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ABSTRACT

From Followers to Leaders: The Career Impact of High-Quality Managers*

How does manager quality affect subordinates' career progression? We examine the causal effect of manager quality on workers' career outcomes in the context of managerial teams at a large construction firm. We exploit quasi-random variation in worker- manager matching through frequent project reassignments to identify the causal effect of high-quality managers on promotions. Working under a high-quality manager increases workers' subsequent promotion rates by 13 percentage points. We provide evidence in support of managerial human capital transmission as the primary mechanism: effects are concentrated among workers and positions that require most managerial skills and exposed workers earn significantly higher performance-based bonuses.

JEL Classification: M51, J24
Keywords: manager quality, promotions, skill transmission

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1 Introduction

Where do managerial skills, including leadership ability, come from? This fundamental question has long provoked debate. Traditional views emphasize two sources: inherent talent and formal training. On the one hand, effective managers are often believed to possess innate traits – charisma, decisiveness, intelligence – that predispose them to lead (Bertrand and Schoar, 2003; Caplin et al., 2023; Conger, 2015; Conger and Kanungo, 1998). On the other hand, formal education and training (e.g., business school, leadership development programs) are seen as crucial to shaping managerial skillsets (Adhvaryu et al., 2023b; Chioda et al., 2021; Giorcelli, 2023). Adding to these views, we highlight a third mechanism: social learning through workplace experience. High-quality managers can serve as on-the-job mentors, imparting skills to their subordinates through both active tutoring and passive channels like daily interactions, observation, and 'workplace osmosis'. In other words, managerial capabilities can be transmitted from the boss to employees via exposure to good management practices and leadership behaviors. This perspective suggests that the best managers in a firm not only excel in their direct responsibilities, but also cultivate the human capital of their teams by modeling effective management. Good managers, therefore, are not just born or made in classrooms – they can be formed on the job by learning from other managers.

Despite the intuitive appeal of this social-learning channel, we know little about its impact on employees' career progression. If exposure to an excellent manager truly helps workers develop into better managers themselves, it has important implications. For firms, it would represent a powerful way that high-quality managers add long-term value – by enhancing their subordinates' skills and future productivity, not just immediate team performance. For employees, working under superior managers could confer substantial career benefits beyond short-term performance gains.

In this paper, we investigate whether and how high-quality managers influence their subordinates' career trajectories through such skill transmission. We draw on detailed personnel data on hierarchical project teams from a large Chinese construction firm. Each team consists entirely of managerial employees, structured into five distinct hierarchical levels, with a project manager at the top and various managerial positions down to foremen at the entry level.[1] Our empirical setting features temporary project teams that are regularly reshuffled. As projects vary in their technical requirements, team size, timing, and duration, the firm systematically reassigns both managers and team members across projects upon completion, generating continuous variation in team composition. This organizational structure, combined with the regular team reassignment process, provides an ideal setting to identify the causal effect of being led by a top project manager.

We analyze an individual-project panel using administrative data covering 1,392 construction projects, covering 222 managers and 2,284 workers at our partner firm. To measure manager quality, we exploit this panel structure to estimate project managers' value-added to project outcomes (Abowd et al., 1999; Bertrand and Schoar, 2003; Lazear et al., 2015). We then classify *top managers* as those with estimated value-added above the 60^{th} percentile.[2] Our key outcome variable is promotion, defined as advancement of at least one hierarchical level between consecutive projects.

Our findings indicate that exposure to a high-quality manager significantly boosts a worker's promotion prospects in subsequent projects. Our main identification strategy uses a staggered difference-in-differences approach, exploiting team member and manager reassignments to estimate the effect of past exposure to a top manager. Our estimates indicate that exposure to top managers increases workers' subsequent promotion rates by 13 percentage points, relative to the sample average of 27% ($p < 0.01$). This effect stems from changes in promotion rates relative to peers working on the same projects, rather than from differential matching between workers and projects following exposure. Our results are robust across various empirical specifications, including the staggered difference-in-differences estimator for imbalanced panels developed by De Chaisemartin and d'Haultfoeuille (2020).

We address potential concerns about our identification strategy in several ways. First, our difference-in-differences strategy relies on parallel trends between exposed and non-exposed workers, which we validate by showing pretrends in promotion rates do not differ. Second, we rule out confounding effects from project and peer quality by demon-

[1]Foremen are also managerial positions who supervise construction workers and specific aspects of projects. Construction workers, who are employed by external contractors rather than directly by the company, are excluded from our analysis.

[2]Our results are robust to using a range of different thresholds and alternative non–value-added based definitions of top managers (Section 6).

strating robustness to controlling for these factors. Third, to mitigate concerns about endogenous worker-manager matching based on unobserved time-varying characteristics, we examine effects among early-career workers, where such selection is less likely due to limited information and lower-stakes decisions. Finally, we rule out differential attrition as an alternative explanation through a bounding exercise, which shows that the magnitude of differential retention rates between high and low productivity workers cannot explain the observed promotion effects.

We complement our difference-in-differences analysis with an instrumental variable approach that exploits variation in top-manager availability when workers begin new projects. Our instrument is the average fraction of top managers among all available managers within a 180-day window around each worker's project start dates, excluding their previous managers. This measure provides a plausibly exogenous variation in exposure probability that is independent of worker characteristics and project matching. The instrument proves strong, with a one percentage point increase associated with a 0.8 percentage point higher likelihood of top manager exposure. IV estimates indicate that such exposure raises promotion rates by 9.3 percentage points ($p < 0.1$), similar to our difference-in-differences findings.

We present evidence that this improvement in promotion rates stems primarily from skills the subordinates acquired via their prior manager, rather than from networking or favoritism. Consistent with a human capital accumulation mechanism, the benefits of exposure are concentrated among workers in roles requiring managerial acumen. Exposed workers also exhibit improved performance outcomes. Exposed workers receive performance-based bonuses that are 1.87 percentage points ($p < 0.1$) higher than the equal-share benchmark. In practical terms, employees who had a top-tier manager are far more likely to rise to higher-ranking managerial positions than those who did not. Exposure to top managers substantially increases promotion probabilities—by 6.4 percentage points (114% of sample mean) for project manager positions and 5.9 percentage points (53% of sample mean) for department manager positions (both $p < 0.01$). These patterns suggest that subordinates truly learn managerial skills from their high-quality superiors. In short, working under superior managers appears to make employees better candidates for leadership themselves. Through this social learning, high-quality managers end up benefiting both the firm and their subordinates in enduring ways, beyond immediate productivity gains on the current project.

