.021)	(0.028)
Female	-0.074	-0.080**	-0.073**	-0.072**
	(0.053)	(0.039)	(0.034)	(0.031)
IC x Female	-0.072**	-0.071***	0.001	0.006
	(0.036)	(0.021)	(0.017)	(0.015)
Asian	-0.364	-0.312	-0.288	-0.280
	(0.361)	(0.323)	(0.307)	(0.299)
IC x Asian	0.317	0.274	0.226	0.218
	(0.220)	(0.185)	(0.168)	(0.164)
Black	-0.253***	-0.190***	-0.121***	-0.109***
	(0.028)	(0.023)	(0.017)	(0.016)
IC x Black	0.033	-0.011	-0.011	-0.005
	(0.028)	(0.024)	(0.017)	(0.016)
Hispanic	-0.151***	-0.102***	-0.063***	-0.049***
	(0.018)	(0.017)	(0.017)	(0.018)
IC x Hispanic	-0.005	-0.047	-0.036	-0.044*
	(0.032)	(0.029)	(0.027)	(0.026)
Other minorities	-0.029	0.000	0.019	0.018
	(0.030)	(0.021)	(0.024)	(0.025)
IC x Other minorities	-0.060	-0.090***	-0.077**	-0.075**
	(0.044)	(0.032)	(0.034)	(0.035)
Observations	9,629,781	9,629,781	9,629,781	9,629,781
Mean of dep. var.	11.272	11.272	11.272	11.272
Age and tenure	X	X	X	X
Firm-Month FE	X			
Firm-Month-TMB FE		X		
Firm-Month-TMB-Job FE			X	
Firm-Month-Layer-Job FE				X

Notes: This table reports individual-level regressions of log pay on an indicator for being an individual contributor (IC), gender and ethnicity indicators, and interactions between IC status and gender/ethnicity. The interaction terms allow the IC pay differential to vary by gender and ethnicity. Specifications always include controls for age and tenure and increasingly detailed fixed effects. Standard errors are clustered by firm. Statistical significance: $***$, $p < 0.01$; $**$, $p < 0.05$; $*$, $p < 0.1$.
Source: Authors' calculations from de-identified employee-level administrative internal HR records from 43 firms, accessed through a collaboration with Visier.

Table 7: Demographics of IC-to-M Transitions

	Race groups					
	Asian		Others		Women	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Log Pay (Rank)						
IC-to-M Transition	3.157	2.036	-8.666***	-7.715*	-5.994***	-3.579
	(2.449)	(3.114)	(2.008)	(4.414)	(1.862)	(4.094)
Observations	2,774,123	2,774,123	3,536,594	3,536,594	4,042,214	4,042,214
Mean dep. var	3.054	3.054	-9.655	-9.655	-6.689	-6.689
Std. dep. var	39.222	39.222	37.386	37.386	38.132	38.132
Panel B: Manager Value Added (Rank)						
IC-to-M Transition	2.383	-1.842	-5.421**	-5.598	-3.195*	-4.881
	(1.772)	(3.697)	(2.254)	(5.634)	(1.732)	(5.084)
Observations	2,774,123	2,774,123	3,536,594	3,536,594	4,042,214	4,042,214
Mean dep. var	1.642	1.642	-5.593	-5.593	-4.687	-4.687
Std. dep. var	41.011	41.011	41.009	41.009	40.949	40.949

Notes: This table reports the gap in post-promotion outcomes between each demographic group and its benchmark (White employees for racial minorities; male employees for women). Each coefficient is the difference between the group-specific and benchmark estimates from a regression of the outcome on an indicator for IC-to-M transitions, estimated by OLS and two-stage least squares (2SLS). In the IV columns, the IC-to-M transition indicator is instrumented with the share of IC-to-M transitions in the same firm-month-job function outside the worker's own team. Panel A uses the rank of average subordinate log pay over all periods as manager as the outcome. Panel B uses the manager value added in pay percentile, defined as the manager fixed effect from an AKM decomposition of subordinate pay rank. The sample pools workers across 12 firms with a sufficient number of IC-to-M transitions in each demographic group. Standard errors are adjusted for clustering at the firm level. Statistical significance: $***$, $p < 0.01$; $**$, $p < 0.05$; $*$, $p < 0.1$.
Source: Authors' calculations from de-identified employee-level administrative internal HR records from 43 firms, accessed through a collaboration with Visier.

Online Appendix

A Additional Figures and Tables

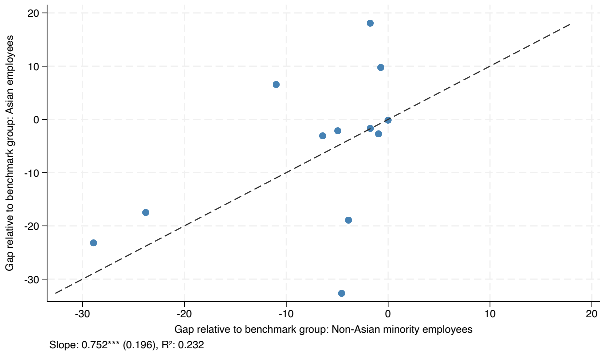
Figure A1: Aggregating Organizational Layers

Original depth	Organizational Layer: 1+2	3	4	5	6	7	8	9	10+
4	T	M	B						
5	T	M	B	B					
6	T	M	B	B	B				
7	T	T	M	B	B	B			
8	T	T	M	B	B	B	B		
9	T	T	M	M	B	B	B	B	
10+	T	T	M	M	B	B	B	B	B

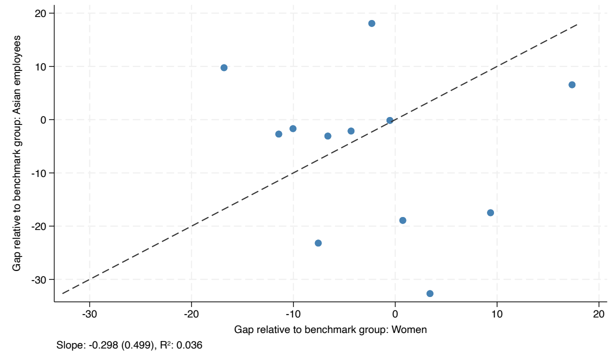
Notes: This figure illustrates how we map a firm's detailed organizational layers into three broad groups (top, middle, and bottom) as a function of the firm's total organizational depth (rows). Columns report the original layer index (with layers 1 and 2 pooled). This coarser classification facilitates comparisons across firms with different depths, since the same layer number can represent very different positions in the hierarchy in shallow versus deep organizations.

Figure A2: IV Estimations, Cross-Firm Scatter Plots

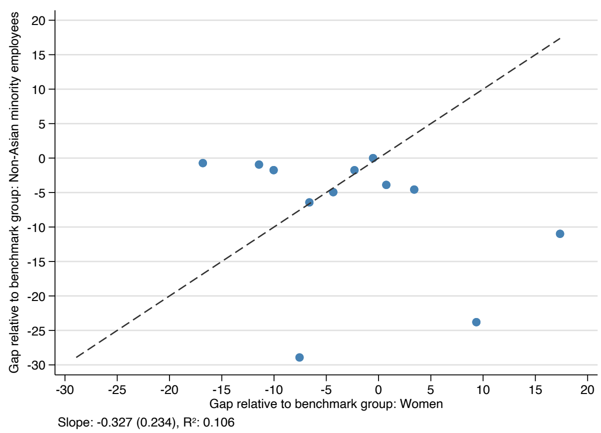
Panel A: Asians vs Non-Asian minorities



Panel B: Asians vs Women



Panel C: Non-Asian minorities vs Women



Notes: This figure presents scatter plots comparing, across firms, the gaps in post-promotion outcomes between two demographic groups per panel. For each firm and each demographic group, we estimate separate two-stage least squares (2SLS) regressions of manager value added on an indicator for IC-to-M transitions, instrumenting with the share of IC-to-M transitions in the same firm-month-job function outside the worker's own team. We then compute the gap for each group as the difference between the group-specific 2SLS coefficient and that of the corresponding benchmark group (White employees for racial minorities; male employees for women). Each point represents one firm. The dashed line is the 45-degree line. The reported slope, standard error, and R-squared are from a robust OLS regression of the vertical-axis gap on the horizontal-axis gap across firms. The sample includes never managers, and we restrict to firms with at least 15 promotions in each of the six main demographic groups.
Source: Authors' calculations from de-identified employee-level administrative internal HR records from 43 firms, accessed through a collaboration with Visier.

Table A1: Other Outcomes and IC Status

Dependent Variable:	Promotion (1)	Promotion (2)	Pay Increase (3)	Pay Increase (4)	Last Month (5)	Last Month (6)
IC	-0.317***	-0.212***	-0.099***	-0.076***	0.283***	0.450***
	(0.070)	(0.066)	(0.014)	(0.008)	(0.085)	(0.067)
Female		0.110***		0.024***		-0.092***
		(0.023)		(0.003)		(0.031)
Asian		-0.125***		-0.031***		0.057
		(0.028)		(0.007)		(0.056)
Black		0.016		-0.003		0.280***
		(0.045)		(0.006)		(0.044)
Hispanic		-0.022		-0.007		-0.053
		(0.029)		(0.005)		(0.046)
Other minorities		-0.029		-0.003		0.241***
		(0.024)		(0.004)		(0.062)
Observations	9,629,781	9,629,781	9,629,781	9,629,781	9,629,781	9,629,781
Mean of dep. var.	1.153	1.153	0.459	0.459	1.927	1.927
Age and tenure	X	X	X	X	X	X
Firm-Month FE	X		X		X	
Firm-Month-TMB FE						
Firm-Month-TMB-Job FE						
Firm-Month-Layer-Job FE		X		X		X

Notes: This table reports regressions of workers' career outcomes on a dummy equal to one if the worker is an individual contributor in month t. The dependent variables are: promotion in month t, which is an indicator equal to one if the worker is promoted (multiplied by 100 to make coefficients easier to interpret) (columns 1 and 2); monthly pay growth from month $t-1$ to month t (multiplied by 100) (columns 3 and 4); and an indicator equal to one if month t is the worker's final observed month with the firm (columns 5 and 6). All specifications include additional worker and firm controls. "Firm-Month-Layer-Job FE" absorb the full interaction of firm, month, organizational layer (where layer refers to the worker's exact layer rather than the coarser top/middle/bottom grouping), and job function. Standard errors are clustered by firm. Statistical significance: $***$, $p < 0.01$; $**$, $p < 0.05$; $*$, $p < 0.1$.
Source: Authors' calculations from de-identified employee-level administrative internal HR records from 43 firms, accessed through a collaboration with Visier.

