Dual Career Ladders: Individual Contributors in Modern Corporate Hierarchies*

Nicola Bianchi, Lydia Cao,
Benjamin U. Friedrich, Kieu-Trang Nguyen

March 26, 2026

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 penalty 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 penalties 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 worker 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.

JEL Classification: D22; J31; L23; M51.
Keywords: Individual contributors, managers, dual career ladders, IC penalty, promotions, knowledge hierarchy, firm heterogeneity.

*Contact information: Nicola Bianchi, Kellogg School of Management, Northwestern University, and NBER, 2211 Campus Drive, Evanston, IL 60208, nicola.bianchi@kellogg.northwestern.edu; Lydia Cao, Kellogg School of Management, Northwestern University, jiarui.cao@kellogg.northwestern.edu; Benjamin U. Friedrich, Kellogg School of Management, Northwestern University, benjamin.friedrich@kellogg.northwestern.edu; Kieu-Trang Nguyen, University of Melbourne, kieu-trang.nguyen@unimelb.edu.au. We thank Visier for engaging in this academic research collaboration, and Anton Smessart, Hossein Ayouqi, Manda Winlaw, and Andrea Derler for their continuous support with the data. We have no financial relationships or other potential conflicts of interest related to this research. Visier had no role in the design of the study, the analysis or interpretation of the data, or the writing of the manuscript. Thomas Barden and Jack Nguyen provided outstanding research assistance.

1 Introduction

Promotions into management roles are a central feature of career advancement within firms, as highlighted by both management practice (Peter and Hull, 1969; Ovans, 2014) and academic research (Lazear, 2004; Benson et al., 2019). However, such transitions are rare, and firms routinely maintain dual career ladders, offering knowledge workers a parallel track that carries higher rank and pay without people-management responsibilities—even toward the very top of the hierarchy. 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 how firms structure dual career ladders—managers responsible for supervising a team of employees versus individual contributors (ICs) without supervisory duties—and how these tracks shape pay and career progression across the hierarchy. 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 penalty widening at higher levels. The magnitude of these average patterns varies substantially across firms, consistent with heterogeneity in the structure of IC career ladders. 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. The data include job titles, direct reporting links, compensation, demographics, and internal job moves, allowing us to track within-firm career moves and organizational structures at high frequency. 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 90 percent of workers at the bottom and over 30 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 penalty 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 penalty 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 accommodate dual career ladders. 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 bear the cost of supervision but can also devote time to solving escalated problems. ICs, by contrast, specialize in problem solving only.

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 penalty 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 penalties that widen at higher levels.

We take the model to the data by estimating a parsimoniously parameterized version for each firm, mapping observed hierarchy moments (spans, IC shares, IC pay penalties, and manager pay ratios across hierarchical tiers) into the model's primitives. We provide a formal identification proof and target additional moments beyond those needed for identification to serve as overidentifying restrictions. The estimated model closely matches the full set of targeted moments and also fits untargeted empirical patterns well.

The estimates highlight a sharp distinction in supervision profiles across firms: about one third assign managers entirely to supervision tasks, while managers in the remaining firms split their time between supervision and problem solving. This distinction is economically meaningful: firms in which managers are not fully specialized in supervision are smaller, have more top-heavy hierarchies, 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 fixed costs of supervision and 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 increase the risk of workers getting stuck in IC roles at the bottom of the hierarchy. These effects are more pronounced at less specialized firms, implying that IC 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 and how these differences evolve up the hierarchy. 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 penalty 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 tran-

sitions from IC to managerial roles across demographic groups. We measure post-promotion managerial performance using the average pay of a manager's subordinates across all months of her managerial spell, expressed as a percentile rank within the firm, and compare it across minority and majority groups. 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 firm-level intensity of IC-to-manager transitions outside a worker's own team to isolate the performance of marginally promoted managers—those who would not have been promoted absent an exogenous increase in managerial openings. 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). 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). More recent 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 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 thanks to our collaboration with Visier, a leading workforce-analytics provider that aggregates and standardizes HR data from a large portfolio of firms. For each of its clients, Visier processes raw HR data from disparate internal systems (for example, payroll, performance, and benefits) and maps them into a firm-specific panel dataset, which enables both longitudinal tracking of workforce flows (hires, separations, internal moves) within firms and cross-firm comparability. The outcome is a uniquely rich panel of firms and employees, which we first describe at a high level before turning to more precise details below.

The sample covers 43 firms of varying workforce size: 47 percent have less 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). All firms but one have the largest portion of their workforce 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 complete stock of employees on the payroll at that point in time. These snapshots include 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 a classification of each employee into one of nine different job functions (for example, sales, admin, R&D), these datasets also contain demographic attributes including age, gender, and race, which allows us to study the representation of demographic groups across jobs and levels of the hierarchy.[1]

Access to the Visier 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 is a necessary condition to study 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, crucially, 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 on the industry mix, gender and racial composition, and only shows 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 the key variables used in our analysis are constructed 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 equal to zero—meaning they do not supervise any other employee—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.

Moreover, 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.

At this stage, we combine the first two layers of the hierarchy for confidentiality reasons, due to the fact that 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 categorize employees in layer 5 in the bottom tier if a firm has five total layers but in 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 yearly 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 in the raw data. First, ICs in lower tiers constitute the majority of total employment, whereas managerial employment is much lower and is spread more evenly across tiers. Second, pay rises with tier for both roles, but the gradient is far steeper for managers: the average IC pay at the top is almost equal to the average managerial pay in the bottom tier. These patterns point to fundamentally distinct career paths within firms. This section establishes four core facts that document their regularities 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 the overwhelming majority of employees (90 percent). Their share declines to 64 percent in the middle tier. Strikingly, ICs continue to represent 44 percent of employees even at the top of the hierarchy. Administrative employees do account for higher-than-average IC shares at all tiers, but especially at the top of the hierarchy. However, removing them does not alter the overall pattern: the share of ICs diminishes at higher hierarchical levels, but remains above one third of the workforce even at the very top.

Fact 2: ICs face a pay penalty and experience slower career progression than managers. Next, we show that ICs are associated with substantially lower pay compared to managers, even after accounting for detailed job information and employee characteristics. Across all specifications, the coefficient on the IC indicator is large, negative, and highly significant (Table 1). In the most demanding specification, we compare pay of an IC and a manager observed 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 their manager peers, and this coefficient is statistically significant at the 1 percent level.

The pay penalty 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 percent less likely to be promoted each month, experience 0.1 percent lower monthly pay growth, and are 0.5 percent 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 and less successful career trajectories overall.

These estimated disadvantages to career progression associated with being an IC are economically meaningful and similar in relative size across outcomes: across promotion, pay growth, and exit, the coefficients imply a 15 to 20 percent change relative to the mean of the dependent variable. 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, to a 24 percent increase relative to the mean monthly exit rate of 1.9 percent.

Finally, we find that the IC penalty 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 that is 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. 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). 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 percent faster pay growth, and 1 percent lower turnover next 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.[4]

Fact 4: IC shares and penalties vary substantially across firms. The analysis so far has focused on average patterns across all firms in our sample. A distinctive aspect of our data is the detailed information it provides on the hierarchies of many different organizations. We exploit this feature to study how IC shares and IC penalties vary across firms.

First, Panel A of Figure 3 plots the IC share across the different firms in the sample. We find substantial variation across firms, ranging from less than 70 percent to more than 95 percent IC roles. Second, the data indicate that a negative IC penalty is a common feature across firms. 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 penalty 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

The empirical patterns characterize dual career ladders across firms. To interpret these 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 provides a framework for linking observed differences in pay, career progression, and organizational structure to underlying features of production and coordination.

[4] 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.

4.1 Set Up

Overview. Closely following Garicano (2000), we model production in a firm as a process of handling a flow of cases that generate 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 and coordination time. We capture this additional task by introducing *managers* (M) whose defining role is to provide supervision/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 who are 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 $f_z' < 0$).[5] 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 also the production of all those lower within their reporting chains. The combined output of each manager at level l totals $Z_{l-1}\rho_{l-1}S_l$, where ρ_{l-1} captures the scale of activity generated by a level-$(l-1)$ worker. [6] Without the manager, this combined output is only $(1-\kappa)Z_{l-1}\rho_{l-1}S_l$,where $\kappa > 0$ denotes the proportion of incremental output made possible by the manager through her supervision activities.

The manager's time cost for supervising S_l subordinates is $F_l + c_l S_l^{\gamma}$, with $\gamma > 1$. This cost structure with fixed and variable components can be interpreted as representing team-level and individual-level costs. For example, managers must learn about internal rules and procedures, and they hold team-level meetings for coordination purposes, two aspects that reflect fixed costs. In addition, monitoring progress of each team member requires individual interactions and supervision, as captured by the variable cost component.

Moreover, each manager can also directly handle problems escalated by K_l^M workers at level $l-1$, generating additional output of $(Z_l - Z_{l-1})\rho_{l-1}K_l^M$. 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.

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

[6] Alternatively, ρ_{l-1} can be interpreted as the expected output generated by the whole reporting chain of a level-$(l-1)$ worker. It is the output that a level-$(l-1)$worker and the entire reporting chain below her can produce without further escalations to level l.

Individual contributors. ICs only handle problems escalated by workers at level $l-1$. Each IC helps K_l^{IC} workers at level $l-1$, generating additional output equal to $(Z_l - Z_{l-1})\rho_{l-1}K_l^{IC}$ at time cost $t_l K_l^{IC}$.

Manager and IC pays. 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 in their whole 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.

It follows that the value added of managers at level l is

$$\kappa Z_l \rho_{l-1} S_l = \kappa \cdot \left(\underbrace{Z_{l-1}\rho_{l-1}S_l}_{\text{subordinates' output}} + \underbrace{(Z_l - Z_{l-1})\rho_{l-1}S_l}_{\text{solved escalations}} \right). \tag{1}$$

Their value added can be decomposed into two components: (i) the output generated by their level-$(l-1)$ subordinates thanks to supervision, $\kappa Z_{l-1}\rho_{l-1}S_l$, and (ii) the output from the problems escalated by their subordinates thanks to supervision and solved at level-l, $\kappa(Z_l - Z_{l-1})\rho_{l-1}S_l$.[8] For an IC at level l, the value added 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, the number of workers managed by level-l managers equals the number of workers at level-$(l-1)$, as either excess management capacity at level l or unmanaged workers at level $l-1$ would be suboptimal. That is, $N_l^M S_l = N_{l-1}$.

Second, similar to Garicano (2000), we require that all problems escalated by level-$(l-1)$ workers are 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, because excess problem solving capacity at level l is also suboptimal, the equilibrium conditions satisfy $N_l^M K_l^M + N_l^{IC} K_l^{IC} = N_{l-1} = N_l^M S_l$.

4.2 The Optimization Problem Across Levels

Given a fixed number of organization 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 to allocate production workers, managers, and individual contributors across its organization 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.