To complement our quantitative analysis, we survey project managers and team members, collecting responses from 1,488 current employees, including 178 past or current project managers. The survey results corroborate both our main findings and the identification of managerial skill transmission as the primary mechanism behind the promotion effects.

By identifying workplace social learning as a pathway for managerial skill formation, our study makes a novel contribution to the literature on human capital development. Much of what we know about building managerial ability comes from research on innate traits (Bertrand and Schoar, 2003; Caplin et al., 2023; Conger, 2015; Conger and Kanungo, 1998) or formal training programs (Adhvaryu et al., 2023b; Chioda et al., 2021; Giorcelli, 2023). Our findings shed light on an informal, on-the-job channel for developing leadership capacity – one that operates through everyday professional interactions rather than in classrooms. More broadly, we contribute to the study of peer effects and knowledge spillovers within organizations. Substantial evidence shows that employees can learn from peers in front-line or non-managerial roles - for example, through productivity spillovers (Bandiera et al., 2010; Bramoullé et al., 2020; Cornelissen et al., 2017, 2023; Guryan et al., 2009; Mas and Moretti, 2009). Far less is known, however, about analogous learning processes among managerial employees. This is an important gap, as managerial personnel stand to gain uniquely from absorbing leadership and people-management skills. Our focus on managerial career development addresses this under-explored area. We provide empirical evidence that future managers can be "grown" by working with excellent managers in a real-world setting. In doing so, we highlight a new mechanism of human capital formation: the transmission of managerial human capital through social learning on the job. This insight enriches our understanding of how organizations can cultivate effective leaders, beyond hiring for talent or sending managers to formal training, by leveraging the influence of high-quality leaders within their ranks.

Our study also extends the growing literature on managers' impact on employee outcomes. Previous research demonstrates that high-quality managers enhance employees' productivity, reduce turnover, and improve job satisfaction in the short term (Adhvaryu et al., 2023a; Delfino and Espinosa, 2025; Frederiksen et al., 2020; Friebel et al., 2022; Hoffman and Tadelis, 2021; Lazear et al., 2015).[3] Our unique focus on managerial employees across different seniority levels distinguishes our work from previous studies that focus on non-managerial employees. Moreover, our unique empirical setting with long-term project panel data allows us to examine persistent effects rather than just immediate impacts. Our study complements Minni (2024), who also finds lasting effects of good managers on worker productivity. First, we study managerial personnel with clear paths to top positions, where acquiring managerial skills is crucial for career advancement, rather than salespeople. Second, the mechanisms differ: while the effects stem from talent reallocation in her paper, ours operate through direct human capital transmission from high-performing managers. Third, we show that an output-based value-added approach of manager quality predicts promotion rates. This provides crucial empirical support for Minni (2024)'s definition of manager quality based on subordinates' promotion speeds. Our study also provides quasi-experimental evidence in support of Toledo (2025) structural estimates suggesting of workers' learning on the job being crucial to internal promotions to managerial positions.

Most related is the segment of literature on how managers shape workers' career trajectories. Prior research demonstrates that various managerial characteristics influence subordinates' career outcomes: managers' gender (Haegele, 2024a; Kunze and Miller, 2017), incentive structures (Haegele, 2024b), subjective evaluations (Benson et al., 2024; Frederiksen et al., 2020), and interpersonal interactions (Cullen and Perez-Truglia, 2023) all affect promotion rates. We use a comprehensive summary measure of managerial quality that captures the overall impact of manager quality on career progression, rather than focusing on specific skills. Supporting this approach, our survey evidence reveals that the transmitted managerial competencies span multiple dimensions: respondents predominantly identify leadership skills (decisiveness, adaptability, problem-solving) and team management skills (motivation, coordination) as the primary transmitted competencies, along with relationship management and operational capabilities. Moreover, our project-based setting provides a unique opportunity to study managerial skill transmission while addressing potential confounding factors. The regular and exogenous team reorganization in our setting not only creates variation in manager exposure but

[3] Hoffman and Stanton (2024), Benson and Shaw (2024) and Roberts and Shaw (2022) provide comprehensive reviews of research on manager importance, influential traits, and impact channels.

also minimizes concerns about talent hoarding—a practice where managers intentionally retain high-performing subordinates to boost their own performance (Haegele, 2024b).

The remainder of this paper proceeds as follows. Section 2 describes our empirical setting and data. Section 3 presents a theoretical framework that guides our empirical strategy. Section 4 reports our main findings. Section 5 examines the transmission of managerial skills as the primary mechanism. Section 6 demonstrates the robustness of our results to alternative measures of manager quality. Section 7 concludes.

2 Context

Firm background Our data come from a large construction firm based in Shandong Province, China. The company operates nationwide throughout China. The firm maintains a clear division of labor: the head office manages business operations, including project bidding and client contract negotiations, while the affiliated project teams execute and manage the construction work (see Figure A1).

Our study focuses on these project teams, where each construction project is managed by a single managerial team. Unlike outsourced construction workers from labor service companies, the project team members are formal employees of the firm's project management department. These employees are responsible for arranging project schedules, managing construction workers, and conducting on-site supervision. Their compensation structure includes a significant end-of-project bonus that is directly tied to the project's realized profit. This profit-sharing mechanism creates strong incentives for team members to maximize project profitability.

Project teams serve as managerial units representing the company. They comprise an average of 13.7 workers, ranging from 2 to 244 members. This translates to 13 million RMB (equivalent to 1.9 million USD[4]) in contract price per employee (see Panel A of Table 1).

[4]The exchange rate used for conversion is 6.8, which is the average rate during our data period from 2003 to 2021.