Table A2: IC Penalty by Hierarchical Levels

Dependent variable:	Log Pay (1)	Log Pay (2)	Log Pay (3)	Log Pay (4)	Log Pay (5)
IC	-0.402***	-0.406***	-0.383***	-0.330***	-0.278***
	(0.029)	(0.030)	(0.030)	(0.019)	(0.020)
IC x Middle	-0.034	-0.020	-0.011	-0.026	-0.055*
	(0.028)	(0.025)	(0.024)	(0.029)	(0.031)
IC x Top	-0.389***	-0.320***	-0.293***	-0.212**	-0.209**
	(0.061)	(0.055)	(0.054)	(0.087)	(0.086)
Middle	0.302***				
	(0.040)				
Top	0.621***				
	(0.123)				
Female			-0.138***	-0.071***	-0.066**
			(0.030)	(0.026)	(0.026)
Asian			-0.086	-0.100	-0.099
			(0.173)	(0.171)	(0.167)
Black			-0.203***	-0.132***	-0.115***
			(0.022)	(0.016)	(0.016)
Hispanic			-0.147***	-0.098***	-0.091***
			(0.030)	(0.030)	(0.029)
Other minorities			-0.083***	-0.051***	-0.051***
			(0.015)	(0.012)	(0.013)
Observations	9,629,781	9,629,781	9,629,781	9,629,781	9,629,781
Mean of dep. var.	11.272	11.272	11.272	11.272	11.272
Age and tenure	X	X	X	X	X
Firm-Month FE	X				
Firm-Month-TMB FE		X	X		
Firm-Month-TMB-Job FE				X	
Firm-Month-Layer-Job FE					X

Notes: This table reports regressions of individual log pay on an indicator for being an individual contributor (IC). The IC indicator is further interacted with indicators for being in the middle and top parts of the hierarchy (with the bottom as the omitted group), allowing the IC pay difference to vary by broad hierarchical position. All specifications include additional worker controls and fixed effects. "Firm-Month-TMB FE" include fixed effects for three-way interactions of firm identifiers, months, and dummies for either the top, middle, or bottom organizational layers. "Firm-Month-TMB-Job FE" further interacts these fixed effects with dummies for the different job functions. "Firm-Month-Layer-Job FE" absorb the full interaction of firm, month, organizational layer (where a refers to the worker's exact layer rather than the coarser top/middle/bottom grouping), and job function. Standard errors are clustered by firm. Statistical significance: $***$, $p < 0.01$; $**$, $p < 0.05$; $*$, $p < 0.1$.
Source: Authors' calculations from de-identified employee-level administrative internal HR records from 43 firms, accessed through a collaboration with Visier.

Table A3: The Minority Gap in IC Status by Hierarchical Levels

Dependent Variable:	IC (1)	IC (2)	IC (3)	IC (4)
Middle	-33.510*** (1.483)			
Top	-51.316*** (3.878)			
Female	2.744*** (0.735)	3.043*** (0.599)	1.598*** (0.360)	1.764*** (0.274)
Female x Middle	11.569*** (1.346)	10.245*** (0.900)	6.137*** (0.728)	5.510*** (0.540)
Female x Top	18.660*** (2.892)	18.064*** (2.246)	7.245*** (1.034)	5.857*** (0.848)
Asian	2.346*** (0.746)	2.466*** (0.753)	1.652** (0.690)	1.290* (0.679)
Asian x Middle	4.027*** (1.559)	2.485** (1.060)	2.219** (0.916)	2.053** (0.868)
Asian x Top	-2.781 (2.444)	0.433 (1.492)	2.423** (1.182)	2.481** (1.190)
Black	4.005*** (0.676)	4.230*** (0.626)	2.854*** (0.449)	1.321*** (0.355)
Black x Middle	6.134*** (1.667)	4.336** (1.962)	3.048** (1.417)	4.046*** (1.320)
Black x Top	14.760*** (2.018)	7.186*** (2.052)	4.316*** (1.468)	5.509*** (1.588)
Hispanic	3.689*** (0.886)	3.705*** (0.855)	2.680*** (0.577)	1.633*** (0.462)
Hispanic x Middle	5.412*** (1.777)	4.950*** (1.279)	3.145*** (1.118)	3.368*** (1.183)
Hispanic x Top	16.943*** (2.311)	11.177*** (2.426)	5.327*** (1.155)	4.875*** (1.029)
Other minorities	3.367*** (0.930)	3.324*** (0.904)	2.619*** (0.740)	1.681*** (0.612)
Other minorities x Middle	5.504*** (1.930)	4.842*** (1.717)	3.568** (1.491)	3.794** (1.583)
Other minorities x Top	10.0404 (3.5211)	7.4299 (3.2342)	3.6620 (1.9748)	4.3711 (1.6891)
Observations	9,629,781	9,629,781	9,629,781	9,629,781
Mean of IC	83.4778	83.4778	83.4778	83.4778
Age and tenure	Y	Y	Y	Y
Firm-Month FE	Y			
Firm-Month-TMB FE		Y		
Firm-Month-TMB-Job FE			Y	
Firm-Month-Layer level-Job FE				Y

Notes: This table reports individual-level regressions of an indicator for being an individual contributor (IC) on demographic characteristics (gender and ethnicity), pooling workers across all firms and months in the sample. The demographic variables are interacted with indicators for being in the middle or top tiers of the hierarchy (leaving the bottom tier as the omitted group), allowing demographic differences in IC status to vary by broad hierarchical levels. Specifications always include controls for age and tenure and increasingly detailed fixed effects. Standard errors are clustered by firm. Statistical significance: $***$, $p < 0.01$; $**$, $p < 0.05$; $*$, $p < 0.1$.
Source: Authors' calculations from de-identified employee-level administrative internal HR records from 43 firms, accessed through a collaboration with Visier.

Table A4: Testing Differences Between Asian Employees and Other Groups

	Asian Employees	Comparison Group	Difference (1)-(2)	P-value (> 0)
	(1)	(2)	(3)	(4)
Panel A: Asian employees vs. Other minority groups				
Log Pay (Rank) - OLS	3.157	-8.666***	11.824	0.000
	(2.449)	(2.008)	(3.307)	
Log Pay (Rank) - IV	2.036	-7.715*	9.751	0.042
	(3.114)	(4.414)	(5.642)	
Manager Value Added (Rank) - IV	-1.842	-5.598	3.756	0.297
	(3.697)	(5.634)	(7.039)	
Panel B: Asian employees vs. Women				
Log Pay (Rank) - OLS	3.157	-5.994***	9.151	0.002
	(2.449)	(1.862)	(3.213)	
Log Pay (Rank) - IV	2.036	-3.579	5.614	0.148
	(3.114)	(4.094)	(5.373)	
Manager Value Added (Rank) - IV	-1.842	-4.881	3.039	0.322
	(3.697)	(5.084)	(6.566)	

Notes: This table tests whether the gap in post-promotion outcomes for Asian employees differs from that of other groups. Columns 1 and 2 report each group's OLS or 2SLS coefficient minus its benchmark (White employees for racial minorities; male employees for women). Column 3 reports the difference between the Asian and comparison group gaps against the benchmark group, and column 4 reports the one-sided p-value for the alternative hypothesis that this difference is positive. Panel A compares Asian employees to other minority groups. Panel B compares Asian employees to women. The sample pools workers across 12 firms with a sufficient number of IC-to-M transitions in each demographic group. Standard errors are adjusted for clustering at the firm level.
Source: Authors' calculations from de-identified employee-level administrative internal HR records from 43 firms, accessed through a collaboration with Visier.

Table A5: Relationship Between Individual and Firm-Level Transitions

	Race groups			Gender groups	
	White	Asian	Others	Men	Women
	(1)	(2)	(3)	(4)	(5)
Firm-level IC-to-M Transitions	0.007***	0.005***	0.005***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	2,143,380	487,541	1,208,818	1,824,629	2,015,110
Mean dep. var	0.003	0.003	0.002	0.003	0.002
SD dep. var	0.053	0.050	0.040	0.052	0.046
Mean indep. var.	0.317	0.364	0.265	0.328	0.286
SD indep. var.	0.510	0.563	0.447	0.517	0.481

Notes: This table reports the relationship between firm-level and individual IC-to-M transitions, separately by demographic group (the first stage of the 2SLS regressions in Table 7). Each coefficient captures the effect of the share of IC-to-M transitions in the same firm-month-job function outside the worker's own team on the worker's own IC-to-M transition probability. The sample pools workers across 12 firms with a sufficient number of IC-to-M transitions in each demographic group. Standard errors are adjusted for clustering at the firm level. Statistical significance: $***$, $p < 0.01$; $**$, $p < 0.05$; $*$, $p < 0.1$.
Source: Authors' calculations from de-identified employee-level administrative internal HR records from 43 firms, accessed through a collaboration with Visier.

Table A6: Cross-Firm Variance in IC-to-M Transitions

	Median (1)	25th Pctl (2)	75th Pctl (3)	75th - 25th (4)	Mean (5)	SD (6)	Neg. (7)	Pos. (8)
Panel A: Log Pay (Rank) - OLS								
Asians	6.257	-0.487	14.147	14.634	6.449	7.915	0.000	0.417
Others	-8.174	-10.980	-4.829	6.150	-8.218	5.076	0.667	0.000
Women	-6.908	-10.782	-1.914	8.868	-6.087	6.293	0.750	0.083
Panel B: Log Pay (Rank) - IV								
Asians	2.832	-11.285	14.589	25.875	2.305	16.488	0.083	0.333
Others	-5.961	-16.274	-1.717	14.556	-8.544	8.428	0.333	0.000
Women	-3.898	-14.177	0.859	15.036	-6.076	9.183	0.333	0.000
Panel C: Manager Value Added (Rank) - IV								
Asians	-2.424	-18.203	3.206	21.409	-5.637	14.699	0.333	0.083
Others	-4.228	-8.707	-1.342	7.365	-7.391	9.426	0.250	0.000
Women	-3.319	-8.797	2.076	10.873	-2.396	9.398	0.083	0.083

Notes: This table reports the cross-firm distribution of the gap in post-promotion outcomes between each demographic group and its benchmark (White employees for racial minorities; male employees for women). For each firm and each demographic group, we estimate separate 2SLS regressions of the outcome on an indicator for IC-to-M transitions, instrumenting with the share of IC-to-M transitions in the same firm-month-job function outside the worker's own team, and compute the gap as the difference between the group-specific and benchmark coefficients. The OLS regressions do not instrument the IC-to-M transitions dummy, but are otherwise similar to the 2SLS specifications. The table reports summary statistics of these firm-level gaps. Columns 6 and 7 report the share of firm-level estimates that are statistically lower and greater than zero, respectively, at the 5% level of significance. Panels A and B use the rank of average subordinate log pay over all periods as manager as the outcome. Panel C uses the manager value added in pay percentile, defined as the manager fixed effect from an AKM decomposition of subordinate pay rank. We restrict to firms with at least 15 IC-to-M transitions for each of the six main demographic groups.
Source: Authors' calculations from de-identified employee-level administrative internal HR records from 43 firms, accessed through a collaboration with Visier.

B Summary Statistics and Benchmarking

B.1 Summary Statistics

Here, we provide additional summary statistics on the firms in our sample and on the main outcomes we study (Table B1, Panel A). Our primary outcome is yearly direct compensation, which includes base salary, overtime pay, and bonuses paid in cash. It does not include indirect forms of compensation such as stock grants, retirement contributions, or health and other benefits. We refer to this measure simply as pay throughout the analysis.