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

[8] This second component includes both (i) the share of escalated problems the manager directly solves ($(Z_l - Z_{l-1})\rho_{l-1}K_l^M$), and (ii) the share of problems escalated by her subordinates that are solved by other managers and ICs at level l ($(Z_l - Z_{l-1})\rho_{l-1}(S_l - K_l^M)$).

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 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, one can show 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.[10] We study this level-by-level minimization problem in the next subsection, additionally taking into account managers' and ICs' time costs and constraints.

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

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

[10] The proof proceeds by contradiction. Suppose that the solution to the "combined" optimization problem differs from that of the "recursive" optimization problem. One can then construct an alternative solution that strictly improves upon the former, yielding a contradiction.

optimization problem is:

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

$$s.t.$$

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

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

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

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

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

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

$$S_l{}^* = \left(\frac{F_l}{c_l(\gamma - 1)}\right)^{1/\gamma} \tag{9}$$

$$K_l^{IC*} = \frac{1}{t_l} \tag{10}$$

$$K_l^{M*} = \frac{1 - F_l \frac{\gamma}{\gamma - 1}}{t_l}. \tag{11}$$

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 costs 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 $F_l \frac{\gamma}{\gamma-1}$ 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 on supervision tasks.* See Appendix C.1 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 managing fixed cost, and smaller c_l and/or larger t_l imply lower managing 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 penalty 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,

$$\pi_l \equiv \ln((Z_l - Z_{l-1})\rho_{l-1}K_l^{IC*}) - \ln(\kappa Z_l \rho_{l-1} {S_l}^*) = \ln\left(\frac{1}{\kappa} \cdot q_l \cdot \frac{1}{t_l} \cdot \frac{1}{{S_l}^*}\right), \tag{13}$$

where $q_l \equiv (Z_l - Z_{l-1})/Z_l$. This (negative) IC penalty widens as F_l, t_l, and κ increase, and as c_l and the knowledge gap q_l decrease. See Appendix C.2 for proof.

4.4 Model Implications

Section 3 documents core facts about the IC share and the IC penalty that hold across firms: (i) the IC share declines toward the top, and (ii) the IC penalty rises toward the top. In addition, empirical hierarchies display a robust pyramidal shape across the top, middle and bottom of the organization. The next proposition characterizes when the model can generate these empirical patterns jointly.

Proposition 3. *Assume $D_l > 0$ for all 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 $F_{l+1} \leq F_l$, $t_{l+1} \leq t_l$, and $c_{l+1} \geq c_l$, with at least one strict inequality.*
2. *The (negative) IC penalty widens toward the top, $\pi_{l+1} < \pi_l$, if $t_l\sqrt{F_l/c_l}/q_l$ increases.*
3. *Employment declines toward the top of the hierarchy, $N_l < N_{l-1}$, if $t_l + 2\sqrt{F_l c_l} < 1$ at each level.*

See Appendix C.3 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. The results provide only sufficient conditions, which implies that many other parameter combinations could also satisfy the empirical regularities. Intuitively, 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 penalties. Finally, with sufficiently small cost parameters, the 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 penalties is a complex function of its underlying costs and knowledge parameters (see Appendix D for further discussion). This is why we will next turn to structural estimation at the firm level to map observed choices into structural parameters that allow us to 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 co-exist 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 penalty and IC shares across firms. In this section, we take the model to the data to deepen our analysis of firm heterogeneity. This estimation provides a typology of firms based on the underlying firm-specific primitives (the supervision technology, the cost of problem solving, and the slope of the knowledge ladder) using a transparent mapping from observed organizational moments (IC shares, spans of control, and pay gradients) into model parameters. Firm types, in turn, can be mapped to other firm characteristics to interpret firms' organizational choices. In addition, we 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 implement estimation, 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 can 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 ($b=1$, $m=2$, $t=3$). In the baseline implementation we further 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 penalties (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}, wr^M_{mb}, and wr^M_{tm}). Together, these 12 measures constitute the vector of targeted moments at 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 the empirical moments with elements $\hat{m}_k$ (for moments $k = 1, \ldots, 12$), $m(\theta)$ 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. Other untargeted moments implied by the model (such as the IC pay ratios or average pay ratios across layers, or employment shares) will be used to test 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: $Z_b = \frac{S_t}{S_b N_m \, wr^M_{tb}}$, $\quad Z_m = Z_b \cdot wr^M_{mb} N_b \cdot \frac{S_b}{S_m}$. The remaining manager pay ratio wr^M_{tm} becomes an overidentifying restriction.

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 penalty π_t identifies κ (using $Z_t = 1$ and Z_m from Step 2), and the bottom-layer IC penalty π_b identifies Z_0. The remaining IC penalty π_m provides an additional overidentifying restriction.

5.3 Estimated Parameters and Model Fit

We briefly summarize the estimation results here and provide full details on parameter estimates and model fit in Appendix D.3, Tables D1 and D2, respectively. Importantly, 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 we will further leverage for a typology of firms below. Specifically, we find a substantial share (33 percent) of firms, highlighted in the red bar, where managers are fully specialized 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 time on both supervision and problem solving.

Table D1 shows that across all firms, problem solving (or escalation) costs t_ℓ decline toward the top of the firm, indicating that each expert can support a larger number of subordinates because the latter are able to solve many problems themselves and require less help. Using the distinction between firms with high or low degrees of managerial specialization, we find that the gradient for the decline in problem-solving costs is steeper for less specialized firms. Variable supervision costs c_ℓ increase toward the top in more specialized firms, but are lower and flat in less specialized ones. Finally, the implied knowledge ladder is somewhat steeper but knowledge levels in the bottom and middle of the organization are lower in less specialized firms. Importantly, both the average estimates across all firms and the results by group satisfy the sufficient conditions laid out in Proposition 3 to match the core empirical facts. The differences across more and less specialized firms will be important when analyzing optimal restructuring in response to shocks across firms.

Table D2 evaluates model fit. Panel A shows that the model matches the targeted moments very well across all firm groups. IC pay gaps and manager pay ratios are captured especially well, while span of control and IC shares are sometimes slightly under-predicted at the bottom and at the top. Panel B reports untargeted moments. Overall, 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. In future work, we aim to revisit the fit for extensions with finer hierarchy levels.

5.4 Interpreting the Firm Types

The estimates suggest a taxonomy of firms based on supervision costs F_ℓ, which maps directly into the optimal time share of managers 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 fully specialized managers. The regression evidence indicates three takeaways. First, specialized firms are larger on average. Specifically, fully specialized firms are 26.6 percentage points (or 57 percent) less likely to have less than 2,000 employees. This difference represents a 57 percent decline compared to the sample mean and is significant at the 10 percent level.

Second, firm types differ in hierarchy shape: while we do not find differences in hierarchy depth, the top-to-bottom span ratio for fully specialized firms is 27 percent lower than average (coefficient 0.229, $p = 0.031$) and the manager pay ratio top-to-bottom is 25 percent higher (coefficient 0.648, $p = 0.077$). In addition, these firms are more bottom-heavy, whereas less specialized firms have 9.2 percentage points (33 percent) higher share of employment at the top and middle of the hierarchy ($p = 0.034$).

Third, fully specialized firms have a different skill and job composition. We combine job functions by skill level and find that the share of skilled workers is 10.5 percentage points lower for fully specialized firms than for less specialized firms.[12] This difference is driven by ICs, as evidenced by a 9.2 percentage points lower share of skilled workers among ICs. Both differences are significant at the 5 percent level. These patterns are in part driven by a lower share of computer/math positions and a higher share of production jobs (coefficients -0.070, $p = 0.008$ and 0.105, $p = 0.081$), even though manufacturing firms are not systematically concentrated in one of the firm groups. In contrast, the share of sales jobs is systematically higher at less specialized firms. 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). These firms with less specialized managers are often in the high-tech sector (tech coefficient on full specialization is -0.342, $p = 0.006$). Indeed, 77 percent of all tech firms in our sample fall into the low-specialization group (Table D3).

These results are consistent with anecdotal evidence that tech firms often emphasize autonomy, technical expertise, and project-based collaboration rather than formal managerial hierarchies. Many of these organizations have sought to provide advancement opportunities for technical experts without requiring them to move into management. Shopify, for instance, has introduced a dual-track promotion system that explicitly recognizes and rewards technical "crafters" alongside managerial "people leaders."[13] Valve Corporation represents a more radical version of an IC-friendly firm, operating without formal managerial hierarchies and granting employees complete autonomy to select projects and form teams (Möller and McCaffrey, 2021). More recently, large technology firms such as Amazon and Google 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 productivity and speed up decision-making.[14]

Finally, we further conduct 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,

[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] https://www.worklife.news/leadership/dual-track-promotion/.

[14] https://www.businessinsider.com/amazon-fewer-managers-leaked-document-2024-9 and https://www.businessinsider.com/google-ceo-company-cut-manager-vp-roles-2024-12.

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 four scenarios (each representing a 1 percent change in one primitive mechanism, for example changing the variable supervision costs c_l at each level by 1 percent) and focus on their impacts on 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. Intuitively, the higher span boosts manager value added (see Equation (1)), especially for managers in higher levels with larger reporting chains. At the same time, the higher managerial span widens the average IC penalty (see Equation (13)), and the top-to-bottom IC-penalty ratio decreases, which indicates a stronger effect at the bottom of the firm driven by the knowledge distribution.[15] The IC employment share increases, especially at the top of the hierarchy, because a higher average span requires fewer managers for supervision. Together, this implies that IC jobs become more prevalent but relatively less attractive than at baseline. Hence, workers face an increased risk of getting stuck on the IC ladder.

B. Lower fixed supervision costs F. Lowering the fixed supervision component has the opposite effect on spans: average spans fall by roughly 0.5%. This change reduces the average IC penalty by 1.45%, and the effect is larger for ICs at the bottom, as reflected by an increase in the IC penalty ratio. The manager pay dispersion increases mildly by about 0.2%, while the average IC share falls slightly (around -0.2%). Compared to Scenario A, the implications for IC careers are flipped: while the IC pay scale becomes flatter, the disadvantage compared to managers declines and a higher ratio of managers to ICs suggests more opportunities to switch ladders.

C. Lower problem-solving costs t. Reducing problem-solving costs has substantial distributional effects despite holding managerial span stable. Since lower costs t boost IC productivity in problem solving, the average IC penalty becomes substantially less negative (by 3%), and the effect is stronger for ICs at the bottom level where their relative knowledge contribution is larger. The manager pay dispersion increases much more than in the supervision-cost counterfactuals (manager pay ratio top-to-bottom rises by about

[15] Specifically, the knowledge gap $(Z_l - Z_{l-1})/Z_l$ is larger at the bottom (Table D1) and acts as a multiplier for the effect of the increasing span on the widening IC penalty.

+1.6% across firms). This effect is driven entirely by changes in relative employment across levels because fewer problem solvers are required at each level and this results in a pyramid that narrows more strongly toward the top. Thus, the reporting chain of managers at the top increases substantially. In line with the increase in problem solving efficiency, the share of ICs declines slightly in this scenario, more so at the top of the firm. Together, these patterns suggest that reductions in problem-solving costs steepen manager pay schedule while raising the level but flattening the slope of the pay scale of ICs, making IC positions overall more attractive but resulting in less frequent promotions along the IC ladder with smaller pay raises.