Table 1: Summary for projects

	Obs	Mean	SD	Min	Max
Panel A: Project scale					
Contract price (10,000 RMB)	1,388	23704	44160	35	444272
Number of employees	1,385	13.72	11.88	2	244
Contract price per employee (10,000 RMB)	1,383	1300	1771	8.75	25028
Time range (months)	1,377	16.23	9.95	0.83	61.83
Panel B: Team composition					
Hierarchy 5: Project manager	1,392	0.99	0.11	0	2
Hierarchy 4: Project specialist	1,392	0.14	0.45	0	5
Hierarchy 3: Department manager	1,392	2.36	1.34	0	13
Hierarchy 2: Supervisor	1,392	2.42	2.32	0	19
Hierarchy 1: Foreman	1,392	6.07	6.95	0	101

Notes: **Table 1 presents summary statistics of projects.** Observations are restricted to 1392 projects that appear in main regressions of Table 5. Panel A shows the project scale, which is measured by contract price and number of team members. Panel B shows the number of employees in each hierarchy within a team. *"Hierarchy 5"* is the highest hierarchy and *"Hierarchy 1"* is the lowest hierarchy.

2.1 Data

Our dataset contains detailed administrative records of 1,442 construction projects, with starting dates ranging from 2003 to 2021. Project characteristics are observable before project initiation.[5] Of the 1,442 projects, 503 have been completed (see Figure A2). Project outcomes are observable only for completed projects.[6]

In addition to project-level information, we have detailed records of individual team members. For each team, we observe members' names and positions. We also have workers' background information from the HR department, including their date of birth, employment start date, gender, and education level.

Data structure We use this data to construct a worker-level panel with projects as the time dimension. For each unique worker, we define "project order" according to the sequence of projects they have worked on. In this panel structure, worker ID serves as

[5]Pre-determined characteristics include contract prices, team size, target profit rate, total team cash deposits, bonus rate, and the within-team distribution of cash deposits.

[6]Post-completion data include revenue, profit, excess profit, and team bonus or penalty amounts. Among the 436 projects receiving team bonuses, bonus distribution data are available for 310 projects. The firm lacks complete bonus distribution records for the remaining projects.

the 'panel' variable and project order as the 'time' variable (see Table A1 for an illustration). Figure A3 shows the distribution of projects per individual. The original data contains 17,033 worker records representing 7,012 unique workers. Of these workers, 3,277 (46.7%) appear in only one project. These workers are excluded from our analysis because we study promotion patterns across multiple projects, resulting in a smaller sample.

Our regression sample contains 8,569 worker records, comprising 2,284 unique workers across 1,392 distinct projects. Of these workers, 2,240 (approximately 98%) can be matched with background information from the HR department.[7]

2.2 Promotions

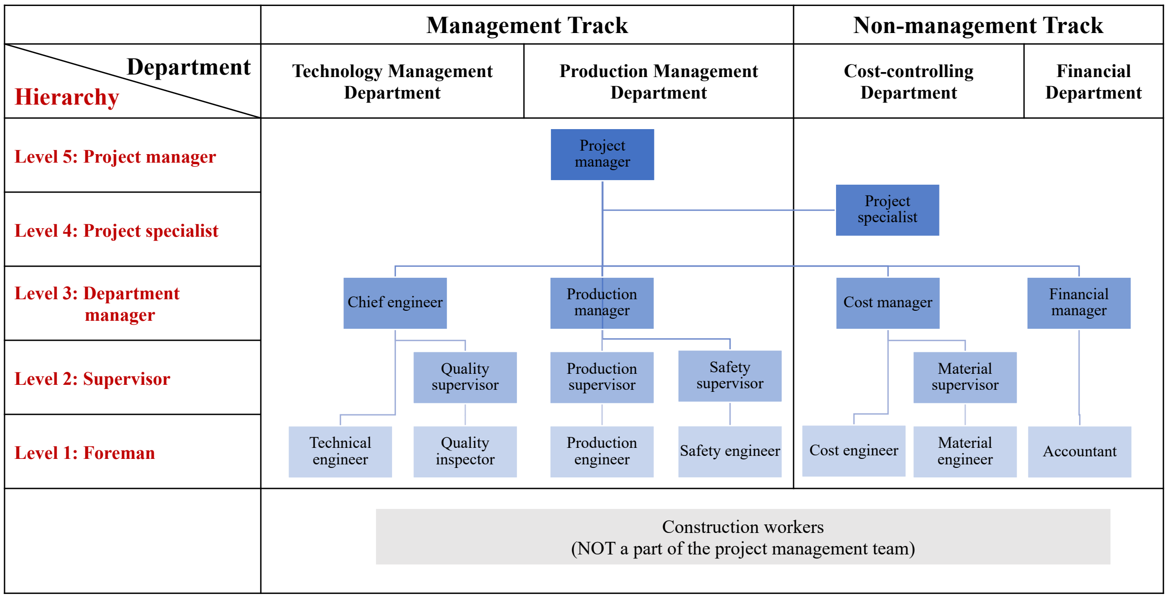
Team composition Positions in teams can be divided into *management* track and *non-management* track (see Figure 1). The *management* track consists of workers in the *production management* department and *technology management* department. The *non-management* track consists of workers in the *cost-controlling* department and *financial* department. Workers typically advance within their respective tracks.

A typical team has a three-level hierarchical structure. The lowest managerial position is *Foreman*. While they don't perform manual construction work, they directly supervise construction workers who are typically outsourced to labor service companies. The number of *Foremen* depends on project size. On average, a project has 6.1 *Foremen*, with a maximum of 101 (see Panel B of Table 1). The highest managerial position is *Project Manager*, with one manager per team responsible for overall project management. The middle level consists of *Department Managers*, who lead different departments and manage department-specific operations. Typically, each department has one *Department Manager*.

Larger projects may include additional positions between these three levels. Between *Project Manager* and *Department Manager* is the *Project Specialist* position. For particularly large or important projects, specialists are assigned to address emerging problems and monitor overall project schedules. Between *Department Manager* and *Foreman* is the *Supervisor* position. Compared to *Department Managers*, supervisors directly oversee *Foremen*

[7] The human resource department collected employee information annually in 2010, 2011, and from 2015 to 2022. Consequently, background information is missing for workers not present in any of these years.