The distribution of mean pay highlights substantial heterogeneity across firms. The average log pay is 11.59, with values ranging from 10.92 in lower-paying firms to 12.68 in higher-paying firms. Translating from logs, this corresponds to annualized mean pay levels between roughly $55,000 and $321,000. Pay disparities within firms are also large. On average, employees in the top layer of the hierarchy earn about 2.8 times more than those at the bottom, and in some firms this ratio exceeds a factor of 7. In addition to pay, we consider three other outcomes that capture career dynamics within the firm: monthly promotion rates, monthly pay growth, and the probability of exit from the firm in the following month. Promotions are defined as moves to a higher hierarchical layer within the firm; monthly pay growth is computed as the percent change in direct compensation relative to the prior month; and next-month exit indicates separation from the firm between month t and month $t+1$.

Managers oversee an average of about eight direct reports, though in some firms the span is as low as 2 and as high as 17. The dataset also classifies employees by job function, which describes the types of tasks performed within firms. To keep the analysis tractable, we group some of these functions into broader categories. In particular, we aggregate workers in four different job functions into a category we label highly skilled workers, who account for about 46 percent of the workforce on average.[23] We also track administrative workers separately, since these roles are by definition more likely to be ICs. In robustness checks, we will demonstrate that our results are not driven by this group: excluding administrative workers leaves all of our findings on the careers of ICs unchanged, confirming that they reflect general career dynamics rather than differences between administrative and non-administrative staff.

Beyond the organizational structure, the data also provide rich information on employee characteristics (Table B1, Panel B). Workers in our sample are on average about 42 years old, with most firms reporting an age distribution centered between the late thirties and mid-forties. Average tenure is 5.8 years. Gender and race both vary widely across firms.[24] The share of women averages 44 percent, ranging from 9 percent to more than 80 percent. Racial composition shows similar heterogeneity. On average, the workforce is 64 percent White, 14 percent Asian, 10 percent Black, and 10 percent Hispanic. To illustrate the cross-firm variation, the share of Asian employees is below 1 percent in some firms and above 50 percent in others; the other racial and ethnic groups display similarly wide ranges. In later sections, we examine directly whether gender and race influence the likelihood of being, and remaining, an IC.

B.2 Benchmarking

To gauge the representativeness of our sample, we benchmark its composition against the U.S. Equal Employment Opportunity Commission's EEO-1 statistics.[25] Although our sample is not exclusively U.S.-based, all but one firm have the largest portion of their workforce located in the United States, making the EEO-1 a natural point of comparison.

We present these results after weighting the EEO-1 data to match the industry mix of our full sample of 43 firms (Table B2, Panel A).[26] Overall, the sample is broadly comparable to the benchmark. For example, the share of individual contributors averages 82.5 percent in our data versus 84.7 percent in the EEO-1 dataset, a small and insignificant difference at the 5 percent level. Gender representation is likewise close: women account for 43.9 percent of employees in our sample compared with 43.4 percent in the benchmark.

Some differences do emerge, particularly in the distribution of skills across firms. Highly skilled workers account for 45.7 percent of the workforce in our sample compared with 51.1 percent in the EEO-1 benchmark. These gaps can reflect real differences between our sample and the benchmark data, as well as the difficulty of perfectly aligning definitions across sources. In our classification, highly skilled workers include employees in business, finance, and legal; computer and math; research and development; and top management. For the benchmark, we constructed the comparable category by combining the EEO-1 classifications for executives, other managers, professionals, and technicians. Because the underlying job functions differ across sources, some degree of discrepancy may be unavoidable, but the resulting shares are nevertheless quite close.

Racial composition is balanced at the aggregate level. Minority employees make up about 36.5 percent of the workforce in our sample, statistically indistinguishable from the 40 percent reported in the EEO-1. At the level of individual groups, there are some small but significant differences, such as a higher share of Asian employees and a lower share of Hispanic employees in our sample relative to the benchmark.

Restricting the comparison to the four largest industries in our sample—manufacturing, high tech, finance, and health care (38 firms)—yields similar conclusions (Table B2, Panel B). These results reinforce the view that, although our sample is not perfectly matched to the EEO-1 statistics, it provides a broadly representative depiction of the workforce composition across large North American firms.

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[23] These functions are business, finance, and legal; computer and math; research and development; and top management.

[24] In our data, Hispanic is coded as a mutually exclusive race category rather than a separate indicator of ethnicity. Thus, Hispanic employees are not double-counted within the other groups.

[25] https://www.eeoc.gov/data/eeo-1-employer-information-report-statistics.

[26] The industry mix is computed using 42 firms, since one firm in our sample does not report industry information.

Table B1: Summary Statistics

	Mean (1)	SD (2)	Min (3)	Max (4)
Panel A: Firm Characteristics				
Share with 0-1999 employees	0.47	0.50	0	1
Share with 2000-3999 employees	0.30	0.46	0	1
Share with 4000+ employees	0.23	0.43	0	1
Share manufacturing	0.28	0.45	0	1
Share high tech	0.30	0.46	0	1
Share finance-real estate	0.21	0.41	0	1
Share health care	0.09	0.29	0	1
Share U.S.	0.98	0.15	0	1
Sample length (months)	81.40	32.71	21	164
Share of IC	0.82	0.08	0.61	0.96
IC-to-M transition rate (0-100)	0.47	0.37	0.10	1.81
M-to-IC transition rate (0-100)	0.24	0.17	0.04	0.91
IC-to-IC transition rate (0-100)	82.24	7.87	60.16	96.20
M-to-M transition rate (0-100)	17.05	7.47	3.67	37.12
Hierachical depth	7.79	1.01	5	9
Share with depth 7	0.28	0.45	0	1
Share with depth 8	0.40	0.49	0	1
Share with depth 9	0.26	0.44	0	1
Mean log pay	11.59	0.41	10.92	12.68
Top-bottom mean pay ratio	2.82	1.28	0.83	7.22
Mean monthly pay growth (0-100)	0.49	0.18	0.06	1.12
Promotion rate (0-100)	1.20	0.66	0.00	3.08
Exit next month (0-100)	1.93	0.76	0.86	4.52
Average span of managers	8.05	3.49	2.35	17.07
Top-bottom average span ratio	0.85	0.37	0.30	1.74
Share of higher-skill workers	0.46	0.17	0.09	0.83
Top-bottom higher-skill ratio	0.11	0.14	0.01	0.71
Panel B: Employee Characteristics				
Age	41.67	3.70	32.89	46.74
Tenure (years)	5.81	3.59	0.20	14.30
Share of women	0.44	0.19	0.09	0.81
Share of White workers	0.64	0.14	0.25	0.90
Share of Asian workers	0.14	0.13	0.01	0.55
Share of Black workers	0.10	0.09	0.01	0.43
Share of Hispanic workers	0.10	0.07	0.02	0.27

Notes: This table reports summary statistics for the main variables used in the analysis. For each firm, we first compute the mean of each variable across all months observed for that firm. Then, we compute the mean, standard deviation, min and max of these firm-level averages across the 43 firms in our sample.
Source: Authors' calculations from de-identified employee-level administrative internal HR records from 43 firms, accessed through a collaboration with Visier.

Table B2: Benchmarking Against EEO

	Sample (1)	Benchmark (2)	Difference (3)	Std. Error (4)	T-statistic (5)	P-value (6)
Panel A: All sectors (43 firms)						
Share of IC workers	0.825	0.847	-0.022	0.012	-1.866	0.069*
Share of higher-skill workers	0.457	0.511	-0.054	0.026	-2.081	0.044**
Share of women	0.439	0.434	0.005	0.029	0.172	0.864
Share of minority workers	0.338	0.366	-0.027	0.020	-1.344	0.186
Share of asian workers	0.136	0.090	0.045	0.019	2.375	0.022**
Share of black workers	0.102	0.126	-0.025	0.014	-1.829	0.074*
Share of hispanic workers	0.101	0.149	-0.048	0.011	-4.512	0.000***
Panel B: 4 main sectors (38 firms)						
Share of IC workers	0.827	0.844	-0.017	0.012	-1.406	0.168
Share of higher-skill workers	0.464	0.528	-0.064	0.029	-2.211	0.033**
Share of women	0.462	0.444	0.018	0.030	0.600	0.552
Share of minority workers	0.350	0.367	-0.017	0.021	-0.811	0.423
Share of asian workers	0.147	0.094	0.052	0.021	2.525	0.016**
Share of black workers	0.104	0.125	-0.021	0.015	-1.424	0.163
Share of hispanic workers	0.099	0.148	-0.049	0.011	-4.541	0.000***

Notes: To gauge the representativeness of our sample, we benchmark its composition against the U.S. Equal Employment Opportunity Commission (EEO-1) statistics. Panel A reports this comparison after re-weighting the EEO-1 data to match the industry mix of our sample. Panel B restricts the comparison to the four largest industries in our sample: manufacturing, high tech, finance/real estate, and health care (38 out of 43 firms). We use two- and three-digit NAICS codes to define industries in the EEO-1 data as follows: finance/real estate (52–53), health care (62), high tech (334, 336, 511, 518, 519, 541), and manufacturing (31–32, 331, 332, 333, 335, 337, 339). We follow the U.S. Census Bureau to select the high-tech NAICS codes (https://www.census.gov/programs-surveys/ces/data/public-use-data/experimental-bds/bds-high-tech/definitions.html). In the EEO-1 data, we proxy "high-skill" workers as the sum of executives, other managers, professionals, and technicians. Moreover, we measure the IC share as 1 minus the combined shares of "Executive/Senior Level Officials and Managers" and "First/Mid-Level Officials and Managers."
Sources: Sample: Authors' calculations from de-identified employee-level administrative internal HR records from 43 firms, accessed through a collaboration with Visier. Benchmark: U.S. Equal Employment Opportunity Commission's EEO-1 statistics, available at https://www.eeoc.gov/data/eeo-1-employer-information-report-statistics.

C Model Proofs

C.1 The Optimization Problem

The proof proceeds by contradiction. Let N_l^* denote the number of workers or managers and ICs at level l in the solution to the "combined" optimization problem (the optimal solution), and N_l^R denote the corresponding quantity in the solution to the "recursive" optimization problem. Note that $\Sigma_{l=0}^{L} N_l^* = \Sigma_{l-0}^{L} N_l^R = N$ and $N_0^* \geq N_0^R$.

Suppose $N_0^* > N_0^R$. Then there must exist at least one level l such that $N_l^* < N_l^R$. Indeed, if no such level existed, we would have $\Sigma_l N_l^* > \Sigma_l N_l^R$, which contradicts the equality above.

Let k denote the lowest level such that $N_k^* < N_k^R$. By definition, this implies $N_{k-1}^* \geq N_{k-1}^R$(note that $k > 0$, so level $k-1$ is well defined). Since N_k^* level-k managers and ICs can "support" (i.e., supervise and solve escalated problems for) N_{k-1}^* level-$(k-1)$ subordinates, the same N_k^* managers and ICs must also be able to support N_{k-1}^R level-$(k-1)$ subordinates, given that $N_{k-1}^R \leq N_{k-1}^*$. However, as $N_k^* < N_k^R$, it follows that N_k^R cannot be the solution to the recursive optimization problem of minimizing the number of level-k managers and ICs needed to support N_{k-1}^R level-$(k-1)$ subordinates. This yields a contradiction.