D. Compress the knowledge ladder (slope of Z). Finally, compressing productivity differentials across layers (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),[16] perhaps surprisingly, exacerbates IC penalties substantially, especially at the bottom of the firm, and reduces manager pay dispersion. Intuitively, the knowledge boost for lower-level workers benefits managers more than ICs because the boost scales by managers' reach. Hence, IC career ladders become substantially less attractive compared to managerial career ladders. Managerial spans and IC shares are unaffected by this scenario because we hold problem solving and supervision costs constant. If problem solving efficiency were to increase in practice as a result of higher productivity, this would counteract the divergence in career ladders as described in scenario C above.

Effects across firm types. Comparing the effects of these different scenarios across firm types shows that changes are especially pronounced in firms with lower managerial specialization in supervision at baseline. While changes in average IC shares and manager pay are relatively similar across firm types in each of the four counterfactuals, the change in the slope of the IC pay scale is always an order of magnitude larger in diversified firms compared to fully specialized firms. Changing the knowledge ladder produces one of the starkest differences across firm types with much stronger effects at firms with less specialization. These differences are consistent with the steeper knowledge ladder and stronger decline in problem-solving costs toward the top at less specialized firms. 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" will 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 fixed costs of supervision or lower problem solving costs lift but flatten IC pay schedules, while lower variable supervision costs or less knowledge dispersion across levels 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 (2025) 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

[16] Specifically, we implement this scenario by setting $Z_l^c = Z_l + 0.01(Z_t - Z_l)$.

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.

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. Importantly, these differences become larger toward the top of the hierarchy. The estimation and counterfactual analysis in Section 5 highlights that the magnitude of this IC penalty and its changes in response to shocks are systematically correlated with important characteristics of the firms' organizational structure.

In this section, we complement these findings by studying whether some worker groups are disproportionately sorted into the less favorable side of the dual ladder. Section 6.1 documents the demographic composition of individual contributors, showing 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 section examines the demographic composition of ICs, focusing on gender, race, and ethnicity. We first document average differences between individual contributors and managers. While the aggregate patterns are informative, they mask substantial variation across firms.

The first finding is that women and racial minorities are more likely to hold IC roles (Table 5).[17] 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 individual contributors, 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. We start from the most saturated specification in Table 1 (column 5), which shows that the mean conditional IC penalty is 0.31 log points and the mean conditional gender pay gap is 0.07 log points in favor of men. Hence, 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 the likelihood of being an IC increases monotonically toward the top of the hierarchy for women and all racial minorities (Table A3). For women, the IC gap relative to men within

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

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. Racial patterns show the same upward trajectory but differ in magnitude. At the bottom of the hierarchy, minority groups display similarly small IC differentials of 1.2 to 1.7 percentage points, but these differences widen sharply at higher levels. 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 points. Hence, the racial differences in the propensity of being IC reported in Table 5 arise mainly from disparities that emerge at the middle and upper layers of the hierarchy.

This pattern is striking for at least two reasons. First, the magnitude of these results is large. For example, the gender gap in IC status at the top—a 7.62-percentage-point higher IC likelihood for women—is equal to 17 percent of the mean IC share in the upper layers (Figure 2). Moreover, it is 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.[18] Second, such widening gaps toward the top of firms' hierarchies are difficult to reconcile with pure statistical discrimination. Under this hypothesis, one would expect convergence across groups in the later career stages, when promotions increasingly depend on observed individual performance rather than noisy signals.

We next examine whether the IC penalty differs systematically by gender or race. To do so, 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 interaction terms capture whether women or minority employees experience a larger or smaller pay gap between ICs and managers relative to otherwise similar men or White employees.

Here, the key finding is that the IC penalty does not vary systematically across gender and racial groups (Table 6). The estimated coefficients are usually small and statistically insignificant. Compared with men and White employees, respectively, women and Asian employees exhibit smaller IC penalties, 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.

Taken together, these results indicate that the distinction between ICs and managers affects gender and racial pay gaps primarily through differences in assignment and promotion into these roles, rather than through group-specific pay setting within roles.

6.2 Transitions Into Managerial Roles across Demographic Groups

Introduction. 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 firms promote workers with systematically different characteristics into managerial roles depending on their race and gender. We start from the simplest possible approach—OLS

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

regressions of post-promotion managerial performance on demographic indicators—and argue that the estimates from this specification conflate several potential mechanisms for cross-group differences in post-promotion performance, including differences in the pool of candidates, in promotion thresholds, and in the teams to which newly promoted managers are assigned. We then progressively refine both the estimation strategy and the outcome variable. How the results change after each refinement reveals the relative importance of distinct classes of explanations.

We start by building a monthly panel that tracks transitions into managerial roles. The sample includes both workers who never leave the IC track and individual contributors who are eventually promoted to managers. The latter workers enter the panel during all months in which they are ICs and contribute one additional observation in the month of their promotion, at which point we measure their post-promotion performance as a manager.

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.[19] Because pay levels vary substantially across firms, we express each mean subordinate pay as a percentile rank within the firm-specific pay distribution. By construction, this dependent variable equals zero during the IC spell and takes a nonzero value only in the promotion month, where it captures the employee's average managerial performance over all post-promotion months and subordinates, collapsed into a single observation.

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 within 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—which measures whether firms promote workers with different levels of managerial ability depending on their demographic group. We restrict the sample to firms with at least fifteen managerial promotions for each of our six main demographic groups (White employees, Asian employees, Hispanic employees, Black employees, women, and men), which leaves twelve firms in the sample.[20]

The OLS estimates in Panel A of Table 7 show that non-Asian minority and female managers lead teams

[19] 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.

[20] One of the robustness checks at the end of this section replicates the results using the full sample of firms.

with significantly lower average pay. Subordinates of non-Asian minority managers rank on average 8.7 percentiles lower in the pay distribution than those supervised by White managers ($p < 0.01$), a gap that amounts to roughly 90 percent of the mean difference between the two groups. 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, by contrast, show no such penalty: the point estimate is positive (3.2 percentiles) but insignificant. In Table A4, a formal test confirms that the $\Delta\beta_g^{OLS}$ coefficient for Asian managers is significantly larger than that for other minority managers (difference of 11.8 percentile points, $p < 0.001$) and for women (9.2 percentile points, $p = 0.002$).

These OLS estimates should be interpreted with caution, as they conflate several distinct mechanisms that could generate cross-group differences in post-promotion managerial performance. For the sake of clarity, we summarize these mechanisms into three broad categories: (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. In the remainder of this section, we introduce two refinements to this initial OLS specification to progressively distinguish between these channels.

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). The OLS coefficients cannot distinguish this channel from differences in the underlying pool of candidates.

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) and Haegele (2025) find that gender differences in application rates are one of the primary drivers of the promotion gap at the European Central Bank and a large multinational firm, respectively. Moreover, Caldwell et al. (2026) shows that women are less likely to negotiate with their employers over working conditions, which may include promotions, than men with comparable qualifications. More broadly, Niederle and Vesterlund (2007) document that women shy away from competitive environments even when equally able. 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. Discriminatory hiring practices may thin the representation of minority workers in promotion-eligible positions from the outset (Bertrand and Mullainathan, 2004; Kline et al., 2022). Differential access to informal networks and mentorship may leave women and minorities less prepared for managerial responsibilities, whether because informal interactions favor same-gender pairs (Cullen and Perez-Truglia, 2023) or because women receive less credit for collaborative work (Sarsons et al., 2021). More generally, firms may underinvest in the visibility and development of women and minority workers (Milgrom and Oster, 1987), for instance, by assigning them fewer of the leadership tasks that serve as stepping stones to promotion (Bircan et al., 2025).

Third, our dependent variable—average 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 as-

signed. For example, women and minorities may be systematically placed in charge of weaker teams upon promotion, in which case the OLS estimates partly capture differences in team composition rather than in managerial performance. This concern is related to the *glass-cliff* hypothesis, which posits that women and minorities are disproportionately appointed to leadership positions in more difficult or precarious circumstances (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 isolate differences in promotion decisions from differences in candidate pools, we follow an instrumental-variable strategy inspired by Benson et al. (2019) and Benson et al. (2026). The core idea is to exploit exogenous variations in promotion opportunities—for example, driven by demand shocks, firm growth, or turnover—that shift the probability of individual promotions independently of the worker's own characteristics. Specifically, 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. This strategy identifies the effect of promotion for workers who are pushed into managerial roles because the firm faces an unusually high need to fill managerial slots, and who would not otherwise have been selected on the basis of their individual observable or unobservable attributes. Therefore, the IV estimates move the focus from the average promoted manager toward the *marginally* promoted manager: the worker within each demographic group who would not have been promoted absent an exogenous increase in opportunities. Hence, comparing β_g^{IV} across demographic groups reveals whether firms promote minority and majority candidates with different managerial abilities, net of any preexisting differences in the pool of candidates.

The IV specification retains the same dependent variable, controls, and fixed effects as the OLS Equation (18). The key difference is that we instrument the IC-to-M transition indicator IC-to-M_{ift}^g with a measure of IC-to-M promotion opportunities outside the focal worker's team. 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 instrument captures firm-level fluctuations in the intensity of IC-to-M transitions that are plausibly unrelated to the focal worker's individual characteristics.

The first stage regresses the individual transition indicator on the instrument:

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

and 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.

We first check the relevance of the instrument by reporting the first-stage estimates for the five main demographic groups, including the benchmark majority groups (Table A5). The coefficient on the share of IC-to-M transitions is positive and significant at the 1 percent level in every column, ranging from 0.005 for Asian employees and other minorities to 0.007 for White employees. These estimates imply that a one-standard-deviation increase in the firm-level promotion share 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. The near-identical 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 states that the share of firm-level promotions must affect post-promotion managerial performance only through individual promotion decisions. This condition is inherently untestable, but we argue that the structure of our estimand limits the scope for violations. Because our object of interest is the difference in β_g^{IV} across demographic groups rather than its level, any correlation between the instrument and unobserved determinants of the outcome that is common across groups cancels out. For instance, if periods of firm-level growth simultaneously raise both promotion rates and subordinate pay, this would shift β_g^{IV} upward for every group but leave the cross-group comparison unaffected.

A violation of the exclusion restriction would require, for example, that the instrument-induced promotions systematically occur during different time periods for different groups, so that some are promoted into more favorable conditions than others. While we cannot rule this out entirely, several features of the design mitigate this concern: the specification includes month-year fixed effects, which absorb aggregate time-series variation; the dependent variable averages subordinate pay across the entire managerial spell, smoothing out transitory conditions at the time of promotion; and later we will replace this measure with a time-invariant estimate of manager value-added, removing further exposure to promotion timing.

Finally, the leave-out construction of the instrument—which excludes all members of the focal worker's team—severs the mechanical link between an individual worker's promotion and the instrument, precluding reverse causality.