Figure 1: Project team structure



Notes: **Figure 1 shows the structure of a typical project management team.** Positions in teams are divided into four departments and five hierarchy levels. The *production management* department manages construction workers and ensures a safe environment for the work site. The *technology management* department takes charge of construction technology and ensures project quality standards are met. The *cost-controlling* department controls overall cost and increases profitability. Finally, the *financial* department deals with accounting. The *production management* and *technology management* departments belong to *management track* as their responsibilities relate to the general management of the construction process. The *cost-controlling* and *financial* departments belong to the *non-management track* as their responsibilities relate to specialized financial and procurement skills. Subordinate to these management teams are a large number of construction workers who are not included in this study. Not all projects have all positions.

and handle detailed departmental operations.

In our main analyses, we define a 5-layer hierarchy, though our results remain robust when using a 4-layer hierarchy to define promotions.

When a project concludes and a new one begins, workers may be assigned to a higher-level position than in their previous project. Career progression patterns are shown in Figures A4 and A5.

Promotion patterns Table 2 presents workers' promotion patterns. For each record, we compare a worker's hierarchical position in their current project with that of their previous project. The lower triangle represents "promotion," with an average promotion

Table 2: Promotion patterns

		Hierarchy in the current project						
		1	**2**	**3**	**4**	**5**	Total	Promotion rate
Hierarchy in the previous project	**5**					756	870	-
	4				39	40	111	36.0%
	3			1,405	49	349	1,973	20.2%
	2		1,211	389	14	71	1,895	25.0%
	1	2,301	817	549	6	47	3,720	38.1%
	Total	2,580	2,143	2,441	142	1,263	8,569	27.2%

Notes: **Table 2 shows the hierarchy transition matrix from project to project.** The sample is restricted to our main regression sample in Table 5. For each record, we compare a worker's hierarchy in the current project with that in the previous project. *Hierarchy 5* (Project manager) is the highest hierarchy and *Hierarchy 1* (Foreman) is the lowest hierarchy. The lower triangle displays promotions. The average promotion rate is 27.2%.

rate of 27.2%. Promotion probability decreases as workers advance up the hierarchy, except for positions at Hierarchy 4. As a robustness check, we combine Hierarchies 4 and 5 into a single level.

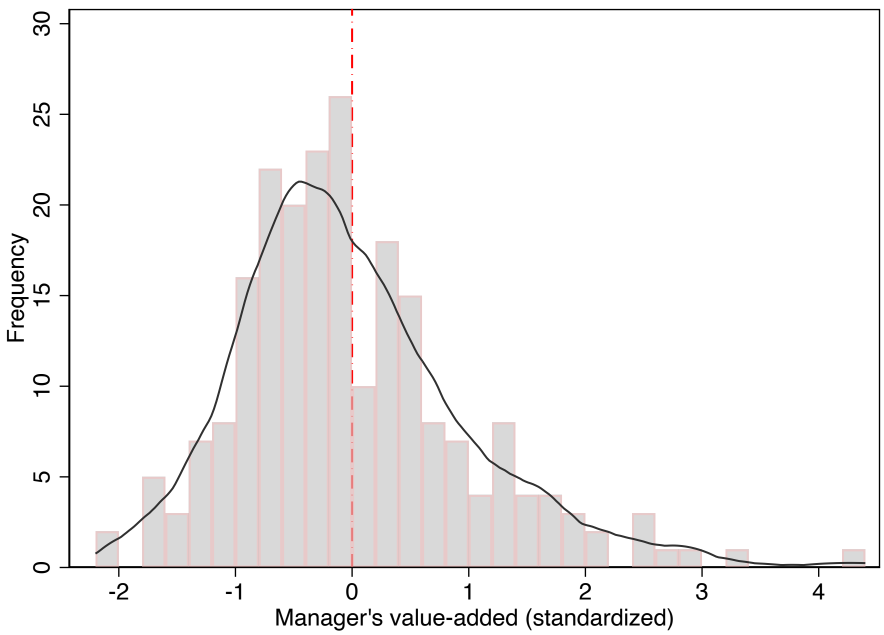
2.3 Defining top managers

To assess manager quality, we estimate a value-added model using two different project outcomes. We regress project outcomes against predetermined project characteristics and individual fixed effects:

$$Y_{ik} = \gamma \cdot X_k + \delta_i + \epsilon_{ik} \tag{1}$$

Y_{ik} is the outcome measure of project k of individual i. We examine two project outcomes. The first is excess profit—the amount of actual profit that exceeds the target profit. The second is the total bonus (negative value indicates punishment). X_k represents predetermined project characteristics, including scale (contract price), team size (number of team members), branch firm fixed effects, and starting year fixed effects. δ_i denotes a set of individual fixed effects, representing individuals' value-added to the project. We exclude employees with only one project to ensure these fixed effects are properly identified.

Figure 2: Manager value added



Notes: **Figure 2 shows the distribution of managers' value added.** Value added is estimated as described in Section 2.3. The vertical line indicates the 60^{th} percentile threshold we use to define top managers.

We define top managers as follows. First, we obtain δ_i^{EP} based on excess profit and δ_i^{TB} based on the total bonus. Second, we standardize these measures (to have mean 0 and standard deviation 1). Third, for each individual, we calculate their value added as the sum of the two standardized measures. To calculate managers' value added, we repeat the second and third steps only for those who have served as project managers for at least one project.

Figure 2 shows the distribution of managers' value added. Among the 222 managers for whom we can obtain value-added measures, we classify the top 40 percent (89 managers) as high-quality managers. We choose a discrete definition of manager quality for three reasons. First, qualitative interviews with workers and managers suggest there is an important, qualitative difference between "great" and merely "good" managers. Second, there is a nonlinear effect of lagged manager value added on workers' promotion probability (see Figure G1). Third, defining a discrete measure of manager quality helps us avoid econometric complications that arise with continuous treatments in two-way fixed effect specifications (De Chaisemartin and d'Haultfoeuille, 2023).