Thus it cannot be the case that $N_0^* > N_0^R$. This implies that $N_0^* = N_0^R$; that is, the solution to the recursive optimization problem is as good as the optimal solution, and thereby is an optimal solution. This concludes the proof.

C.2 Proof of Proposition 1

For any level l, we first show that under an interior optimum with both worker types present, both time constraints must bind, i.e. equations (6) and (7) hold with equality. First, if $K_l^{IC} < 1/t_l$, one can increase K_l^{IC} slightly while keeping all other choices fixed and then lower N_l^{IC} to continue satisfying (5). This lowers the objective $N_l^M + N_l^{IC}$, a contradiction. Hence,

$$K_l^{IC*} = \frac{1}{t_l}.$$

Second, if $F_l + c_l S_l^\gamma + t_l K_l^M < 1$, one can increase K_l^M slightly while keeping S_l fixed and then reduce N_l^{IC} so that (5) still holds. Again the objective falls, a contradiction. Hence,

$$K_l^M = \frac{1 - F_l - c_l S_l^\gamma}{t_l}.$$

In the second step, we substitute Equations (4)–(7) into Equation (3) to yield:

$$\begin{aligned} N_l^M + N_l^{IC} &= \frac{N_{l-1}}{S_l} + \left(N_{l-1} - \frac{N_{l-1}}{S_l} K_l^M\right) \frac{1}{K_l^{IC}} \\ &= N_{l-1}\left(\frac{1}{S_l} + t_l - \frac{t_l K_l^M}{S_l}\right) \\ &= N_{l-1}\left(\frac{1}{S_l} + t_l - \frac{1-(F_l + c_l S_l^\gamma)}{S_l}\right) \\ &= N_{l-1}\left(t_l + \frac{F_l}{S_l} + c_l S_l^{\gamma-1}\right). \end{aligned} \tag{22}$$

Here, the first line comes from substituting in equilibrium conditions (4) and (5). The second line comes from substituting in the ICs' time constraint (7). The third line comes from substituting in the managers' time constraint (6).

Thus, minimizing $N_l^M + N_l^{IC}$ reduces to minimizing $f(S_l) = \frac{F_l}{S_l} + c_l S_l^{\gamma-1}$, with first-order condition

$$f'(S) = -\frac{F_l}{S_l^2} + c_l(\gamma-1)S_l^{\gamma-2} = 0,$$

and the unique solution

$$c_l(\gamma-1)S_l^\gamma = F_l \quad \Longleftrightarrow \quad S_l{}^* = \left(\frac{F_l}{(\gamma-1)c_l}\right)^{1/\gamma}.$$

The second derivative at the optimum is given by

$$f''(S^*) = \frac{2F}{(S^*)^3} + c(\gamma-1)(\gamma-2)(S^*)^{\gamma-3} = c(\gamma-1)\gamma(S^*)^{\gamma-3} > 0.$$

Next, we can substitute this solution for $S_l{}^*$ into the manager time constraint 6 to yield

$$K_l^{M*} = \frac{1 - F_l - c_l S_l^\gamma}{t_l} = \frac{1 - F_l - \frac{F_l}{\gamma-1}}{t_l} = \frac{1 - \frac{\gamma}{\gamma-1}F_l}{t_l}.$$

This equation shows that the assumption $F \leq (\gamma-1)/\gamma$ guarantees $K_l^{M*} \geq 0$.

C.3 Proof of Proposition 2

This result assumes coexistence of ICs and managers at level l. From Proposition 1, this assumption requires $S_l{}^* - K_l^{M*} > 0$ and we can use Equations (9) and (11) to characterize

$$D_l \equiv S_l{}^* - K_l^{M*} > 0 \quad \iff \quad D_l \equiv t_l \left(\frac{F_l}{(\gamma - 1)c_l} \right)^{1/\gamma} - 1 + \frac{\gamma}{\gamma - 1} F_l > 0. \tag{23}$$

This step is convenient for the proof of Proposition 2 because D_l can be used to write the IC share.

Part 1: IC share. First note that from the equilibrium conditions (4) and (5),

$$N_l^M K_l^M + N_l^{IC} K_l^{IC} = N_{l-1} = N_l^M S_l.$$

Hence,

$$N_l^{IC} K_l^{IC} = N_l^M (S_l - K_l^M) \quad \Longrightarrow \quad N_l^{IC} = N_l^M \frac{S_l - K_l^M}{K_l^{IC}}.$$

Therefore, the IC share can be written as

$$\xi_l = \frac{N_l^{IC}}{N_l^M + N_l^{IC}} = \frac{\frac{S_l - K_l^M}{K_l^{IC}}}{1 + \frac{S_l - K_l^M}{K_l^{IC}}} = \frac{S_l - K_l^M}{K_l^{IC} + S_l - K_l^M}.$$

Substituting in the results from Proposition 1 yields

$$\xi_l = \frac{\left(\frac{F_l}{(\gamma-1)c_l} \right)^{1/\gamma} - \frac{1 - \frac{\gamma}{\gamma-1} F_l}{t_l}}{\frac{1}{t_l} + \left(\frac{F_l}{(\gamma-1)c_l} \right)^{1/\gamma} - \frac{1 - \frac{\gamma}{\gamma-1} F_l}{t_l}} = \frac{t_l \left(\frac{F_l}{(\gamma-1)c_l} \right)^{1/\gamma} - \left(1 - \frac{\gamma}{\gamma-1} F_l \right)}{1 + t_l \left(\frac{F_l}{(\gamma-1)c_l} \right)^{1/\gamma} - \left(1 - \frac{\gamma}{\gamma-1} F_l \right)}$$

which, using Equation (23), implies

$$\xi_l \equiv \frac{N_l^{IC}}{N_l^M + N_l^{IC}} = \frac{S_l - K_l^M}{K_l^{IC} + S_l - K_l^M} = \frac{D_l}{1 + D_l}. \tag{24}$$

Because $\partial \xi_l / \partial D_l = 1/(1 + D_l)^2 > 0$, it suffices to sign the derivatives of D_l. Using Equation (23), we find

$$\begin{aligned}
\frac{\partial D_l}{\partial t_l} &= \left(\frac{F_l}{(\gamma - 1)c_l} \right)^{1/\gamma} > 0, \\
\frac{\partial D_l}{\partial c_l} &= -\frac{t_l}{\gamma c_l} \left(\frac{F_l}{(\gamma - 1)c_l} \right)^{1/\gamma} < 0, \\
\frac{\partial D_l}{\partial F_l} &= \frac{t_l}{\gamma F_l} \left(\frac{F_l}{(\gamma - 1)c_l} \right)^{1/\gamma} + \frac{\gamma}{\gamma - 1} > 0.
\end{aligned}$$

Hence ξ_l is increasing in F_l and t_l, and decreasing in c_l.

Part 2: IC penalty. From Section 4.1, the added value of an IC at level l is proportional to

$$(Z_l - Z_{l-1}) \rho_{l-1} K_l^{IC*},$$

while the added value of a manager at level l is proportional to

$$\kappa Z_l \rho_{l-1} S_l{}^* + (1 - \kappa)(Z_l - Z_{l-1}) \rho_{l-1} K_l^{M*}.$$

Hence the IC penalty π_l, defined as the difference between IC pay and manager pay, can be expressed by the log difference in their added value,

$$\begin{aligned}
\pi_l &= \ln\left((Z_l - Z_{l-1})\rho_{l-1}K_l^{IC*}\right) - \ln\left(\kappa Z_l \rho_{l-1} S_l{}^* + (1-\kappa)(Z_l - Z_{l-1})\rho_{l-1}K_l^{M*}\right) \\
&= -\ln\left(\kappa \frac{Z_l}{Z_l - Z_{l-1}} \frac{S_l{}^*}{K_l^{IC*}} + (1-\kappa)\frac{K_l^{M*}}{K_l^{IC*}}\right) \\
&= -\ln\left(\kappa \frac{1}{q_l} t_l S_l{}^* + (1-\kappa)(1 - \frac{\gamma}{\gamma - 1}F_l)\right)
\end{aligned}$$

where the last row uses the results from Proposition 1 and defines the knowledge increment ratio

$$q_l \equiv \frac{Z_l - Z_{l-1}}{Z_l}. \tag{25}$$

As $\kappa \frac{1}{q_l} t_l S_l{}^* = \kappa \frac{1}{q_l} t_l \left(\frac{F_l}{(\gamma-1)c_l}\right)^{1/\gamma}$ is increasing in t_l and decreasing in c_l and q_l while $(1-\kappa)(1 - \frac{\gamma}{\gamma-1}F_l)$ does not depend on t_l, c_l, and q_l, the expression inside the logarithm is also increasing in t_l and decreasing in c_l and q_l. Because the logarithm is strictly decreasing and hence its negative is strictly decreasing, the IC penalty π_l is decreasing in t_l and increasing in c_l and q_l.

Manager's added value is increasing in κ, as evident from Equation (1), while IC's added value does not depend on κ. As a result, the IC penalty π_l, i.e., the difference between ICs' added value and managers' added value, is decreasing in κ.

Notice that π_l is negative, and therefore a decreasing π_l indicates a larger penalty.

C.4 Proof of Proposition 3

For Part (1), Proposition 1 implies that since $\xi_l = \frac{D_l}{1+D_l}$, we have

$$\xi_{l+1} < \xi_l \iff \frac{D_{l+1}}{1+D_{l+1}} < \frac{D_l}{1+D_l} \iff D_{l+1} < D_l.$$

Under $\gamma = 2$,

$$D_l = t_l\sqrt{\frac{F_l}{c_l}} - 1 + 2F_l.$$

If $t_l\sqrt{F_l/c_l} + 2F_l$ is increasing in l, then

$$D_{l+1} = t_{l+1}\sqrt{\frac{F_{l+1}}{c_{l+1}}} - 1 + 2F_{l+1} < t_l\sqrt{\frac{F_l}{c_l}} - 1 + 2F_l = D_l.$$

Hence $\xi_{l+1} < \xi_l$, proving Part (1).

For Part (2), under $\gamma = 2$,

$$\pi_l = -\ln\left(\kappa \frac{t_l\sqrt{F_l/c_l}}{q_l} + (1-\kappa)(1-2F_l)\right).$$

Define

$$H_l \equiv \kappa \frac{t_l\sqrt{F_l/c_l}}{q_l} - 2(1-\kappa)F_l.$$

Then

$$\pi_l = -\ln(1 - \kappa + H_l).$$

Because the logarithm is strictly increasing, if H_l is increasing in l, then $-\ln(1-\kappa+H_l)$ is decreasing in l, and therefore

$$\pi_{l+1} < \pi_l$$

such that the IC penalty widens toward the top of the hierarchy.