The IV estimates in Panel A of Table 7 are qualitatively consistent with the OLS results but uniformly shifted toward zero. The reduction in magnitude is accompanied by an increase in standard errors, so that none of the IV coefficients is significant at the 5 percent level. We will further explore this loss of precision when we estimate the model at the firm level.

As discussed earlier, the IV design isolates the performance of marginally promoted managers, stripping out differences in the composition of eligible candidates from the OLS estimates. For women, this shift is particularly pronounced: the IV coefficient is 40% smaller in magnitude than the OLS estimate, suggesting that a substantial share of the OLS gap reflects a weaker female candidate pool for promotion, rather than differential firm thresholds for otherwise similar candidates. This finding points to a large role played by gender disparities that originate earlier in the pipeline, for example, through differential hiring, higher turnover, lower application rates for managerial positions, less investment in career development, or weaker

preferences for management roles. The attenuation in the coefficient for Asian employees is proportionally similar (35 percent), but of opposite sign. For other minorities, the IV coefficient declines by only 11% relative to the OLS, indicating that most of the gap for this group persists even after removing the influence of candidate composition.

Table A4 shows that, in spite of the overall attenuation, the difference in the $\Delta\beta_g^{IV}$ between Asian employees and other minorities remains significant at 5 percent, while the gap between Asian employees and women is no longer significant.

Manager value added. Mean subordinate pay reflects not only the manager's influence on her subordinates' career progression but also the preexisting ability of the workers assigned to each team. If demographic groups differ systematically in team composition, then differences in post-promotion managerial performance may reflect team characteristics rather than managerial ability. To isolate the manager's contribution, we estimate a two-way fixed effects model in the tradition of Abowd et al. (1999) applied to manager-worker teams (Lazear et al., 2015), which decomposes log 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):

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

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.

We implement the model using the PyTwoWay package (Bonhomme et al., 2023), restricting estimation to the largest connected set of workers and managers within each firm. We assume homoskedastic errors and apply the bias correction to account for limited-mobility bias (Andrews et al., 2008). Following standard practice, we drop workers who appear under a single manager for only one period and retain workers who leave and return to the same manager. Then, the estimated manager fixed effect ψ_m, expressed as a percentile in the firm-specific distribution function, replaces the percentile rank of mean 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.

Replacing mean subordinate pay with manager value added as the dependent variable produces sizable shifts in the IV estimates, but unlike the move from OLS to IV, the changes are not uniformly toward zero (Table 7, Panel B, IV columns). For women and other minorities, the coefficients move in opposite

directions. The female gap widens to −4.9 percentiles, suggesting that female managers were on average matched to teams with higher non-manager-driven pay. In contrast, the gap for other minorities narrows to −5.6 percentiles—a reduction much larger than the decline observed when moving from OLS to IV—indicating that unfavorable team assignments accounted for a substantial share of this group's initial $\Delta\beta_g$.

We observe the most dramatic change for Asian employees, whose coefficient swings from 2.0 to −1.8 percentiles. After removing the influence of team composition, marginally promoted Asian managers no longer outperform their White counterparts. Consistent with this finding, Table A4 shows that 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.

Firm-level estimations. We now turn to estimating the OLS and IV regressions separately by firm. The sample remains the same twelve firms with at least fifteen IC-to-M transitions for each of the six main demographic groups, but we now allow all coefficients to vary at the firm level.

Figure 5 plots the firm-level $\Delta\beta_g^{OLS}$ and $\Delta\beta_g^{IV}$ estimates with 95 percent confidence intervals, ranking firms by the magnitude of the gap between minority and majority groups. The data show a striking degree of heterogeneity across firms. Across all specifications—from OLS regressions with mean subordinate pay as outcome in Panel A to IV regressions with manager value added as outcome in Panel D—every demographic comparison features firms with positive, near-zero, and negative estimates. Hence, some firms appear to promote minority candidates who go on to outperform their majority counterparts, while others exhibit the opposite pattern. This heterogeneity is not only visually apparent but also economically meaningful. Table A6 reports that the interquartile range of firm-level $\Delta\beta_g$ estimates is large for each specification and demographic group. For example, in the IV specification with mean subordinate pay, the interquartile range is 25.9 percentiles for Asian employees: a firm at the 75th percentile of the $\Delta\beta_{asian}^{IV}$ 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 the face of such heterogeneity, the aggregate estimates in Table 7 may diverge substantially from the experience of workers in any individual firm. This finding echoes Kline et al. (2022), who document similarly large variation across firms in callback rates for otherwise identical resumes.

The last two columns of Table 7 provide a summary of the contribution of each broad category of explanations for differences in post-promotion performance, reporting the share of firms with statistically significant $\Delta\beta_g$ estimates (separately for negative and positive effects). 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, Figure A2 examines whether promotion decisions are correlated across minority groups and within firms. The data indicate that the within-firm correlation is positive, large, and statistically significant between Asians and other racial minorities, indicating that firms that set higher promotion thresholds for one racial minority group tend to do the same for the other. The correlation between each racial group and women, however, is negative, smaller in magnitude, and insignificant, suggesting that firm-level promotion practices toward racial minorities do not extend to gender.

Limitations, robustness checks, and additional results. 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 A7, 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 A7, Panel B).

Third, we verify that our decision to aggregate non-Asian minority groups into a single category does not mask heterogeneous effects (Table A8).

Fourth, we replicate the analysis without imposing minimum thresholds on the number of promotions per demographic group (Table A9 and Table A10).

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 A11, 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 A11, 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.

7 Conclusion

Using personnel records from 43 firms, we show 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 our structural estimates reveal systematic differences in organizational structure and career ladders across firms that can be mapped to heterogeneity in observable firm characteristics. We then show how 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 policy implications based on our findings. First, the framework is well suited for analyzing organizational change and career consequences of new technologies, making it especially relevant in the context of the rise of 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 decisions made during their workers' earlier career stages, including hiring, job assignments, mentoring, and skill development, that facilitate access to management-track pathways.

References

Abowd, John M., Francis Kramarz, and David N. Margolis. 1999. "High Wage Workers and High Wage Firms." *Econometrica*, 67(2): 251–333.

Alonso, Ricardo, Wouter Dessein, and Niko Matouschek. 2008. "When Does Coordination Require Centralization?" *American Economic Review*, 98(1): 145–79.

Andrews, Martyn J., Len Gill, Thorsten Schank, and Richard Upward. 2008. "High Wage Workers and Low Wage Firms: Negative Assortative Matching or Limited Mobility Bias?" *Journal of the Royal Statistical Society Series A*, 171(3): 673–697.

Baker, George, Michael Gibbs, and Bengt Holmstrom. 1994. "The Internal Economics of the Firm: Evidence from Personnel Data." *The Quarterly Journal of Economics*, 109(4): 881–919.

Benson, Alan, Danielle Li, and Kelly Shue. 2019. "Promotions and the Peter Principle." *The Quarterly Journal of Economics*, 134(4): 2085–2134.

Benson, Alan, Danielle Li, and Kelly Shue. 2026. ""Potential" and the Gender Promotion Gap." *American Economic Review*, 116(2): 375–417.

Bertrand, Marianne and Sendhil Mullainathan. 2004. "Are Emily and Greg More Employable Than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination." *American Economic Review*, 94(4): 991–1013.

Bertrand, Marianne, Claudia Goldin, and Lawrence F. Katz. 2010. "Dynamics of the Gender Gap for Young Professionals in the Financial and Corporate Sectors." *American Economic Journal: Applied Economics*, 2(3): 228–255.

Bircan, Çağatay, Guido Friebel, and Tristan Stahl. 2025. "Gender Promotion Gaps in Knowledge Work: The Role of Task Assignment in Teams." *Discussion Paper Series 18/25*.

Blau, Francine D. and Lawrence M. Kahn. 2017. "The Gender Wage Gap: Extent, Trends, and Explanations." *Journal of Economic Literature*, 55(3): 789–865.

Bonhomme, Stéphane, Kerstin Holzheu, Thibaut Lamadon, Elena Manresa, Magne Mogstad, and Bradley Setzler. 2023. "How Much Should We Trust Estimates of Firm Effects and Worker Sorting?" *Journal of Labor Economics*, 41(2): 291–322.

Caldwell, Sydnee, Ingrid Haegele, and Jörg Heining. 2026. "Bargaining and Inequality in the Labor Market." *The Quarterly Journal of Economics*, 141(1): 315–371.

Caliendo, Lorenzo, Ferdinando Monte, and Esteban Rossi-Hansberg. 2015. "The Anatomy of French Production Hierarchies." *Journal of Political Economy*, 123(4): 809 – 852.

Caliendo, Lorenzo, Giordano Mion, Luca David Opromolla, and Esteban Rossi-Hansberg. 2020. "Productivity and Organization in Portuguese Firms." *Journal of Political Economy*, 128(11): 4211–4257.

Calvo, Guillermo A and Stanislaw Wellisz. 1978. "Supervision, Loss of Control, and the Optimum Size of the Firm." *Journal of Political Economy*, 86(5): 943–952.

Cullen, Zoë and Ricardo Perez-Truglia. 2023. "The Old Boys' Club: Schmoozing and the Gender Gap." *American Economic Review*, 113(7): 1703–1740.

Dessein, Wouter, Desmond (Ho-Fu) Lo, and Chieko Minami. 2022. "Coordination and Organization Design: Theory and Micro-Evidence." *American Economic Journal: Microeconomics*, 14(4): 804–43.

Doeringer, Peter B. and Michael J. Piore. 1970. *Internal Labor Markets and Manpower Analysis.* Lexington, MA.

Espinosa, Miguel and Christopher Stanton. 2025. "Training, Communications Patterns, and Spillovers Inside Organizations." *Journal of Political Economy*, Forthcoming.

Friedrich, Benjamin U. 2022. "Trade Shocks, Firm Hierarchies, and Wage Inequality." *The Review of Economics and Statistics*, 104(4): 652–667.

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

Garicano, Luis and Esteban Rossi-Hansberg. 2006. "Organization and Inequality in a Knowledge Economy." *The Quarterly Journal of Economics*, 121(4): 1383–1435.

Garicano, Luis and Thomas N. Hubbard. 2007. "Managerial Leverage is Limited By the Extent of the Market: Hierarchies, Specialization, and the Utilization of Lawyers' Human Capital." *The Journal of Law and Economics*, 50(1): 1–43.

Gibbons, Robert and Michael Waldman. 1999. "A Theory of Wage and Promotion Dynamics Inside Firms." *The Quarterly Journal of Economics*, 114(4): 1321–1358.

Guadalupe, Maria and Julie Wulf. 2010. "The Flattening Firm and Product Market Competition: The Effect of Trade Liberalization on Corporate Hierarchies." *American Economic Journal. Applied Economics*, 2(4): 105–127.

Haegele, Ingrid. 2025. "The broken rung: Gender and the leadership gap."

Hoffman, Mitchell and Christopher T. Stanton. 2025. "Chapter 9 - People, practices, and productivity: a review of new advances in personnel economics." In *Handbook of Labor Economics*. Vol. 6 of *Handbook of Labor Economics*, , ed. Christian Dustmann and Thomas Lemieux, 729–818. Elsevier.