Table 3: Manager characteristics

	Top Managers		Non-top Managers		
	Mean	Obs	Mean	Obs	Δ
Panel A: Project histories					
Number of projects as a manager	3.21	89	3.54	133	-0.33
Rewarded projects	1.73	89	1.98	133	-0.25
Punished projects	0.07	89	0.26	133	-0.19***
Avg team size	15.78	89	13.19	133	2.59**
Avg contract price (10,000 RMB)	31095	89	18746	133	12349***
Avg profit (10,000 RMB)	4627	89	1703	133	2924***
Avg profit rate (%)	19.62	89	15.44	133	4.18***
Excess profit per project (10,000 RMB)	2922	89	839	133	2083***
Bonus per project (10,000 RMB)	401	89	168	133	233***
Panel B: Individual characteristics					
Male	1	84	1	130	0
Education					
Primary school	0.01	84	0.01	130	0
High school	0.18	84	0.25	130	-0.07
Technical college	0.30	84	0.30	130	0
College	0.51	84	0.44	130	0.07
Age					
Beginning of the panel	29.68	84	31.17	130	-1.49
End of the panel	39.43	84	40.67	130	-1.24
Experience					
Beginning of the panel	6.94	84	9.28	130	-2.34**
End of the panel	16.69	84	18.75	130	-2.06*

Notes: **Table 3 describes top managers and non-top managers in our sample.** We observe 222 project managers in 503 finished projects with value-added estimation. Top managers are defined as being in the top 40% of managers in terms of value-added, which is estimated as described in Section 2.3. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Comparison between top and non-top managers Table 3 displays summary statistics for managers. Top managers and non-top managers have significantly different project histories, though they share similar individual characteristics. Projects led by top managers are larger in scale. Regarding outcomes, top managers have fewer projects resulting in penalties. Their projects generate higher profits and bonuses. This aligns with our classification criteria—they are designated as top managers based on their superior performance record.

2.4 Matching between managers and workers

Process of assembling teams When a new project is acquired, the head office assigns a manager to the project. Key considerations in manager selection include availability, experience, and willingness to undertake the project. Project managers are ultimately responsible for the overall management of the project. Team members are then jointly selected by the firm and the manager based on skill requirements and worker availability.

The manager's discretion in selecting team members is significantly constrained for several reasons. First, the number of positions at different hierarchy levels is determined by the firm, not the manager. Workers must meet specific skill requirements to be eligible for these positions, limiting the manager's selection to candidates within these narrow criteria. Second, according to firm policy, workers cannot work on two projects simultaneously. At any given time, fewer than 3% of workers are available for new projects, creating a limited pool of potential team members.

While managers retain some discretion in selecting workers within these constraints, their influence on team composition is limited. Consequently, though the assignment of workers and managers is not fully random, it operates within substantial institutional constraints.

Comparison between exposed and non-exposed workers Table 4 displays summary statistics for workers in the regression sample. We define a worker as "exposed" if they have ever been led by a top manager. As workers who remain with the company longer are more likely to be exposed, their observable characteristics differ slightly from non-exposed workers. We observe exposed workers across more projects, and they are older with more years of experience at the panel's end.

Due to changes in workforce composition over time, exposed workers tend to be older when hired, less educated, and more likely to be male. We account for these differences using a difference-in-differences framework with individual fixed effects.

Exposed workers appear in 5.2 projects on average, compared to 4.2 projects for unexposed workers. This difference arises mechanically, as the probability of being led by top managers increases with the number of observed projects. Exposed workers are also older and more experienced than unexposed workers both at the beginning and end of the panel.

Table 4: Workers characteristics

	All workers		Exposed workers		Unexposed workers		
	Mean	Obs	Mean	Obs	Mean	Obs	Δ
Number of projects	4.75	2,284	5.19	2,284	4.20	2,284	0.99***
Male	0.91	2,240	0.89	1248	0.93	992	-0.03***
Education							
Primary school	0.05	2,239	0.05	1247	0.04	992	0.01
High school	0.16	2,239	0.19	1247	0.12	992	0.07***
Technical college	0.25	2,239	0.25	1247	0.24	992	0.01
College	0.55	2,239	0.50	1247	0.60	992	-0.10***
Age							
Beginning of the panel	29.20	2,240	29.49	1248	28.84	992	0.66**
End of the panel	36.01	2,240	37.43	1248	34.23	992	3.20***
Experience							
Beginning of the panel	6.79	2,239	7.17	1247	6.32	992	0.86**
End of the panel	13.59	2,239	15.10	1247	11.70	992	3.39***

Notes: **Table 4 presents worker summary statistics.** The sample is restricted to 2284 individuals who are used in our main regression in Table 5. Missing data is due to incomplete HR records. "Exposed" workers are defined as ever having worked on a project led by a top manager in our sample. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3 Theoretical Framework

We use a simple theoretical framework to motivate our estimation strategy. We assume that promotions are determined by workers' productivity and project-specific factors. A worker i on project p has productivity $a_{i,p}$. The worker is promoted if their productivity on project p exceeds a project-specific productivity threshold $\bar{a}_p$. This threshold $\bar{a}_p$ may vary with the composition of project peers, and other project characteristics such as the availability of positions at different levels.

For simplicity, we assume there are two hierarchical levels and consider a worker starting at the lower level. Equation 2 describes the relationship between promotion probability and worker productivity:

$$P(promotion_{i,p} = 1) = P(a_{i,p} > \bar{a}_p) \tag{2}$$

where $promotion_{i,p}$ is a dummy variable indicating a promotion when joining project p.

We decompose worker productivity $a_{i,p}$ into four components:

$$a_{i,p} = \delta_i + \gamma_t + \beta exposure_{i,p} + \varepsilon_{i,p} \tag{3}$$

Here, $exposure_{i,p}$ is the main variable of interest, a dummy variable indicating whether a worker was exposed to at least one top manager prior to project p. This specification assumes that exposure to top managers has a permanent impact on worker productivity that does not accumulate with additional exposures (we test this assumption empirically in Section 4).

δ_i represents the time-invariant individual productivity of worker i, reflecting factors such as innate ability and education. γ_t represents time-specific components that capture workers' productivity evolving nonparametrically over time, where t indexes the number of consecutive projects within the firm. These γ_t terms capture changes in workers' average productivity throughout their careers. $\varepsilon_{i,p}$ captures idiosyncratic factors affecting worker i's productivity on project p.