For Part (3), we use the accounting identities

$$N_l = N_l^M + N_l^{IC}, \qquad \xi_l = \frac{N_l^{IC}}{N_l}, \qquad N_l^M S_l^* = N_{l-1}.$$

The first two imply $N_l^M = (1-\xi_l)N_l$. Substituting into $N_l^M S_l{}^* = N_{l-1}$ yields

$$(1-\xi_l)N_l S_l{}^* = N_{l-1},$$

and therefore we get an employment recursion

$$N_l = \frac{N_{l-1}}{S_l{}^*(1-\xi_l)}.$$

Under $\gamma = 2$, the optimal span is

$$S_l{}^* = \sqrt{\frac{F_l}{c_l}}.$$

Moreover, from the formula for the IC share,

$$\xi_l = \frac{t_l S_l - 1 + 2F_l}{t_l S_l + 2F_l},$$

which simplifies to

$$1-\xi_l = \frac{1}{t_l S_l + 2F_l}.$$

Substituting into the employment recursion yields

$$\frac{N_l}{N_{l-1}} = \frac{1}{S_l(1-\xi_l)} = \frac{t_l S_l + 2F_l}{S_l} = t_l + \frac{2F_l}{S_l}.$$

Using $S_l = \sqrt{F_l/c_l}$, we obtain

$$\frac{N_l}{N_{l-1}} = t_l + 2\sqrt{F_l c_l}.$$

Hence, if

$$t_l + 2\sqrt{F_l c_l} < 1 \ \forall\ l \in \{1, L\},$$

then

$$\frac{N_l}{N_{l-1}} < 1,$$

and therefore $N_l < N_{l-1}$ at every level. This proves Part (3).

D Additional Details on Estimation

This appendix section provides additional details on the estimation strategy, identification, and results.

D.1 Targeted Moments

The estimation targets the following list of moments,

$$\mathscr{M} = \{S_b, S_m, S_t,\ \pi_b, \pi_m, \pi_t,\ \xi_b, \xi_m, \xi_t,\ wr_{tm}^M, wr_{tb}^M\}.$$

The model implies closed forms for these moments, for each $\ell \in \{b, m, t\}$,

$$S_\ell = \left(\frac{F_\ell}{c_\ell}\right)^{1/2}, \tag{26}$$

$$\pi_\ell = -\ln\left(\kappa \frac{1}{q_l} t_l S_l{}^* + (1-\kappa)(1 - \frac{\gamma}{\gamma - 1} F_l)\right), \tag{27}$$

$$\xi_\ell = \frac{t_\ell N_{\ell-1} - \left(\frac{N_{\ell-1}}{S_\ell}\right)(1-2F_\ell)}{t_\ell N_{\ell-1} + \left(\frac{N_{\ell-1}}{S_\ell}\right) 2F_\ell}, \tag{28}$$

where $q_l \equiv (Z_l - Z_{l-1})/Z_l$. Employment evolves according to

$$N_\ell = t_\ell N_{\ell-1} + \left(\frac{N_{\ell-1}}{S_\ell}\right) 2F_\ell. \tag{29}$$

The manager pay-ratio moments can be written as

$$wr^M_{tb} = \frac{\kappa S_t + (1-\kappa)(1-Z_m)\frac{1-2F_t}{t_t}}{\kappa Z_b S_b + (1-\kappa)(Z_b - Z_0)\frac{1-2F_b}{t_b}} \cdot \frac{1}{N_m}, \tag{30}$$

$$wr^M_{mb} = \frac{\kappa Z_m S_m + (1-\kappa)(Z_m - Z_b)\frac{1-2F_m}{t_m}}{\kappa Z_b S_b + (1-\kappa)(Z_b - Z_0)\frac{1-2F_b}{t_b}} \cdot \frac{1}{N_b}, \tag{31}$$

$$wr^M_{tm} = \frac{\kappa S_t + (1-\kappa)(1-Z_m)\frac{1-2F_t}{t_t}}{\kappa Z_m S_m + (1-\kappa)(Z_m - Z_b)\frac{1-2F_m}{t_m}} \cdot \frac{N_b}{N_m}. \tag{32}$$

Note that $wr^M_{mb} = wr^M_{tb}/wr^M_{tm}$ does not provide independent variation. Further note that the IC pay-ratio moments similarly have closed forms, which we use as untargeted moments to assess the model's goodness of fit.

$$wr^{IC}_{tm} = \frac{(1-Z_m)\frac{1}{t_t}}{(Z_m - Z_b)\frac{1}{t_m}} \frac{N_b}{N_m} \tag{33}$$

$$wr^{IC}_{tb} = \frac{(1-Z_m)\frac{1}{t_t}}{(Z_b - Z_0)\frac{1}{t_b}} \frac{1}{N_m} \tag{34}$$

$$wr^{IC}_{mb} = \frac{(1-Z_m)\frac{1}{t_m}}{(Z_b - Z_0)\frac{1}{t_b}} \frac{1}{N_b} \tag{35}$$

D.2 Identification

Assuming the moments in $\mathscr{M}$ are observed without sampling error, we show how to uniquely recover θ using the maintained parametric restrictions (14)–(15) and the closed forms above.

Step 1: Identify (N_b, N_m) from (S_ℓ, ξ_ℓ) only

We begin by simplifying the IC-share expression (28). Divide numerator and denominator by $N_{\ell-1}/S_\ell$ to remove $N_{\ell-1}$:

$$\xi_\ell = \frac{t_\ell S_\ell - (1-2F_\ell)}{t_\ell S_\ell + 2F_\ell}. \tag{36}$$

From (36),

$$1-\xi_\ell = 1-\frac{t_\ell S_\ell-(1-2F_\ell)}{t_\ell S_\ell+2F_\ell} = \frac{(t_\ell S_\ell+2F_\ell)-(t_\ell S_\ell-(1-2F_\ell))}{t_\ell S_\ell+2F_\ell} = \frac{1}{t_\ell S_\ell+2F_\ell}. \tag{37}$$

Equivalently,

$$t_\ell S_\ell+2F_\ell = \frac{1}{1-\xi_\ell}. \tag{38}$$

Now use the employment recursion (29):

$$N_\ell = t_\ell N_{\ell-1}+\left(\frac{N_{\ell-1}}{S_\ell}\right)2F_\ell = \frac{N_{\ell-1}}{S_\ell}\Big(t_\ell S_\ell+2F_\ell\Big).$$

Substitute (38) to eliminate the unknown composite:

$$N_\ell = \frac{N_{\ell-1}}{S_\ell(1-\xi_\ell)}. \tag{39}$$

With $N_0 = 1$, we obtain the explicit inversion

$$N_b = \frac{1}{S_b(1-\xi_b)}, \qquad N_m = \frac{N_b}{S_m(1-\xi_m)}. \tag{40}$$

Hence (N_b, N_m) are point-identified from $\{S_b, S_m, \xi_b, \xi_m\}$.

Step 2: Identify (F_0, α_F) using cross-layer linearity of $\log c_\ell$ and $\log t_\ell$

This step exploits the parametric restrictions that $\log c_\ell$ and $\log t_\ell$ are linear in ℓ from (15), while F_ℓ follows the two-parameter logistic profile (14). The key idea is to derive two restrictions (denoted $(R1)$ and $(R2)$) that depend only on (F_0, α_F) and observable moments.

Step 2a: Derive $(R1)$ from spans and log-linearity of c_ℓ From the span formula (26),

$$S_\ell^2 = \frac{F_\ell}{c_\ell} \quad\Longrightarrow\quad c_\ell = \frac{F_\ell}{S_\ell^2}. \tag{41}$$

Taking logs yields

$$\log c_\ell = \log F_\ell - 2\log S_\ell. \tag{42}$$

Under the maintained parametric restriction (15),

$$\log c_\ell = c_0 + \alpha_c \ell,$$

so $\log c_\ell$ must lie on a straight line as a function of ℓ. With three layers $\{b, m, t\}$, this requires equality of adjacent slopes:

$$\frac{\log c_m - \log c_b}{m-b} = \frac{\log c_t - \log c_m}{t-m}. \tag{43}$$

Substitute $\log c_\ell = \log(F_\ell/S_\ell^2)$ from (41) to eliminate parameters (c_0, α_c):

$$\frac{\log(F_m/S_m^2)-\log(F_b/S_b^2)}{m-b} = \frac{\log(F_t/S_t^2)-\log(F_m/S_m^2)}{t-m}. \qquad (R1) \tag{44}$$

All quantities on the right-hand side are observable moments except F_b, F_m, F_t, which are determined by (F_0, α_F) through (14). Thus $(R1)$ is one scalar restriction in (F_0, α_F).

Step 2b: Derive $(R2)$ from IC shares and log-linearity of t_ℓ Start from the simplified IC-share expression (36):

$$\xi_\ell = \frac{t_\ell S_\ell - (1-2F_\ell)}{t_\ell S_\ell + 2F_\ell}.$$

Solve this equation for t_ℓ. Multiplying both sides by the denominator and collecting terms yields:

$$\xi_\ell(t_\ell S_\ell + 2F_\ell) = t_\ell S_\ell - (1-2F_\ell),$$
$$(1-\xi_\ell)\,t_\ell S_\ell = 1 - 2(1-\xi_\ell)F_\ell.$$

Dividing by $(1-\xi_\ell)S_\ell$ yields the inversion:

$$t_\ell = \frac{\frac{1}{1-\xi_\ell} - 2F_\ell}{S_\ell}. \tag{45}$$

Under the maintained parametric restriction (15),

$$\log t_\ell = t_0 + \alpha_t \ell,$$

so $\log t_\ell$ must be linear in ℓ. As above, with three layers this is equivalent to equality of adjacent slopes:

$$\frac{\log t_m - \log t_b}{m-b} = \frac{\log t_t - \log t_m}{t-m}. \tag{46}$$

Substitute t_ℓ from (45) to eliminate parameters (t_0, α_t):

$$\frac{\log\left(\frac{\frac{1}{1-\xi_m}-2F_m}{S_m}\right) - \log\left(\frac{\frac{1}{1-\xi_b}-2F_b}{S_b}\right)}{m-b} = \frac{\log\left(\frac{\frac{1}{1-\xi_t}-2F_t}{S_t}\right) - \log\left(\frac{\frac{1}{1-\xi_m}-2F_m}{S_m}\right)}{t-m}. \qquad (R2) \tag{47}$$

Again, all quantities are observable moments except F_b, F_m, F_t, which are determined by (F_0, α_F) via (14). Thus $(R2)$ is a second scalar restriction in (F_0, α_F).

Step 2c: Point identification of (F_0, α_F) Define the two functions

$$g_1(F_0,\alpha_F) := \text{LHS}(R1) - \text{RHS}(R1), \qquad g_2(F_0,\alpha_F) := \text{LHS}(R2) - \text{RHS}(R2),$$

where $(R1)$ and $(R2)$ are given by (44) and (47), and where F_b, F_m, F_t are constructed from (F_0, α_F) using (14). This system of two equations identifies $(F_0^\star, \alpha_F^\star)$ if the Jacobian matrix

$$J(F_0,\alpha_F) = \begin{pmatrix} \partial g_1/\partial F_0 & \partial g_1/\partial \alpha_F \\ \partial g_2/\partial F_0 & \partial g_2/\partial \alpha_F \end{pmatrix}$$

has full rank at $(F_0^\star, \alpha_F^\star)$.