Hospido, Laura, Luc Laeven, and Ana Lamo. 2022. "The Gender Promotion Gap: Evidence From Central Banking." *Review of Economics and Statistics*, 104(5): 981–996.

Huang, Ruidi, Erik J. Mayer, and Darius P. Miller. 2024. "Gender Bias in Promotions: Evidence From Financial Institutions." *The Review of Financial Studies*, 37(5): 1685–1728.

Ke, Rongzhu, Jin Li, and Michael Powell. 2018. "Managing Careers in Organizations." *Journal of Labor Economics*, 36(1): 197–252.

Kline, Patrick, Evan K. Rose, and Christopher R. Walters. 2022. "Systemic Discrimination Among Large U.S. Employers." *The Quarterly Journal of Economics*, 137(4): 1963–2036.

Lang, Kevin and Ariella Kahn-Lang Spitzer. 2020. "Race Discrimination: An Economic Perspective." *Journal of Economic Perspectives*, 34(2): 68–89.

Lazear, Edward P. 2004. "The Peter Principle: A Theory of Decline." *Journal of Political Economy*, 112(S1): S141–S163.

Lazear, Edward P. and Sherwin Rosen. 1981. "Rank-Order Tournaments as Optimum Labor Contracts." *Journal of Political Economy*, 89(5): 841–864.

Lazear, Edward P., Kathryn L. Shaw, and Christopher T. Stanton. 2015. "The Value of Bosses." *Journal of Labor Economics*, 33(4): 823–861.

Mas, Alexandre and Amanda Pallais. 2017. "Valuing Alternative Work Arrangements." *American Economic Review*, 107(12): 3722–3759.

Milgrom, Paul and Sharon Oster. 1987. "Job Discrimination, Market Forces, and the Invisibility Hypothesis." *The Quarterly Journal of Economics*, 102(3): 453–476.

Möller, Ulrich and Matthew McCaffrey. 2021. "Levels Without Bosses? Entrepreneurship and Valve's Organizational Design." In *The Invisible Hand in Virtual Worlds: The Economic Order of Video Games.* , ed. Matthew McCaffrey. Cambridge, UK:Cambridge University Press.

Niederle, Muriel and Lise Vesterlund. 2007. "Do Women Shy Away From Competition? Do Men Compete Too Much?" *The Quarterly Journal of Economics*, 122(3): 1067–1101.

Ovans, Andrea. 2014. "Overcoming the Peter Principle." *Harvard Business Review*.

Peter, Laurence J. and Raymond Hull. 1969. *The Peter Principle: Why Things Always Go Wrong.* New York:William Morrow & Company, Inc.

Rajan, Raghuram G. and Julie Wulf. 2006. "The Flattening Firm: Evidence from Panel Data on the Changing Nature of Corporate Hierarchies." *The Review of Economics and Statistics*, 88(4): 759–773.

Rim, Nayoung, Roman Rivera, Andrea Kiss, and Bocar Ba. 2024. "The Black-White Recognition Gap in Award Nominations." *Journal of Labor Economics*, 42(1): 1–23.

Roberts, John and Kathryn L Shaw. 2022. "Managers and the Management of Organizations." National Bureau of Economic Research Working Paper 30730.

Rosen, Sherwin. 1982. "Authority, Control, and the Distribution of Earnings." *Bell Journal of Economics*, 13(2): 311–323.

Ryan, Michelle K. and S. Alexander Haslam. 2005. "The Glass Cliff: Evidence that Women are Over-Represented in Precarious Leadership Positions." *British Journal of Management*, 16(2): 81–90.

Ryan, Michelle K. and S. Alexander Haslam. 2007. "The Glass Cliff: Exploring the Dynamics Surrounding the Appointment of Women to Precarious Leadership Positions." *Academy of Management Review*, 32(2): 549–572.

Sarsons, Heather, Klarita Gërxhani, Ernesto Reuben, and Arthur Schram. 2021. "Gender Differences in Recognition for Group Work." *Journal of Political Economy*, 129(1): 101–147.

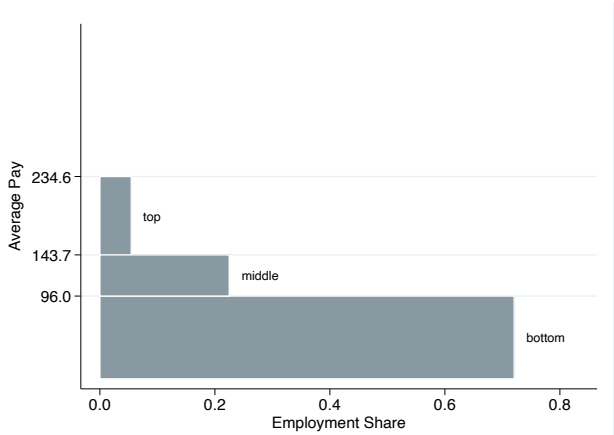
Williamson, Oliver E. 1967. "Hierarchical Control and Optimum Firm Size." *Journal of Political Economy*, 75: 123–138.

Wiswall, Matthew and Basit Zafar. 2018. "Preference for the Workplace, Investment in Human Capital, and Gender." *The Quarterly Journal of Economics*, 133(1): 457–507.

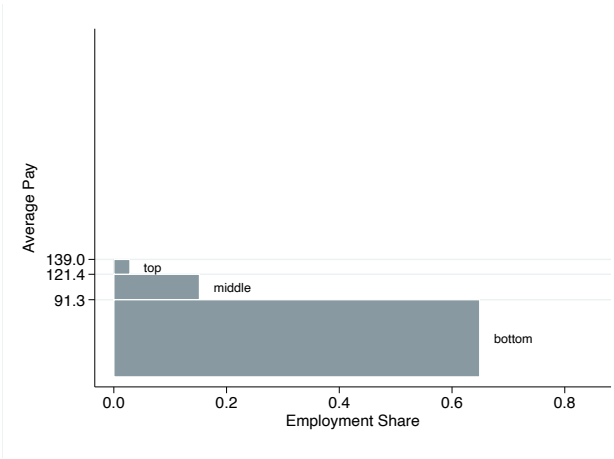
Figures and Tables

Figure 1: Summary of the Organizational Structures

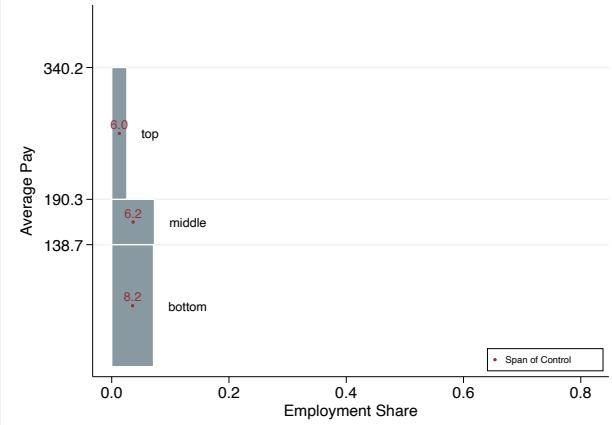
Panel A: All workers



Panel B: ICs

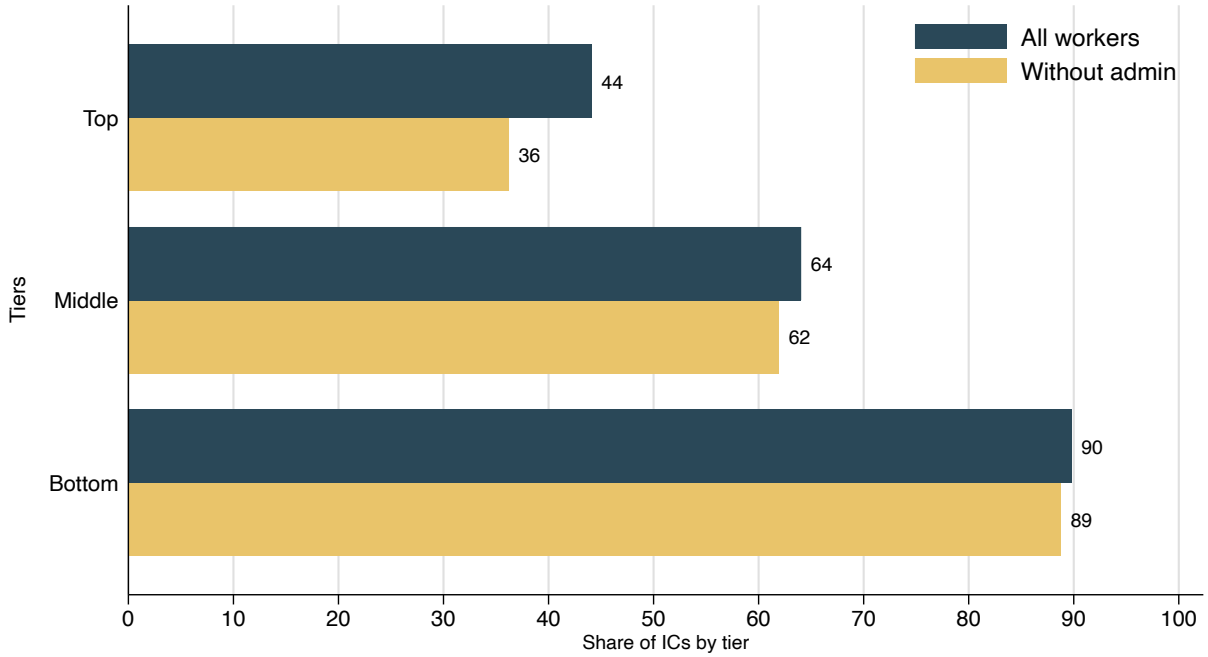


Panel C: Managers



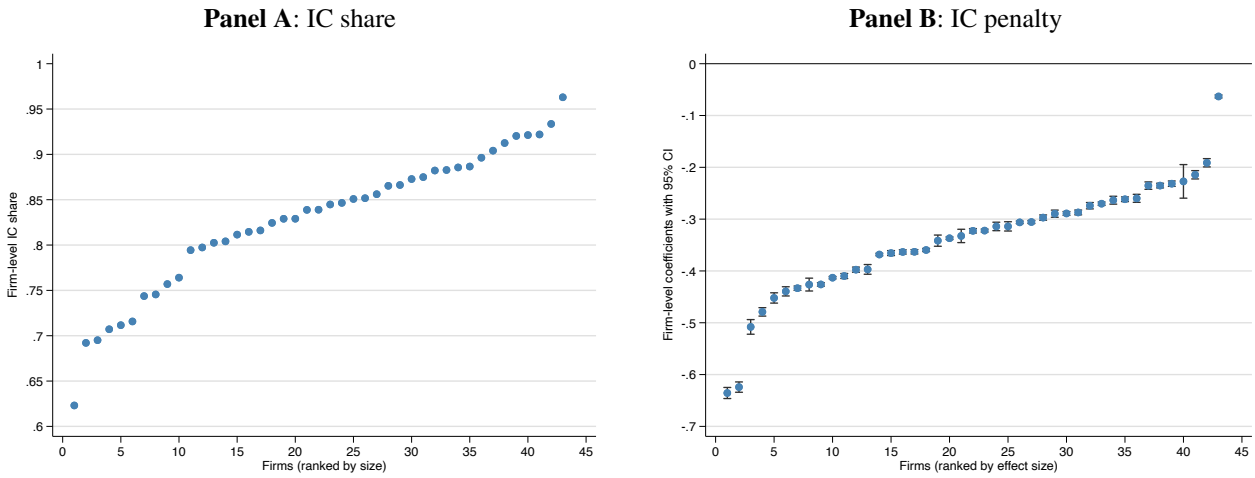
Notes: This figure summarizes three aspects of firm organizational structure by hierarchical position (top, middle, bottom) and role (individual contributors ICs vs. managers). For each group, the horizontal bars report the group's employment share, and the vertical height of the bars reports average 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