Combining the two equations yields an expression that relates exposure to top managers to i's promotion probability:

$$P(promotion_{i,p} = 1) = P(\delta_i + \gamma_t + \beta exposure_{i,p} + \varepsilon_{i,p} - \bar{a}_p > 0) \tag{4}$$

This equation relates promotion probability to individual-, time-, and project-specific factors, as well as past exposure to top managers. The key parameter of interest is β, which captures the relationship between exposure to top managers and the likelihood of promotion. We hypothesize that $\beta > 0$, meaning exposure to top managers influences workers' promotion probability positively through its impact on worker productivity.[8]

3.1 Specification

To estimate Equation 4, we linearly approximate individual i's promotion probability and use a linear regression to estimate the impact of exposure to top managers on promotion rates:

$$P_{itp} = \tilde{\beta} \cdot Exposed_{it} + \tilde{\delta}_i + \tilde{\gamma}_t + \tilde{a}_p + \epsilon_{itp} \tag{5}$$

P_{itp} is a dummy indicating whether worker i is promoted from their $(t-1)^{th}$ project

[8]This setup assumes that the firm perfectly observes $a_{i,p}$ for its promotion decisions. However, if the firm observes an unbiased proxy of productivity $\hat{a}_{i,p} = a_{i,p} + \mu_{i,p}$, an increase in $a_{i,p}$ will still increase i's promotion probability.

into their t^{th} project. We treat this variable as missing for the first observed project of worker i to avoid arbitrary assumptions about promotion into the first project. $Exposed_{it}$ is a dummy indicating whether worker i in their t^{th} project has ever worked with a top manager prior to this project. $Exposed_{it}$ is the main treatment variable of interest, and $\tilde{\beta}$ captures the effect of prior exposure to a top manager on promotions.

This specification includes a range of fixed effects motivated by the model. Worker fixed effects ($\tilde{\delta}_i$) capture workers' idiosyncratic, time-constant productivity levels and other time-invariant individual factors affecting promotion probability. Project order fixed effects ($\tilde{\gamma}_t$) capture systematic variations in productivity over workers' tenure. Together, these fixed effects represent time and individual fixed effects in a classical two-way fixed effect regression model.[9]

Following the theoretical framework, Equation 5 includes project fixed effects ($\tilde{a}_p$) to capture the project-specific promotion threshold. We include these fixed effects to focus on the productivity-enhancing effect of top managers and to account for potential differences in projects where exposed and non-exposed workers are assigned. The coefficient $\tilde{\beta}$ captures the effect of exposure to top managers on promotion relative to peers working on the same project, holding project characteristics constant. This specification is preferred as it isolates effects driven by productivity differences rather than potential impacts on project selection. Our results remain robust without project fixed effects, as shown in subsequent analyses.

Difference-in-differences identification Under which conditions is the OLS estimator $\hat{\beta}$ an unbiased estimator of the true parameter $\tilde{\beta}$? An ideal experiment would randomly assign managers and workers to projects to ensure that exposure to top managers is uncorrelated with other factors influencing promotion outcomes. This strict assumption may be violated in our context, as both managers and workers have some influence in choosing projects and team members.

The matching between managers and workers follows a relatively strict process. While project managers are responsible for assembling the project team, they are strongly restricted in their choice of team members for several reasons. First, the firm, not the manager, determines the number of positions at different hierarchy levels. Workers must

[9]The De Chaisemartin and d'Haultfoeuille (2020) difference-in-differences estimator yields similar results.

meet specific criteria regarding experience and formal skill requirements to be eligible for these positions—factors absorbed by project fixed effects in our preferred specification. Additionally, most workers are typically working on other projects, further limiting the pool of eligible workers. These factors limit managers' discretion in team member selection.

Our difference-in-difference specification further relaxes the identification assumption. We only need to assume that assignment is uncorrelated with trends in promotion prospects once we condition on project-order and individual fixed effects. In other words, we assume that exposed and unexposed workers would follow parallel promotion trajectories absent exposure to top managers.[10] This implies that managers and workers may be matched on characteristics affecting the level of promotion probability but cannot be matched on factors correlated with trends in their promotion probability.

We provide empirical support for this assumption by showing that exposed and unexposed workers' promotion rates exhibited no pre-treatment differences (Section 4.1). Section 4.2 demonstrates our results remain robust when controlling for peer and project characteristics from previous projects that might correlate with manager quality. Section 4.3 demonstrates that effects concentrate among early-career workers, about whom managers have less information, thus limiting the scope for endogenous matching. Finally, we strengthen our findings in Section 4.4 by using the exogenous worker-project-level exposure probability to instrument workers' actual exposure status.

4 Main Results

Using our preferred specification, we find that exposure to top managers has a large and robust positive effect on workers' career trajectories. Prior exposure to at least one top manager increases the average promotion rate by 12.8 percentage points relative to workers on the same project without prior exposure ($p < 0.01$; column 1, Table 5). This effect

[10] Table 4 compares the observable characteristics of exposed and unexposed workers. There are mechanical differences between these groups, as workers with longer tenure (i.e., more projects) are mechanically more likely to be exposed to top managers. This relates to exposed workers being older, less likely to be college educated (as educational achievement levels increased in the general population during this period), and, at the beginning of the panel, more experienced. Individual-level differences are absorbed by individual fixed effects in our specification. Moreover, these differences do not predict treatment effects in our sample (Tables F1, F2, and F3). Tenure differences are absorbed by project order fixed effects. Our effects are not driven by individuals who are exposed later in their tenure at our partner firm (Table F4).

Table 5: The effects of top managers on workers' promotion

	Dependent variable: promotion						
	Baseline	Excl. Project FE	Exposure Project	Excl. Always-treated	Year FE	4-layer Hierarchy	C-D Estimator
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Exposed to Top Manager	0.128***	0.101***	0.122***	0.139***	0.123***	0.122***	0.177***
	(0.022)	(0.022)	(0.031)	(0.026)	(0.024)	(0.023)	(0.071)
Outcome mean	0.270	0.272	0.270	0.253	0.270	0.266	–
# Observations	8475	8569	8475	5828	8359	8475	3328
# Projects	1305	1392	1305	1149	1291	1305	–
# Individuals	2275	2284	2275	1568	2259	2275	–
Project order FE	Yes	Yes	Yes	Yes	Yes	Yes	–
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	–
Project FE	Yes	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	Yes	No	No

Notes: **Table 5 shows that exposure to top managers increases promotion rates.** The outcome variable is a dummy indicating a promotion relative to the previous project. *"Exposed to Top Manager"* means whether he has been exposed to a top manager at any time before the current project. The level of observation is individual-project. Column 1 shows results from our preferred specification (Equation 5). Columns 2-6 are variants of column 1. Column 2 excludes project fixed effects; Column 3 adds a dummy indicating the project in which the worker is first exposed to a top manager; Column 4 excludes individuals who are exposed to a top manager in the first project in our sample; Column 5 adds in fixed effects indicating the starting year of project; Column 6 uses a 4-hierarchy to define promotion, merging hierarchy 5 and 4 into one single hierarchy. Column 7 shows the staggered difference-in-differences estimator proposed by De Chaisemartin and d'Haultfoeuille (2020). Standard errors in parentheses are clustered at both individual level and project level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

represents 47% of the sample's average promotion rate of 27%, indicating that exposure to top managers serves as a key driver of promotions.