Step 3: Recover (c_0, α_c) and (t_0, α_t)

Given (F_0, α_F), we obtain F_ℓ for $\ell \in \{b, m, t\}$ from (14). Then:

Recover (c_0, α_c). Compute

$$c_\ell = \frac{F_\ell}{S_\ell^2}$$

from (41). Since $\log c_\ell = c_0 + \alpha_c \ell$ is linear in ℓ, we can recover (c_0, α_c) from any two layers, e.g.

$$\alpha_c = \frac{\log c_m - \log c_b}{m-b}, \qquad c_0 = \log c_b - \alpha_c b,$$

with the third layer providing an overidentifying restriction.

Recover (t_0, α_t). Compute

$$t_\ell = \frac{\frac{1}{1-\xi_\ell} - 2F_\ell}{S_\ell}$$

from (45). Since $\log t_\ell = t_0 + \alpha_t \ell$ is linear in ℓ, recover

$$\alpha_t = \frac{\log t_m - \log t_b}{m-b}, \qquad t_0 = \log t_b - \alpha_t b,$$

again with the third layer providing an overidentifying restriction.

Step 4: Identify relative knowledge gaps from manager pay ratios and IC-pay penalties

Given (N_b, N_m) and spans (S_b, S_m, S_t), as well as the cost parameters F_ℓ, c_ℓ, t_ℓ for $\ell \in \{b, m, t\}$, the IC-penalty formulas (27) for top and mid level, as well as the manager pay-ratio formula (32) can be written as functions of the relative knowledge gaps defined as

$$d_t \equiv Z_t - Z_m = 1 - Z_m, \qquad d_m \equiv Z_m - Z_b, \qquad d_b \equiv Z_b - Z_0,$$

where the normalization $Z_t = 1$ has been imposed.

In particular, we exponentiate (27) to yield

$$\exp(\pi_t) = \frac{1}{t_t} \cdot \frac{1 - Z_m}{\kappa S_t + (1-\kappa)(1-Z_m)\frac{1-2F_t}{t_t}} \tag{48}$$

$$\exp(\pi_m) = \frac{1}{t_m} \cdot \frac{Z_m - Z_b}{\kappa Z_m S_m + (1-\kappa)(Z_m - Z_b)\frac{1-2F_m}{t_m}} \tag{49}$$

$$\exp(\pi_b) = \frac{1}{t_b} \cdot \frac{Z_b - Z_0}{\kappa Z_b S_b + (1-\kappa)(Z_b - Z_0)\frac{1-2F_b}{t_b}} \tag{50}$$

Note that the ratios of these IC penalties across levels can be expressed as functions of observed pay ratios for managers and previously identified fundamentals, as well as a function of the knowledge levels:

$$\frac{\exp(\pi_m)}{\exp(\pi_t)} = \frac{t_t}{t_m} \cdot \frac{\kappa S_t + (1-\kappa)(1-Z_m)\frac{1-2F_t}{t_t}}{\kappa Z_m S_m + (1-\kappa)(Z_m - Z_b)\frac{1-2F_m}{t_m}} \cdot \frac{Z_m - Z_b}{1 - Z_m} = wr_{tm}^M \cdot \frac{t_t}{t_m} \cdot \frac{N_m}{N_b} \cdot \frac{Z_m - Z_b}{1 - Z_m}$$
$$\frac{\exp(\pi_b)}{\exp(\pi_t)} = \frac{t_t}{t_b} \cdot \frac{\kappa S_t + (1-\kappa)(1-Z_m)\frac{1-2F_t}{t_t}}{\kappa Z_b S_b + (1-\kappa)(Z_b - Z_0)\frac{1-2F_b}{t_b}} \cdot \frac{Z_b - Z_0}{1 - Z_m} = wr_{tb}^M \cdot \frac{t_t}{t_b} \cdot N_m \cdot \frac{Z_b - Z_0}{1 - Z_m}$$

Therefore, the manager pay-ratio moments imply

$$wr_{tm}^M = \frac{d_t}{d_m} \frac{t_m}{t_t} \frac{\exp(\pi_m)}{\exp(\pi_t)} \frac{N_b}{N_m},$$

and

$$wr_{tb}^M = \frac{d_t}{d_b} \frac{t_b}{t_t} \frac{\exp(\pi_b)}{\exp(\pi_t)} \frac{1}{N_m},$$

and the observed moments identify the relative knowledge gaps

$$r_m \equiv \frac{d_m}{d_t} = \frac{\exp(\pi_m)}{\exp(\pi_t)} \frac{t_m}{t_t} \frac{N_b}{N_m wr_{tm}^M},$$

and

$$r_b \equiv \frac{d_b}{d_t} = \frac{\exp(\pi_b)}{\exp(\pi_t)} \frac{t_b}{t_t} \frac{1}{N_m wr_{tb}^M}.$$

At this stage, the moments identify the relative knowledge gaps (r_m, r_b), but not yet the absolute scale of the knowledge ladder.

Step 5: Identify the scale of the knowledge ladder and κ. Let $d \equiv d_t$. Given the relative gaps identified in Step 4,

$$d_t = d, \qquad d_m = r_m d, \qquad d_b = r_b d.$$

Hence the knowledge levels can be written as functions of d:

$$Z_m = 1 - d,$$

$$Z_b = 1 - (1 + r_m)d,$$

and

$$Z_0 = 1 - (1 + r_m + r_b)d.$$

To identify d and κ, we can use the level equations for the IC penalties. The IC-penalty equation at layer ℓ is

$$\exp(\pi_\ell) = \frac{d_\ell}{\kappa t_\ell Z_\ell S_\ell + (1-\kappa) d_\ell (1 - 2F_\ell)}.$$

Equivalently,

$$\kappa = \frac{d_\ell \left(\frac{1}{\exp(\pi_\ell)} - (1 - 2F_\ell) \right)}{t_\ell Z_\ell S_\ell - d_\ell (1 - 2F_\ell)}.$$

Let

$$G_\ell \equiv \frac{1}{\exp(\pi_\ell)} - (1 - 2F_\ell).$$

Using the top layer gives

$$\kappa = \frac{dG_t}{t_t S_t - d(1 - 2F_t)}.$$

Using the middle layer gives

$$\kappa = \frac{r_m d G_m}{t_m (1-d) S_m - r_m d (1 - 2F_m)}.$$

Equating these two expressions identifies d:

$$\frac{dG_t}{t_t S_t - d(1 - 2F_t)} = \frac{r_m d G_m}{t_m (1-d) S_m - r_m d (1 - 2F_m)}.$$

Solving for d yields

$$d = \frac{G_t t_m S_m - r_m G_m t_t S_t}{G_t (t_m S_m + r_m (1 - 2F_m)) - r_m G_m (1 - 2F_t)}.$$

This identifies $d_t = d$, and therefore

$$Z_m = 1 - d, \qquad Z_b = 1 - (1 + r_m)d, \qquad Z_0 = 1 - (1 + r_m + r_b)d.$$

Finally, κ is identified from the top IC-penalty equation:

$$\kappa = \frac{dG_t}{t_t S_t - d(1 - 2F_t)}.$$

The bottom-layer IC-penalty equation provides an overidentifying restriction:

$$\kappa = \frac{r_b d G_b}{t_b Z_b S_b - r_b d B_b}.$$

D.3 Estimation Results

Table D1: Estimation Results: Parameter Estimates

	All Firms		**highF**		**lowF**	
Variable	Mean	SD	Mean	SD	Mean	SD
Z_0	0.247	0.230	0.267	0.247	0.239	0.227
Z_{bot}	0.655	0.131	0.662	0.135	0.651	0.131
Z_{mid}	0.906	0.056	0.907	0.054	0.906	0.058
F_{bot}	0.245	0.208	0.492	0.026	0.150	0.163
F_{mid}	0.258	0.198	0.497	0.009	0.165	0.152
F_{top}	0.290	0.185	0.498	0.005	0.209	0.154
t_{bot}	0.875	0.658	0.586	0.161	0.987	0.741
t_{mid}	0.425	0.164	0.336	0.149	0.460	0.158
t_{top}	0.242	0.138	0.214	0.147	0.253	0.135
c_{bot}	0.006	0.008	0.011	0.009	0.004	0.006
c_{mid}	0.007	0.007	0.014	0.007	0.005	0.005
c_{top}	0.011	0.008	0.019	0.007	0.008	0.006
κ	0.125	0.108	0.233	0.119	0.084	0.068

Notes: This table presents a summary of parameter estimates from the structural estimation conducted separately for each firm in the sample as described in detail in Section 5. We present the mean firm-level estimates and the standard deviation across firms in the first two columns. Remaining columns split the firm sample into two groups based on the estimated profile of supervision fixed costs F. The first group (denoted maxF) has high fixed costs, corresponding to full specialization of managers on supervision tasks, whereas managers in the second group of firms (denoted lowF) spend less time on supervision.
Source: Authors' calculations based on de-identified employee-level administrative internal HR records from 43 firms, accessed through a collaboration with Visier.

Table D2: Estimation Results: Model Fit

	All Firms		**highF**		**lowF**	
Variable	Model	Data	Model	Data	Model	Data
Panel A: Targeted Moments						
IC Gap (Bottom)	-0.315	-0.315	-0.371	-0.371	-0.293	-0.293
IC Gap (Middle)	-0.337	-0.337	-0.383	-0.382	-0.319	-0.320
IC Gap (Top)	-0.546	-0.550	-0.705	-0.712	-0.484	-0.488
Span of Control (Bottom)	7.830	8.424	8.328	9.187	7.637	8.128
Span of Control (Middle)	6.866	6.458	6.644	6.127	6.952	6.586
Span of Control (Top)	5.823	6.268	5.417	5.504	5.980	6.564
IC Share (Bottom)	0.816	0.898	0.806	0.912	0.820	0.893
IC Share (Middle)	0.670	0.639	0.656	0.636	0.676	0.640
IC Share (Top)	0.424	0.441	0.475	0.509	0.404	0.415
Pay Ratio M (Top/Mid)	1.709	1.792	1.969	2.257	1.608	1.612
Pay Ratio M (Top/Bot)	2.584	2.564	3.376	3.322	2.277	2.271
Panel B: Untargeted Moments						
Worker Share (Bottom)	0.600	0.724	0.595	0.784	0.602	0.701
Worker Share (Middle)	0.295	0.221	0.286	0.178	0.298	0.238
Worker Share (Top)	0.105	0.054	0.119	0.038	0.099	0.061
Pay Ratio M (Mid/Bot)	1.481	1.412	1.682	1.452	1.403	1.397
Pay Ratio IC (Top/Mid)	1.400	1.148	1.439	1.173	1.386	1.138
Pay Ratio IC (Mid/Bot)	1.457	1.382	1.674	1.528	1.373	1.326
Pay Ratio IC (Top/Bot)	2.064	1.575	2.423	1.790	1.926	1.491
Pay Ratio All (Top/Mid)	1.761	1.739	1.918	2.025	1.701	1.629
Pay Ratio All (Mid/Bot)	1.546	1.599	1.783	1.776	1.454	1.531
Pay Ratio All (Top/Bot)	2.779	2.819	3.495	3.647	2.502	2.498

Notes: This table presents a summary of model fit from the structural estimation conducted separately for each firm in the sample as described in detail in Section 5. Panel A lists all targeted moments, while Panel B presents untargeted moments. For each moment, we present the average value in the data and generated by the estimated model in the first two columns. Remaining columns split the firm sample into two groups based on the estimated profile of supervision fixed costs F. The first group (denoted maxF) has high fixed costs, corresponding to high specialization of managers on supervision tasks, whereas managers in the second group of firms (denoted lowF) spend less time on supervision.
Source: Authors' calculations based on de-identified employee-level administrative internal HR records from 43 firms, accessed through a collaboration with Visier.