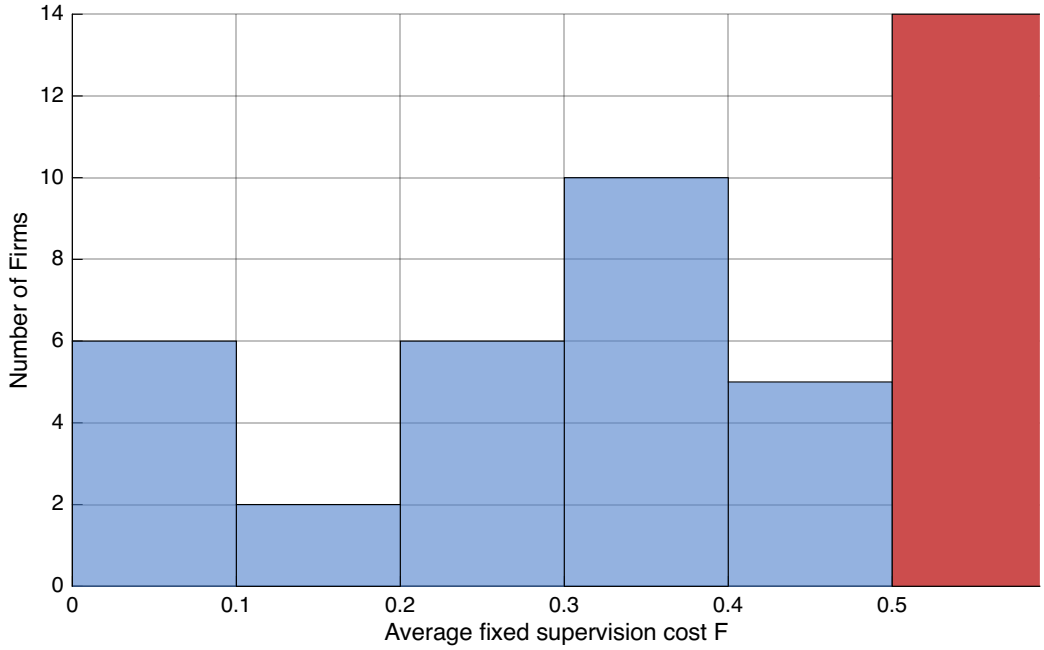
Notes: The figure reports, by hierarchical tier, the share of workers who are individual contributors (ICs), shown separately for (i) all workers and (ii) workers who do not hold an administrative job. We compute IC shares within each firm-tier-month, average them over the months observed for each firm, 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



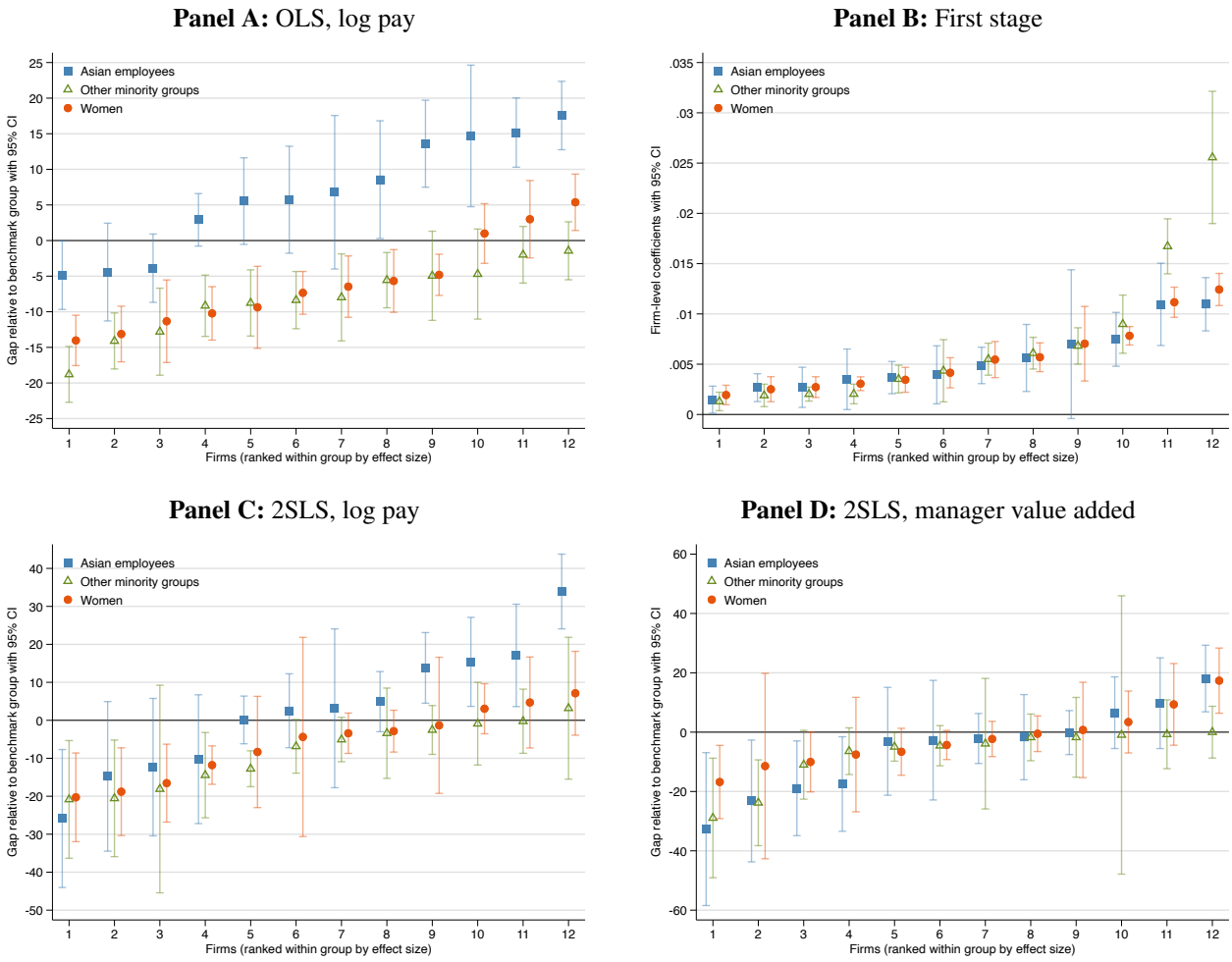
Notes: Panel A plots the share of ICs across the different firms in the sample. Panel B plots firm-specific estimates of the association between IC status and pay. Each point is the coefficient on an IC indicator from a separate firm-level regression of log pay on IC status, controlling for firm by month 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	$\hat{\beta}$ (maxF)	SE	p-value	Mean
High-tech sector	-0.342***	0.117	0.006	0.302
Manufacturing sector	0.116	0.154	0.458	0.279
Firms with less than 2000 employees	-0.266*	0.156	0.095	0.465
Firm depth	0.204	0.300	0.499	7.791
Span of control (bottom)	0.977	1.213	0.425	8.424
Span of control (top)	-1.049	0.680	0.131	6.268
Span ratio (top/bottom)	-0.229**	0.102	0.031	0.848
Estimated IC penalty	-0.105***	0.033	0.003	-0.341
Estimated IC-to-M pay raise	0.101***	0.036	0.008	0.286
Average IC pay	-0.076	0.139	0.585	11.452
IC pay ratio (top/bottom)	0.113	0.172	0.515	1.575
M pay ratio (top/bottom)	0.648*	0.357	0.077	2.564
Pay ratio (top/bottom)	0.596	0.472	0.214	2.819
Skilled worker share	-0.105**	0.052	0.047	0.457
Cond. share of skilled at bottom layer	-0.128**	0.055	0.024	0.437
Share of top-mid workers	-0.092**	0.042	0.034	0.276
Firm share of skilled IC	-0.094**	0.041	0.029	0.358
IC share (bottom)	-0.002	0.019	0.903	0.898
IC share (middle)	-0.032	0.038	0.406	0.641
IC share (top)	0.099*	0.056	0.085	0.441
Computer/Math occupation share	-0.070**	0.029	0.022	0.166
Production occupation share	0.105*	0.059	0.081	0.130
Sales occupation share	-0.094***	0.034	0.008	0.154
F (average)	0.222***	0.029	0.000	0.351

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	-1.43	-3.44	0.20	0.14	0.32	-0.09
maxF	0.52	-1.13	-0.62	0.30	0.15	0.16	-0.14
lowF	0.51	-1.63	-4.90	0.14	0.14	0.41	-0.07
Panel B. Reduce fixed supervision costs $(0.99 \times F)$							
All Firms	-0.49	1.45	4.32	0.20	-0.19	-0.83	-0.09
maxF	-0.49	1.17	0.64	0.30	-0.23	-0.79	-0.14
lowF	-0.50	1.65	6.22	0.14	-0.17	-0.85	-0.07
Panel C. Reduce problem solving costs $(0.99 \times t)$							
All Firms	0.05	2.97	10.19	1.63	-0.18	-0.64	-0.54
maxF	0.06	2.35	1.30	1.42	-0.19	-0.31	-0.46
lowF	0.05	3.40	14.78	1.75	-0.18	-0.83	-0.57
Panel D. Reduce slope of the knowledge ladder $(0.99 \times Z$ *slope)*							
All Firms	0.00	-3.81	-11.42	-0.53	0.00	0.00	0.00
maxF	0.00	-2.85	-2.14	-0.37	0.00	0.00	0.00
lowF	0.00	-4.48	-16.21	-0.62	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	IC	IC	IC
	(1)	(2)	(3)	(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