The exclusion of project fixed effects does not substantially affect the results. The treatment effect remains highly significant but slightly smaller at 10.1 percentage points when omitting project fixed effects ($p < 0.01$; column 2).[11]

We also rule out that the effects are driven by a drop in promotion rates during initial exposure projects where workers first meet a top manager: adding a dummy variable for the exposure project barely changes the results (column 3). Our results remain robust to excluding always-exposed workers for whom we cannot observe pre-trends (column 4) and to including year dummies that control for potentially diverging time trends in

[11] This slight reduction in treatment effects is consistent with the fact that exposed workers end up working on projects with better peers but similar team sizes, potentially resulting in higher thresholds for promotion (Table E1).

promotion and exposure rates (column 5). The results are also robust to collapsing the top two hierarchies to account for numerous projects lacking project specialists (column 6). Additionally, our estimates hold when using the alternative difference-in-differences estimator proposed by De Chaisemartin and d'Haultfoeuille (2023) (column 7). Their estimator addresses the negative weighting of observations that can occur in staggered difference-in-differences designs with heterogeneity in treatment effects estimated using two-way fixed effect regressions. Using their estimator, the treatment effect increases to 17.7 percentage points ($p < 0.01$).[12]

4.1 Parallel trends and dynamic effects

Next, we estimate treatment effects before and after exposure to top managers. The absence of pre-exposure treatment effects would indicate parallel trends in promotion probabilities between exposed and non-exposed workers. Examining post-treatment effect dynamics allows us to assess the persistence of these effects over time. We estimate dynamic treatment effects using the following regression:

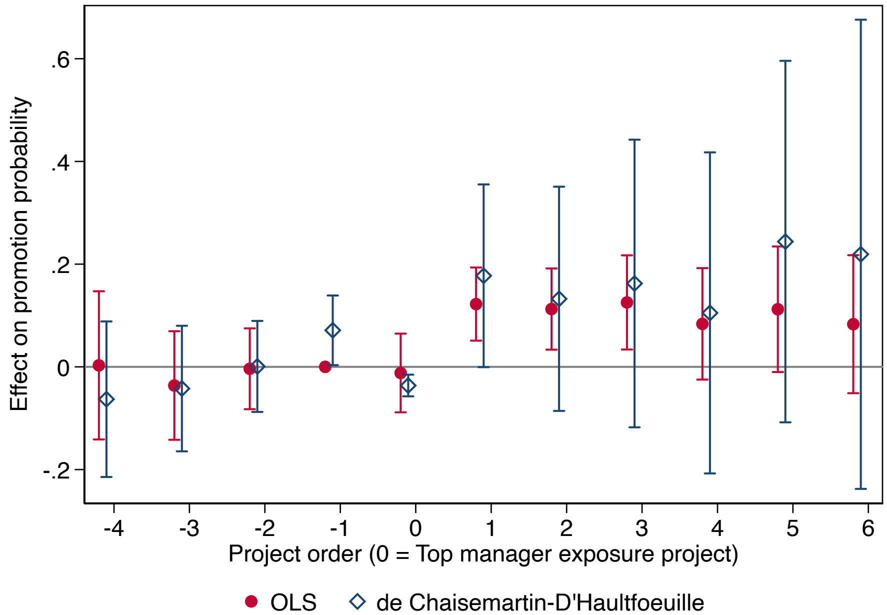
$$P_{itp} = \sum_{k \neq -1} \beta_k \cdot D_{it}^k + \tilde{\delta}_i + \tilde{\gamma}_t + \tilde{a}_p + \epsilon_{itp} \tag{6}$$

where D_{it}^k represents a set of indicators for the relative project order of worker i's t^{th} project compared to their first exposure to a top manager. We set $k = 0$ for the exposure project and normalize the treatment effect at $k = -1$ to zero. All other variables follow the definitions in Equation 5. Figure 3 presents the estimated treatment effects $\hat{\beta}_k$.

Prior to exposure to a top manager, we find no significant differences in promotion rate trends between exposed and non-exposed workers. The point estimates are small and statistically insignificant. A joint test of all pre-treatment coefficients yields $p = 0.977$. The exposure project itself shows no effect on promotions, indicating that working under a top manager does not increase contemporaneous promotion rates. These findings support the key identification assumption of parallel promotion rate trends.

[12] Worker demotions are relatively rare and we find no effect of top managers on workers' demotions (Table E2).

Figure 3: The dynamic effects of top manager exposure



Notes: **Figure 3 shows top manager effects over time.** The red dots represent treatment effect coefficients estimated using OLS following Equation 6, with the exposure project normalized to $k = 0$ and the period $k = -1$ serving as the reference period (β_{-1}=0). The blue dots indicate alternative difference-in-differences estimates following De Chaisemartin and d'Haultfoeuille (2023). We truncate the x-axis at -4 and 6 due to limited observations beyond these points. The red and blue bars denote 95% confidence intervals.

Dynamics Figure 3 demonstrates that the treatment effects are both immediate and persistent. The impact on promotion rates reaches 11.6 percentage points in the first post-exposure project and remains significantly elevated for three subsequent periods. Even 4 and 5 periods after exposure, the treatment effect remains substantial at 7 to 8.8 percentage points, showing only modest decline. We do not display estimates beyond this point as the smaller sample size precludes reliable inference.