D.4 Post-Estimation Analysis

Table D3: Estimated Firm Types and Observed Firm Characteristics: Summary Statistics

	All Firms		**highF**		**lowF**	
Variable	Mean	SD	Mean	SD	Mean	SD
N (firms)	43		12		31	
High-tech sector (share)	0.302		0.000		0.419	
Manufacturing sector (share)	0.279		0.333		0.258	
Firms with less than 2000 employees	0.465		0.417		0.484	
Firm depth	7.791	1.013	7.833	0.718	7.774	1.117
Span of control (bottom)	8.424	3.877	9.187	3.316	8.128	4.085
Span of control (top)	6.268	2.801	5.504	1.249	6.564	3.176
Span ratio (top/bottom)	0.848	0.367	0.673	0.286	0.915	0.377
Estimated IC Penalty	-0.341	0.107	-0.385	0.105	-0.323	0.105
Estimated IC-to-M pay raise	0.286	0.115	0.332	0.093	0.268	0.119
Average IC pay	11.452	0.407	11.150	0.267	11.568	0.394
IC pay ratio (top/bottom)	1.575	0.442	1.790	0.643	1.491	0.310
M pay ratio (top/bottom)	2.564	0.999	3.322	1.232	2.271	0.722
Pay ratio (top/bottom)	2.819	1.284	3.647	1.809	2.498	0.854
Skilled worker share	0.457	0.171	0.361	0.180	0.494	0.154
Cond. share of skilled at bottom layer	0.437	0.182	0.322	0.186	0.482	0.161
Share of top-mid workers	0.276	0.161	0.216	0.102	0.299	0.175
Firm share of skilled IC	0.358	0.145	0.281	0.138	0.388	0.139
IC share (bottom)	0.898	0.061	0.912	0.049	0.893	0.066
IC share (middle)	0.639	0.114	0.636	0.104	0.640	0.119
IC share (top)	0.441	0.174	0.509	0.200	0.415	0.158
Computer/Math occupation share	0.166	0.113	0.106	0.063	0.190	0.120
Production occupation share	0.130	0.172	0.202	0.227	0.103	0.140
Sales occupation share	0.154	0.132	0.093	0.052	0.178	0.146

Notes: This table presents results summary statistics for a set of observed firm characteristics (listed in the rows). We split the firm sample into two groups based on the estimated profile of supervision fixed costs F. The first group (denoted maxF) has high fixed costs, corresponding to full specialization of managers on supervision tasks, whereas managers in the second group of firms (denoted lowF) spend less time on supervision. For all firms combined and for each firm group separately, we present the mean and standard deviation for each firm characteristic.
Source: Authors' calculations based on de-identified employee-level administrative internal HR records from 43 firms, accessed through a collaboration with Visier.

Table D4: Estimated Full Specialization and Observed Firm Characteristics

Dependent variable: If highF	(1)	(2)	(3)	(4)	(5)
Small firm (<2000)	-0.054	-0.054	-0.034	-0.069	0.019
	(0.140)	(0.142)	(0.120)	(0.116)	(0.115)
Firm depth		0.011	-0.037	-0.038	-0.009
		(0.059)	(0.054)	(0.052)	(0.073)
Span ratio (top/bottom)			-0.403**	-0.257*	-0.382
			(0.150)	(0.143)	(0.245)
M-pay ratio (top/bottom)			0.231***	0.225***	0.204***
			(0.057)	(0.057)	(0.068)
Share top-mid			-0.160	-0.069	0.294
			(0.321)	(0.344)	(0.592)
Skilled at bottom				-2.621*	-2.181
				(1.409)	(2.132)
Conditional share of skilled IC on IC				1.864	1.269
				(1.496)	(3.289)
Administrative worker share					-0.204
					(1.168)
Business/Finance/Legal worker share					0.861
					(3.225)
Computer and Math worker share					-0.203
					(3.020)
Production worker share					0.245
					(0.864)
Research and Development worker share					-1.079
					(2.975)
Sales worker share					-0.591
					(0.734)
Top management worker share					0.045
					(2.980)
Observations	43	43	43	43	43
R^2	0.004	0.004	0.354	0.463	0.558

Notes: This table presents results from multivariate regressions with the dependent variable being an indicator for firms with estimated supervision costs F corresponding to full specialization of managers on supervision tasks (denoted maxF). Regressors include varying sets of observed firm characteristics (listed in the rows). For each regression model, we present the coefficient estimates, standard errors, and the model's R-squared. Standard errors are heteroskedasticity robust. Statistical significance: $***$, $p < 0.01$; $**$, $p < 0.05$; $*$, $p < 0.1$.
Source: Authors' calculations based on de-identified employee-level administrative internal HR records from 43 firms, accessed through a collaboration with Visier.

Table D5: Counterfactual Analysis: Levels of Outcomes for Adjusting Career Ladders

	Average Span		IC Penalty		IC Penalty Ratio		M Pay Ratio		IC Share		IC Share Ratio		Top+Mid Empl. Share	
	Baseline	CF Value	Baseline	CF Value	Baseline	CF Value	Baseline	CF Value	Baseline	CF Value	Baseline	CF Value	Baseline	CF Value
Panel A. Reduce variable supervision costs ($0.99 \times c$)														
All Firms	7.332	7.370	-0.347	-0.351	1.671	1.636	2.584	2.589	0.738	0.740	0.521	0.523	0.400	0.400
highF	7.493	7.532	-0.415	-0.420	1.995	1.979	3.376	3.386	0.731	0.733	0.584	0.585	0.405	0.404
lowF	7.270	7.307	-0.321	-0.324	1.545	1.503	2.277	2.280	0.741	0.742	0.497	0.499	0.398	0.398
Panel B. Reduce problem solving costs ($0.99 \times t$)														
All Firms	7.332	7.336	-0.347	-0.340	1.671	1.755	2.584	2.625	0.738	0.737	0.521	0.518	0.400	0.397
highF	7.493	7.498	-0.415	-0.405	1.995	2.029	3.376	3.425	0.731	0.730	0.584	0.583	0.405	0.403
lowF	7.270	7.273	-0.321	-0.316	1.545	1.648	2.277	2.316	0.741	0.739	0.497	0.493	0.398	0.395
Panel C. Reduce slope of the knowledge ladder ($0.99 \times Z$ *slope*)														
All Firms	7.332	7.332	-0.347	-0.357	1.671	1.537	2.584	2.574	0.738	0.738	0.521	0.521	0.400	0.400
highF	7.493	7.493	-0.415	-0.429	1.995	1.926	3.376	3.356	0.731	0.731	0.584	0.584	0.405	0.405
lowF	7.270	7.270	-0.321	-0.329	1.545	1.386	2.277	2.271	0.741	0.741	0.497	0.497	0.398	0.398

Notes: This table presents results from counterfactual simulations based on the model estimates from Table D1. For each firm separately, we simulate optimal organizational restructuring in response to changes in structural parameters. We consider four different scenarios, reported in Panels A–D, each affecting the value of one specific primitive (variable supervision costs, fixed supervision costs, problem-solving costs, knowledge ladder) and perturbing it by 1% of its baseline value. We focus on several organizational outcomes in the columns and compute their averages across firms under the counterfactual scenario. We report the average value at baseline and the value under the counterfactual scenario for each outcome. We split the firm sample into two groups based on the estimated profile of supervision fixed costs F. The first group has high fixed costs, corresponding to full specialization of managers on supervision tasks, whereas managers in the second group of firms spend less time on supervision.
Source: Authors' calculations based on model estimates using de-identified employee-level administrative internal HR records from 43 firms, accessed through a collaboration with Visier.

E IV Analysis: Limitations and Robustness Checks

We subject the main findings to a series of robustness checks, which lead to qualitatively similar results.

First, to further guard against the possibility that the instrument captures broad economic trends that differentially affect demographic groups, we construct a more disaggregated version of firm-level promotions. Specifically, we compute the number of IC-to-M transitions among workers in the same firm, month-year, job function, and hierarchical level who do not share the focal worker's direct manager, divided by the total number of employees in the same firm, month-year, job function, and hierarchical level (Table E1, Panel A). By conditioning on hierarchical level in addition to job function, this instrument is less likely to reflect aggregate factors that could differentially affect workers across demographic groups.

Second, we augment the baseline OLS and 2SLS specifications with job function and hierarchical level fixed effects, so that comparisons across marginally promoted managers are made within finer cells of observably similar workers (Table E1, Panel B).

Third, we verify that our decision to aggregate non-Asian minority groups into a single category does not mask heterogeneous effects (Table E2).

Fourth, we replicate the analysis without imposing minimum thresholds on the number of promotions per demographic group (Table E3 and Table E4).

Fifth, the baseline results indicated that Asian employees and women are matched to more favorable teams on average, as evidenced by the shift in their coefficients when replacing mean subordinate pay with manager value added. We examine this further using two outcome variables designed to measure sorting between managers and teams: the mean worker fixed effect of subordinates (from the AKM model) and team size, both measured in the first month after promotion (Table E5, Panels A and B). While the estimates are not statistically significant, the signs are consistent with prior findings: relative to their majority counterparts, and unlike other minorities, marginally promoted Asian employees and women lead teams with higher average worker ability and smaller size.

Finally, we consider two alternative measures of managerial performance (Table E5, Panels C and D). Panel C replaces mean subordinate pay with the average subordinate retention rate over all managerial periods. The estimates are noisier but display patterns broadly consistent with the baseline results. Panel D uses the share of subordinates ranked as high performers. Here we find estimates close to zero across all specifications, likely reflecting limited underlying variation in the dependent variable.