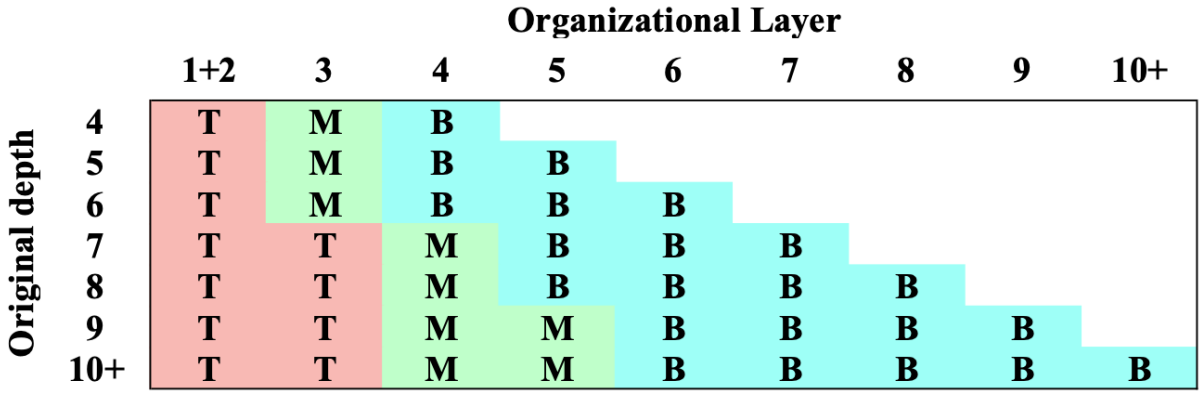
Notes: This table reports the gap in post-promotion outcomes between each demographic group and its benchmark (White employees for racial minorities; male employees for women). Each coefficient is the difference between the group-specific and benchmark estimates from a regression of the outcome on an 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

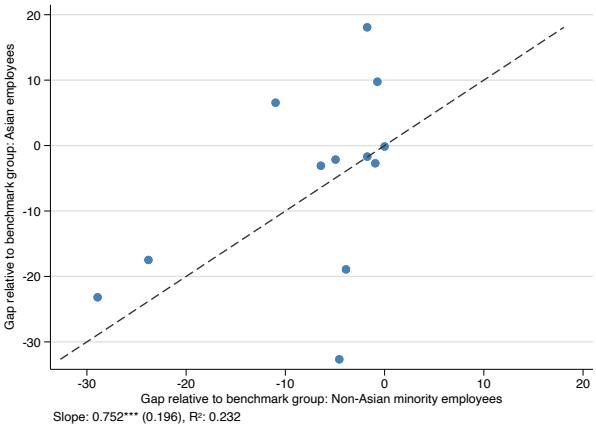
Figure A1: Aggregating Organizational Layers



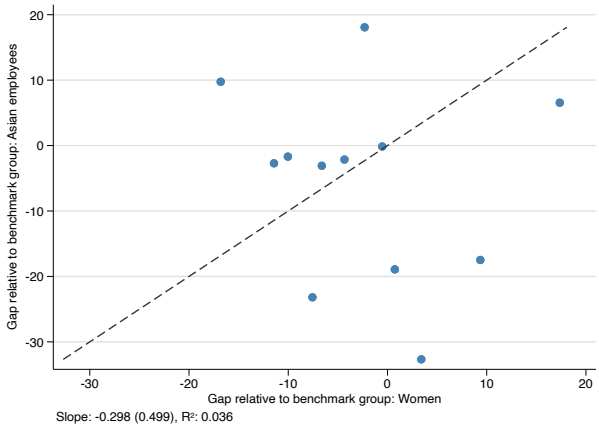
Notes: This figure illustrates how we map a firm's detailed organizational layers into three broad groups (top, middle, and bottom) as a function of the firm's total organizational depth (rows). Columns report the original layer index (with layers 1 and 2 pooled). This coarser classification facilitates 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

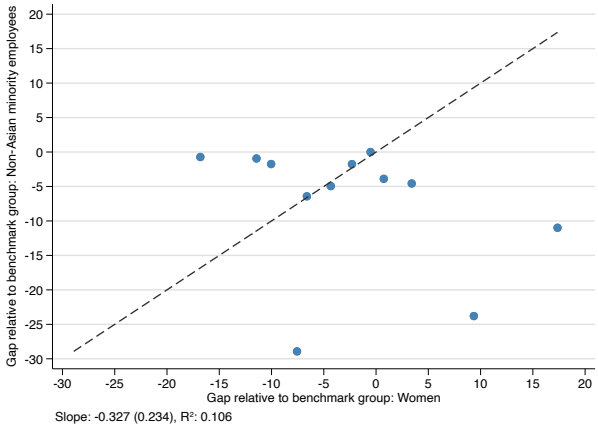
Panel A: Asians vs Non-Asian minorities



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 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 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***	3.043***	1.598***	1.764***
	(0.735)	(0.599)	(0.360)	(0.274)
Female x Middle	11.569***	10.245***	6.137***	5.510***
	(1.346)	(0.900)	(0.728)	(0.540)
Female x Top	18.660***	18.064***	7.245***	5.857***
	(2.892)	(2.246)	(1.034)	(0.848)
Asian	2.346***	2.466***	1.652**	1.290*
	(0.746)	(0.753)	(0.690)	(0.679)
Asian x Middle	4.027***	2.485**	2.219**	2.053**
	(1.559)	(1.060)	(0.916)	(0.868)
Asian x Top	-2.781	0.433	2.423**	2.481**
	(2.444)	(1.492)	(1.182)	(1.190)
Black	4.005***	4.230***	2.854***	1.321***
	(0.676)	(0.626)	(0.449)	(0.355)
Black x Middle	6.134***	4.336**	3.048**	4.046***
	(1.667)	(1.962)	(1.417)	(1.320)
Black x Top	14.760***	7.186***	4.316***	5.509***
	(2.018)	(2.052)	(1.468)	(1.588)
Hispanic	3.689***	3.705***	2.680***	1.633***
	(0.886)	(0.855)	(0.577)	(0.462)
Hispanic x Middle	5.412***	4.950***	3.145***	3.368***
	(1.777)	(1.279)	(1.118)	(1.183)
Hispanic x Top	16.943***	11.177***	5.327***	4.875***
	(2.311)	(2.426)	(1.155)	(1.029)
Other minorities	3.367***	3.324***	2.619***	1.681***
	(0.930)	(0.904)	(0.740)	(0.612)
Other minorities x Middle	5.504***	4.842***	3.568**	3.794**
	(1.930)	(1.717)	(1.491)	(1.583)
Other minorities x Top	10.040***	7.429**	3.662*	4.371***
	(3.521)	(3.234)	(1.974)	(1.689)
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.

Table A7: 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 A8: 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 A9: IC-to-M Transitions, All Firms

	Race groups					
	Asian		Others		Women	
	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 A10: 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 A11: 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.

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.[21] 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.[22] 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.[23] 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).[24] 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

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

[22] 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.

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

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

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.

Table B1: Summary Statistics

	Mean	SD	Min	Max
	(1)	(2)	(3)	(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 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

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

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.2 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

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

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

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

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

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

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 value added of an IC at level l is proportional to

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

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

$$\kappa Z_l \rho_{l-1} S_l^*.$$

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,

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

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

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

The comparative statics follow from differentiating the penalty,

$$\frac{\partial \pi_l}{\partial F_l} = -\frac{1}{\gamma F_l} < 0, \qquad \frac{\partial \pi_l}{\partial t_l} = -\frac{1}{t_l} < 0, \qquad \frac{\partial \pi_l}{\partial \kappa} = -\frac{1}{\kappa} < 0,$$

$$\frac{\partial \pi_l}{\partial c_l} = \frac{1}{\gamma c_l} > 0, \qquad \frac{\partial \pi_l}{\partial q_l} = \frac{1}{q_l} > 0.$$

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

C.3 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 $\gamma = 2$,

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

Now suppose that

$$F_{l+1} \le F_l, \qquad t_{l+1} \le t_l, \qquad c_{l+1} \ge c_l,$$

with at least one strict inequality. Then

$$\frac{F_{l+1}}{c_{l+1}} \le \frac{F_l}{c_l},$$

again with strict inequality unless both F and c are constant across levels. Taking square roots and multiplying by $t_{l+1} \le t_l$ implies

$$t_{l+1} \sqrt{\frac{F_{l+1}}{c_{l+1}}} \le t_l \sqrt{\frac{F_l}{c_l}},$$

with strict inequality whenever at least one of the three primitive inequalities is strict. Also,

$$2F_{l+1} \le 2F_l.$$

Therefore,

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

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

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

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

Define

$$H_l \equiv \frac{t_l \sqrt{F_l/c_l}}{q_l}.$$

Then

$$\pi_l = -\ln \kappa - \ln H_l.$$

Because the logarithm is strictly increasing, if H_l increases with l, then $-\ln H_l$ decreases with 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

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

Hence, if

$$t_l + 2\sqrt{c_l F_l} < 1 \qquad \text{for every } l,$$

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,

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

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

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

$$\pi_\ell = \ln\left(\frac{Z_\ell - Z_{\ell-1}}{\kappa Z_\ell} \cdot \frac{1}{t_\ell S_\ell}\right), \tag{27}$$

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

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

$$wr^M_{tb} = \frac{S_t}{Z_b S_b} \cdot \frac{1}{N_m}, \tag{30}$$

$$wr^M_{mb} = \frac{Z_m S_m}{Z_b S_b} \cdot \frac{1}{N_b}, \tag{31}$$

$$wr^M_{tm} = \frac{S_t}{Z_m S_m} \cdot \frac{N_b}{N_m}. \tag{32}$$

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):

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

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 (Z_b, Z_m) from manager pay ratios and Step 1

Given (N_b, N_m) and spans (S_b, S_m, S_t), the manager pay-ratio formulas (30)–(31) can be inverted to yield

$$wr^M_{tb} = \frac{S_t}{Z_b S_b}\cdot\frac{1}{N_m} \quad\Longrightarrow\quad Z_b = \frac{S_t}{S_b N_m\, wr^M_{tb}}, \tag{41}$$

$$wr^M_{mb} = \frac{Z_m S_m}{Z_b S_b}\cdot\frac{1}{N_b} \quad\Longrightarrow\quad Z_m = Z_b \cdot wr^M_{mb} N_b \cdot \frac{S_b}{S_m}. \tag{42}$$

Therefore (Z_b, Z_m) are point identified from

$$\{S_b, S_m, S_t, \xi_b, \xi_m, wr^M_{tb}, wr^M_{mb}\}.$$

The third manager ratio wr^M_{tm} in (32) becomes an overidentifying restriction.

Step 3: 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 3a: Derive $(R1)$ from spans and log-linearity of c_ℓ From the span formula (26),

$$S^2_\ell = \frac{F_\ell}{c_\ell} \quad\Longrightarrow\quad c_\ell = \frac{F_\ell}{S^2_\ell}. \tag{43}$$

Taking logs yields

$$\log c_\ell = \log F_\ell - 2\log S_\ell. \tag{44}$$

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:

$$\frac{\log c_m - \log c_b}{m-b} = \frac{\log c_t - \log c_m}{t-m}. \tag{45}$$

Substitute $\log c_\ell = \log(F_\ell/S_\ell^2)$ from (43) to eliminate parameters (c_0, α_c):

$$\frac{\log(F_m/S_m^2) - \log(F_b/S_b^2)}{m-b} = \frac{\log(F_t/S_t^2) - \log(F_m/S_m^2)}{t-m}. \qquad (R1) \tag{46}$$

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 3b: 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:

$$\begin{aligned} \xi_\ell(t_\ell S_\ell + 2F_\ell) &= t_\ell S_\ell - (1-2F_\ell), \\ (1-\xi_\ell)\, t_\ell S_\ell &= 1 - 2(1-\xi_\ell)F_\ell. \end{aligned}$$

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

$$t_\ell = \frac{\frac{1}{1-\xi_\ell} - 2F_\ell}{S_\ell}. \tag{47}$$

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:

$$\frac{\log t_m - \log t_b}{m-b} = \frac{\log t_t - \log t_m}{t-m}. \tag{48}$$

Substitute t_ℓ from (47) to eliminate parameters (t_0, α_t):

$$\frac{\log\left(\frac{\frac{1}{1-\xi_m} - 2F_m}{S_m}\right) - \log\left(\frac{\frac{1}{1-\xi_b} - 2F_b}{S_b}\right)}{m-b} = \frac{\log\left(\frac{\frac{1}{1-\xi_t} - 2F_t}{S_t}\right) - \log\left(\frac{\frac{1}{1-\xi_m} - 2F_m}{S_m}\right)}{t-m}. \qquad (R2) \tag{49}$$

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 3c: 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 (46) and (49), 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 4: 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 (43). 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 (47). 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 5: Identify κ and Z_0 from IC-penalty moments

From (27), exponentiate:

$$\exp(\pi_\ell) = \frac{Z_\ell - Z_{\ell-1}}{\kappa Z_\ell} \cdot \frac{1}{t_\ell S_\ell}. \tag{50}$$

Identify κ using π_t (top layer). Use $Z_t = 1$ and $Z_{t-1} = Z_m$ (identified in Step 2):

$$\exp(\pi_t) = \frac{1 - Z_m}{\kappa} \cdot \frac{1}{t_t S_t} \quad \Longrightarrow \quad \kappa = \frac{1 - Z_m}{t_t S_t \exp(\pi_t)}.$$

Identify Z_0 using π_b (bottom layer). With κ known, and Z_b known (Step 2), (50) at $\ell = b$ gives:

$$\exp(\pi_b) = \frac{Z_b - Z_0}{\kappa Z_b} \cdot \frac{1}{t_b S_b} \quad \Longrightarrow \quad Z_0 = Z_b - \kappa Z_b t_b S_b \exp(\pi_b).$$

The middle-layer penalty π_m then becomes an overidentifying restriction.

D.3 Estimation Results

Table D1: Estimation Results: Parameter Estimates

	All Firms		**maxF**		**lowF**	
Variable	Mean	SD	Mean	SD	Mean	SD
Z_0	0.307	0.252	0.405	0.209	0.259	0.260
Z_{bot}	0.685	0.127	0.741	0.086	0.659	0.136
Z_{mid}	0.913	0.049	0.931	0.022	0.905	0.056
F_{bot}	0.361	0.171	0.500	0.000	0.294	0.172
F_{mid}	0.359	0.173	0.500	0.000	0.292	0.175
F_{top}	0.331	0.197	0.500	0.000	0.249	0.193
t_{bot}	0.838	0.349	0.603	0.160	0.951	0.360
t_{mid}	0.422	0.154	0.333	0.136	0.464	0.145
t_{top}	0.241	0.164	0.200	0.136	0.261	0.174
c_{bot}	0.010	0.012	0.012	0.008	0.010	0.014
c_{mid}	0.011	0.011	0.015	0.006	0.009	0.012
c_{top}	0.013	0.011	0.020	0.008	0.010	0.012
κ	0.155	0.087	0.179	0.096	0.143	0.082

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		maxF		lowF	
Variable	Model	Data	Model	Data	Model	Data
Panel A: Targeted Moments						
IC Gap (Bottom)	-0.315	-0.315	-0.407	-0.407	-0.271	-0.271
IC Gap (Middle)	-0.337	-0.337	-0.404	-0.403	-0.305	-0.305
IC Gap (Top)	-0.548	-0.550	-0.665	-0.670	-0.492	-0.492
Span of Control (Bottom)	7.851	8.424	8.081	9.083	7.740	8.106
Span of Control (Middle)	6.898	6.458	6.490	5.874	7.095	6.739
Span of Control (Top)	5.582	6.268	5.359	5.561	5.689	6.609
IC Share (Bottom)	0.831	0.898	0.805	0.896	0.844	0.899
IC Share (Middle)	0.691	0.641	0.652	0.619	0.709	0.651
IC Share (Top)	0.425	0.441	0.467	0.508	0.405	0.409
Pay Ratio M (Top/Mid)	1.763	1.792	1.918	2.062	1.688	1.661
Pay Ratio M (Mid/Bot)	1.411	1.412	1.474	1.426	1.380	1.406
Pay Ratio M (Top/Bot)	2.537	2.564	2.907	3.002	2.358	2.353
Panel B: Untargeted Moments						
Worker Share (Bottom)	0.583	0.724	0.595	0.786	0.577	0.694
Worker Share (Middle)	0.304	0.222	0.289	0.176	0.311	0.244
Worker Share (Top)	0.114	0.054	0.117	0.038	0.113	0.062
Pay Ratio IC (Top/Mid)	1.441	1.114	1.491	1.053	1.416	1.143
Pay Ratio IC (Mid/Bot)	1.387	2.435	1.485	4.633	1.339	1.374
Pay Ratio IC (Top/Bot)	2.031	1.575	2.267	1.651	1.917	1.538
Pay Ratio All (Top/Mid)	1.827	1.700	1.917	1.735	1.784	1.682
Pay Ratio All (Mid/Bot)	1.355	2.018	1.164	2.966	1.447	1.560
Pay Ratio All (Top/Bot)	2.549	2.819	2.350	3.221	2.645	2.625

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		**maxF**		**lowF**	
Variable	Mean	SD	Mean	SD	Mean	SD
N (firms)	43		14		29	
High-tech sector (share)	0.302		0.071		0.414	
Manufacturing sector (share)	0.279		0.357		0.241	
Firms with less than 2000 employees	0.465		0.286		0.552	
Firm depth	7.791	1.013	7.929	0.829	7.724	1.099
Span of control (bottom)	8.424	3.877	9.083	3.613	8.106	4.020
Span of control (top)	6.268	2.801	5.561	1.103	6.609	3.291
Span ratio (top/bottom)	0.848	0.367	0.693	0.274	0.922	0.387
Estimated IC Penalty	-0.341	0.107	-0.411	0.107	-0.306	0.091
Estimated IC-to-M pay raise	0.286	0.115	0.354	0.119	0.253	0.099
Average IC pay	11.452	0.407	11.400	0.446	11.476	0.393
IC pay ratio (top/bottom)	1.575	0.442	1.651	0.604	1.538	0.346
M pay ratio (top/bottom)	2.564	0.999	3.002	1.228	2.353	0.809
Pay ratio (top/bottom)	2.819	1.284	3.221	1.626	2.625	1.061
Skilled worker share	0.457	0.171	0.386	0.154	0.491	0.170
Cond. share of skilled at bottom layer	0.437	0.182	0.350	0.165	0.479	0.177
Share of top-mid workers	0.276	0.161	0.214	0.098	0.306	0.178
Firm share of skilled IC	0.358	0.145	0.295	0.115	0.388	0.150
IC share (bottom)	0.898	0.061	0.896	0.054	0.899	0.065
IC share (middle)	0.641	0.111	0.619	0.122	0.651	0.106
IC share (top)	0.441	0.174	0.508	0.177	0.409	0.166
Computer/Math occupation share	0.166	0.113	0.119	0.070	0.189	0.123
Production occupation share	0.130	0.172	0.201	0.194	0.096	0.152
Sales occupation share	0.154	0.132	0.091	0.078	0.185	0.142

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 maxF	(1)	(2)	(3)	(4)	(5)
Small firm (<2000)	-0.235	-0.232	-0.213	-0.235*	-0.155
	(0.140)	(0.141)	(0.134)	(0.132)	(0.163)
Firm depth		0.040	0.003	-0.002	0.027
		(0.062)	(0.055)	(0.052)	(0.075)
Span ratio (top/bottom)			-0.380**	-0.299**	-0.651***
			(0.150)	(0.136)	(0.222)
M-pay ratio (top/bottom)			0.155**	0.148**	0.183**
			(0.062)	(0.066)	(0.075)
Share top-mid			-0.153	-0.105	-0.270
			(0.325)	(0.356)	(0.570)
Skilled at bottom				-0.858	-3.018
				(1.719)	(2.663)
Conditional share of skilled IC on IC				0.139	-0.900
				(1.759)	(2.681)
Administrative worker share					-2.893***
					(0.765)
Business/Finance/Legal worker share					3.251
					(3.388)
Computer and Math worker share					2.034
					(3.454)
Production worker share					-0.995
					(0.690)
Research and Development worker share					2.012
					(3.202)
Sales worker share					-0.908
					(0.582)
Top management worker share					5.420
					(3.570)
Observations	43	43	43	43	43
R^2	0.062	0.070	0.259	0.330	0.529

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	7.315	7.353	-0.349	-0.354	1.659	1.602	2.537	2.542	0.750	0.751	0.513	0.515	0.417	0.417
maxF	7.282	7.320	-0.438	-0.443	1.735	1.724	2.907	2.916	0.726	0.727	0.574	0.575	0.405	0.405
lowF	7.331	7.368	-0.306	-0.311	1.623	1.543	2.358	2.361	0.762	0.763	0.484	0.486	0.423	0.423
Panel B. Reduce fixed supervision costs $(0.99 \times F)$														
All Firms	7.315	7.279	-0.349	-0.344	1.659	1.731	2.537	2.542	0.750	0.749	0.513	0.509	0.417	0.417
maxF	7.282	7.247	-0.438	-0.433	1.735	1.746	2.907	2.916	0.726	0.725	0.574	0.569	0.405	0.405
lowF	7.331	7.295	-0.306	-0.301	1.623	1.724	2.358	2.361	0.762	0.761	0.484	0.480	0.423	0.423
Panel C. Reduce problem solving costs $(0.99 \times t)$														
All Firms	7.315	7.319	-0.349	-0.338	1.659	1.828	2.537	2.578	0.750	0.749	0.513	0.510	0.417	0.415
maxF	7.282	7.287	-0.438	-0.427	1.735	1.757	2.907	2.948	0.726	0.725	0.574	0.572	0.405	0.403
lowF	7.331	7.334	-0.306	-0.296	1.623	1.862	2.358	2.399	0.762	0.761	0.484	0.480	0.423	0.421
Panel D. Reduce slope of the knowledge ladder $(0.99 \times Z$ *slope)*														
All Firms	7.315	7.315	-0.349	-0.362	1.659	1.470	2.537	2.523	0.750	0.750	0.513	0.513	0.417	0.417
maxF	7.282	7.282	-0.438	-0.450	1.735	1.698	2.907	2.896	0.726	0.726	0.574	0.574	0.405	0.405
lowF	7.331	7.331	-0.306	-0.320	1.623	1.360	2.358	2.343	0.762	0.762	0.484	0.484	0.423	0.423

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.