Table E1: IC-to-M Transitions, More Specifications

	Race groups					
	Asian		Others		Women	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Alternative Instrument						
Log Pay (Rank)						
IC-to-M Transition	3.157	1.743	-8.666***	-8.760*	-5.994***	-5.958
	(2.449)	(3.552)	(2.008)	(4.839)	(1.862)	(3.714)
Observations	2,774,123	2,774,123	3,536,594	3,536,594	4,042,214	4,042,214
Mean dep. var	3.054	3.054	-9.655	-9.655	-6.689	-6.689
Std. dep. var	39.222	39.222	37.386	37.386	38.132	38.132
Manager Value Added (Rank)						
IC-to-M Transition	2.383	-1.740	-5.421**	-4.217	-3.195*	-6.105
	(1.772)	(3.670)	(2.254)	(5.783)	(1.732)	(4.076)
Observations	2,774,123	2,774,123	3,536,594	3,536,594	4,042,214	4,042,214
Mean dep. var	1.642	1.642	-5.593	-5.593	-4.687	-4.687
Std. dep. var	41.011	41.011	41.009	41.009	40.949	40.949
Panel B: Additional Controls						
Log Pay (Rank)						
IC-to-M Transition	3.159	1.948	-8.632***	-6.011*	-5.989***	-3.438
	(2.449)	(2.950)	(1.991)	(3.032)	(1.855)	(2.952)
Observations	2,774,123	2,774,123	3,536,594	3,536,594	4,042,214	4,042,214
Mean dep. var	3.054	3.054	-9.655	-9.655	-6.689	-6.689
Std. dep. var	39.222	39.222	37.386	37.386	38.132	38.132
Manager Value Added (Rank)						
IC-to-M Transition	2.393	-2.355	-5.408**	-4.845	-3.159*	-2.929
	(1.770)	(3.377)	(2.233)	(4.552)	(1.718)	(4.003)
Observations	2,774,123	2,774,123	3,536,594	3,536,594	4,042,214	4,042,214
Mean dep. var	1.642	1.642	-5.593	-5.593	-4.687	-4.687
Std. dep. var	41.011	41.011	41.009	41.009	40.949	40.949

Notes: Panel A replicates the main IV estimates using an alternative instrument. The instrument is the share of IC-to-M transitions in the same firm-job function-hierarchy level outside the worker's own team, rather than the firm-job function level used in the baseline specification. Panel B replicates the main OLS and IV estimates by including controls for job function and hierarchical level. The sample pools workers across 12 firms with a sufficient number of IC-to-M transitions in each demographic group. Standard errors are adjusted for clustering at the firm level. Statistical significance: $***$, $p < 0.01$; $**$, $p < 0.05$; $*$, $p < 0.1$.
Source: Authors' calculations from de-identified employee-level administrative internal HR records from 43 firms, accessed through a collaboration with Visier.

Table E2: IC-to-M Transitions, More Demographic Groups

	Asian		Black		Hispanic	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Log Pay (Rank)						
IC-to-M Transition	3.157	2.036	-11.597***	-10.806**	-7.194***	-6.182
	(2.449)	(3.114)	(2.818)	(5.172)	(1.790)	(5.079)
Observations	2,774,123	2,774,123	2,805,914	2,805,914	2,872,021	2,872,021
Mean dep. var	3.054	3.054	-13.808	-13.808	-8.040	-8.040
Std. dep. var	39.222	39.222	37.673	37.673	37.065	37.065
Panel B: Manager Value Added (Rank)						
IC-to-M Transition	2.383	-1.842	-6.265*	-4.438	-4.181*	-4.799
	(1.772)	(3.697)	(3.559)	(7.158)	(2.117)	(5.652)
Observations	2,774,123	2,774,123	2,805,914	2,805,914	2,872,021	2,872,021
Mean dep. var	1.642	1.642	-8.105	-8.105	-3.646	-3.646
Std. dep. var	41.011	41.011	41.487	41.487	40.552	40.552

Notes: This table presents OLS and IV estimates separately for Asian, Black, and Hispanic employees. The sample pools workers across 12 firms with a sufficient number of IC-to-M transitions in each demographic group. Standard errors are adjusted for clustering at the firm level. Statistical significance: $***$, $p < 0.01$; $**$, $p < 0.05$; $*$, $p < 0.1$.
Source: Authors' calculations from de-identified employee-level administrative internal HR records from 43 firms, accessed through a collaboration with Visier.

Table E3: IC-to-M Transitions, All Firms

	Race groups				Women	
	Asian		Others			
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: First Stage						
Firm-level IC-to-M Transitions	0.003***		0.003***		0.003***	
	(0.001)		(0.001)		(0.001)	
Observations	881,680		2,190,912		3,861,124	
Mean dep. var	0.002		0.001		0.002	
Std. dep. var	0.047		0.035		0.041	
Panel B: Log Pay (Rank)						
IC-to-M Transition	2.975*	1.034	-8.323***	-7.217*	-7.005***	-4.528
	(1.679)	(2.721)	(1.451)	(3.701)	(1.266)	(3.359)
Observations	5,751,296	5,751,296	7,164,077	7,164,077	8,084,266	8,084,266
Mean dep. var	0.908	0.908	-9.816	-9.816	-5.979	-5.979
Std. dep. var	43.462	43.462	41.009	41.009	41.845	41.845
Panel C: Manager Value Added (Rank)						
IC-to-M Transition	1.821	-2.456	-5.088***	-5.334	-3.142**	-3.732
	(1.251)	(3.108)	(1.586)	(4.412)	(1.211)	(3.833)
Observations	5,751,296	5,751,296	7,164,077	7,164,077	8,084,266	8,084,266
Mean dep. var	-1.303	-1.303	-7.114	-7.114	-3.602	-3.602
Std. dep. var	44.302	44.302	43.980	43.980	44.088	44.088

Notes: This table replicates the baseline results using all firms, without restricting to firms with a minimum number of IC-to-M transitions in each demographic group. Panel A reports the first-stage relationship between individual and firm-level IC-to-M transitions. Panels B and C report the gap in post-promotion outcomes between each demographic group and its benchmark (White employees for racial minorities; male employees for women), estimated by OLS and 2SLS. Panel B uses the rank of average subordinate log pay over all periods as manager as the outcome. Panel C uses the manager value added in pay percentile. Standard errors are adjusted for clustering at the firm level. Statistical significance: $***$, $p < 0.01$; $**$, $p < 0.05$; $*$, $p < 0.1$.
Source: Authors' calculations from de-identified employee-level administrative internal HR records from 43 firms, accessed through a collaboration with Visier.

Table E4: Cross-Firm Variance, All Firms

	Median (1)	25th Pctl (2)	75th Pctl (3)	75th - 25th (4)	Mean (5)	SD (6)	Neg. (7)	Pos. (8)
Panel A: Log Pay (Rank) - OLS								
Asians	7.723	2.001	15.395	13.394	8.716	11.760	0.056	0.472
Others	-6.548	-9.157	-1.440	7.717	-6.125	7.495	0.378	0.000
Women	-8.009	-12.411	-4.499	7.912	-7.852	8.813	0.658	0.026
Panel B: Log Pay (Rank) - IV								
Asians	4.037	-16.716	16.234	32.950	-102.717	588.042	0.083	0.222
Others	-6.853	-14.449	3.341	17.790	-6.515	40.464	0.162	0.027
Women	-7.096	-15.834	4.689	20.523	73.792	497.172	0.211	0.000
Panel C: Manager Value Added (Rank) - IV								
Asians	-6.346	-19.026	7.093	26.119	-231.804	1297.732	0.139	0.056
Others	-3.889	-13.884	5.901	19.786	-7.764	42.780	0.135	0.027
Women	-2.495	-12.602	9.788	22.390	93.579	566.345	0.053	0.053

Notes: This table reports the cross-firm distribution of the gap in post-promotion outcomes between each demographic group and its benchmark (White employees for racial minorities; male employees for women). For each firm and each demographic group, we estimate separate 2SLS regressions of the outcome on an indicator for IC-to-M transitions, instrumenting with the share of IC-to-M transitions in the same firm-month-job function outside the worker's own team, and compute the gap as the difference between the group-specific and benchmark coefficients. The OLS regressions do not instrument the IC-to-M transition dummy, but are otherwise similar to the 2SLS specifications. The table reports summary statistics of these firm-level gaps. Columns 6 and 7 report the share of firm-level estimates that are statistically lower and greater than zero, respectively, at the 5% level of significance. Panels A and B use the rank of average subordinate log pay over all periods as manager as the outcome. Panel C uses the manager value added in pay percentile, defined as the manager fixed effect from an AKM decomposition of subordinate pay rank. We include all firms in the initial sample.
Source: Authors' calculations from de-identified employee-level administrative internal HR records from 43 firms, accessed through a collaboration with Visier.

Table E5: IC-to-M Transitions, More Outcomes

	Race groups					
	Asian		Others		Women	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Worker FE (First month, Rank)						
IC-to-M Transition	0.331	4.483	-0.721	-0.931	0.265	4.210
	(4.509)	(5.568)	(3.131)	(4.783)	(3.244)	(4.276)
Observations	2,774,123	2,774,123	3,536,594	3,536,594	4,042,214	4,042,214
Mean dep. var	0.194	0.194	-0.645	-0.645	-0.881	-0.881
Std. dep. var	43.688	43.688	42.800	42.800	43.125	43.125
Panel B: Team Size						
IC-to-M Transition	-0.764	-1.264	1.296	1.158	-0.564	-0.819
	(0.767)	(0.850)	(0.927)	(1.337)	(0.835)	(1.104)
Observations	2,774,123	2,774,123	3,536,594	3,536,594	4,042,214	4,042,214
Mean dep. var	-0.008	-0.008	1.404	1.404	-0.397	-0.397
Std. dep. var	11.095	11.095	9.036	9.036	9.214	9.214
Panel C: Retention (Residualized, Rank)						
IC-to-M Transition	0.244	0.094	-2.367**	-0.197	-0.927	1.978
	(1.121)	(2.345)	(0.993)	(1.451)	(0.871)	(1.685)
Observations	2,774,123	2,774,123	3,536,594	3,536,594	4,042,214	4,042,214
Mean dep. var	-0.614	-0.614	-1.978	-1.978	-0.767	-0.767
Std. dep. var	42.027	42.027	42.013	42.013	42.057	42.057
Panel D: Promotion rate of subordinates						
IC-to-M Transition	-0.001	0.006	-0.001	-0.001	-0.001	-0.002
	(0.003)	(0.008)	(0.003)	(0.005)	(0.003)	(0.006)
Observations	2,774,123	2,774,123	3,536,594	3,536,594	4,042,214	4,042,214
Mean dep. var	-0.002	-0.002	0.000	0.000	-0.002	-0.002
Std. dep. var	0.038	0.038	0.046	0.046	0.044	0.044

Notes: This table reports additional post-promotion outcomes. Each coefficient represents the gap between each demographic group and its benchmark (White employees for racial minorities; male employees for women), estimated by OLS and 2SLS. Panel A uses the rank of average subordinate worker fixed effects on pay as the outcome, where worker fixed effects are estimated from an AKM decomposition and averaged across subordinates assigned to the manager at the time of promotion. Panel B uses the team size in the first month of promotion. The sample pools workers across 12 firms with a sufficient number of IC-to-M transitions in each demographic group. Standard errors are adjusted for clustering at the firm level. Statistical significance: $***$, $p < 0.01$; $**$, $p < 0.05$; $*$, $p < 0.1$.
Source: Authors' calculations from de-identified employee-level administrative internal HR records from 43 firms, accessed through a collaboration with Visier.