The persistence of these effects is not driven by repeated exposure to top managers. Table B1 reveals diminishing returns from multiple exposures: a second exposure increases promotion probability by only 5.4 percentage points, while third and fourth exposures show smaller and statistically insignificant effects. These findings suggest that exposure to a single top manager produces lasting impacts on career trajectories.

Table 6: Disentangle manager, peer, and project effects

	Dependent variable: promotion					
	(1)	(2)	(3)	(4)	(5)	(6)
Exposed to Top Manager	0.126***	0.118***	0.115***	0.084***	0.083***	0.065***
	(0.023)	(0.022)	(0.023)	(0.023)	(0.022)	(0.023)
Lag(Peer VA)	0.008		0.012	0.020		0.023*
	(0.013)		(0.013)	(0.013)		(0.013)
Lag(Project scale)		0.043***	0.042***		0.053***	0.051***
		(0.009)	(0.009)		(0.009)	(0.009)
Outcome mean	0.277	0.270	0.277	0.280	0.272	0.280
# Observations	7853	8466	7848	8003	8560	7998
# Projects	1187	1305	1187	1314	1392	1314
# Individuals	2134	2274	2134	2160	2283	2160
Project order FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Project FE	Yes	Yes	Yes	No	No	No

Notes: **Table 6 shows that our main treatment effects are robust to controlling for past peer and project characteristics.** The dependent variable is a dummy indicating a promotion from the previous to the current project. Columns 1, 3, 4, and 6 control for lagged average value added of peers on the previous project (excluding the manager and the worker himself). Columns 2, 4, 5, and 6 control for the size of the previous project as measured by the standardized contract volume. Columns 1 to 3 show effects with project fixed effects. Columns 4 and 6 show effects without project fixed effects. Standard errors in parentheses are clustered at both individual level and project level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.2 Manager, peer, or project effects?

A potential concern with our empirical strategy is that exposure to top managers might correlate with working on high-profile projects or with high-quality peers. As shown in Table 3, top managers indeed lead larger and more profitable projects. If exposure to top managers merely proxies for project size or peer quality, this could explain our observed treatment effects. To disentangle these effects, we augment our main specification with controls for project size (standardized contract value) and peer quality (average value-added of coworkers) from the last project.[13]

Table 6 demonstrates that top manager effects remain robust when controlling for project and peer quality. In our preferred specification, point estimates show minimal change after including peer and project controls and maintain high statistical significance (columns 1 to 3). When we exclude project fixed effects (columns 4 to 6), the estimated

[13] We estimate peer value-added using the methodology described in Section 2.3.

top manager effects decrease slightly but retain high statistical significance ($p < 0.01$).

Project size consistently shows a significant relationship with future promotions. A 1% increase in previous project size corresponds to a 4 to 5 percentage point increase in promotion probability for the next project ($p < 0.01$). However, this effect appears largely independent of manager effects. Lagged peer quality shows only weak association with promotion rates, with point estimates between 0.8 and 2.3 percentage points, reaching significance at the 10% level in only one of four estimates. These findings suggest that top manager coefficients capture genuine manager effects rather than correlated peer or project effects.

4.3 Effects among early career workers

To further address concerns about endogenous matching between workers and managers on unobserved time-varying characteristics, we focus on early-career workers where such selection is less likely. We restrict our sample in two ways. First, we limit exposed workers to those who encountered top managers while still in entry-level positions. This restriction to early-career workers is motivated by managers having limited information about these typically recent university graduates. Additionally, managers tend to be less selective about lower-ranked workers, who are less critical to project success. Second, we exclude never-exposed individuals who did not begin at the lowest hierarchy level, as these senior hires would not serve as an appropriate control group for early-career workers. These restrictions retain 56% of the individuals from our original sample.

Table C1 confirms the robustness of our results in this restricted sample. Treatment effects are positive, substantially larger, and highly significant across all main specifications. While pre-trend coefficients are more noisily estimated than in the full sample, they show no significant deviations (Figure C1). Point estimates range from 25 to 34 percentage points, indicating that early-career workers benefit disproportionately from top manager exposure.

Table F5 verifies that early-career exposure to top managers yields greater benefits than later exposure. This pattern aligns with a skill transmission mechanism: workers need managerial skills for promotion, but those already promoted likely possess these skills and thus have less to learn from top managers. We examine this and other mechanisms further in Section 5.

4.4 Instrumental variable approach

Next, we use an instrumental variable approach to complement our difference-in-differences identification strategy. We exploit quasi-exogenous variation in the availability of top managers when workers start their next project. This variation arises from projects having staggered start dates and different durations, meaning that only a subset of managers is available for new projects at any given time. Specifically, we instrument exposure status with the average probability of having been exposed to top managers during previous projects. We construct this instrument in three steps.

First, for each worker-project observation, we define counterfactual projects to which the worker could have been assigned instead of their actual project. These counterfactual projects must be in the same branch as the focus project, and their start dates must fall within a 90-day window on either side of the focus project's start date. We further restrict the time frame to begin after the end of the worker's previous project.[14] This restriction reflects that workers' availability for new projects is constrained by the company. Central management ensures workers are quickly assigned to new projects to minimize unproductive idle time.[15]

Second, we calculate the fraction of relevant projects (including both counterfactual projects and the actual project) that were led by top managers. Importantly, we exclude the manager of the worker's previous project, as their top manager status might be correlated with worker quality and promotion prospects. This fraction, $P_{ip}(exposed)$, serves as our proxy for the probability of being assigned a top manager on the focus project. [16]

Finally, we aggregate the exposure probability proxy over time to construct a proxy of the exposure probability on any prior projects, as our main treatment variable is the absorbing state of ever having been exposed to a top manager. For each worker-project observation, we calculate our proxy of the probability of ever having been exposed on

[14] The results are robust to using thresholds between 30 and 120 days (Table G1).

[15] The median duration between a project's end date and the start date of the next project is 109 days.

[16] It is not the actual unconditional probability of being assigned a top manager for two reasons. First, we exclude the worker i's previous manager to avoid correlations with worker characteristics. Second, this measure does not account for newly promoted or joining managers. Thus, a value of $P_{ip}(exposed) = 1$ does not imply a 100% probability of being exposed. Similarly, a value of $P_{ip}(exposed) = 0$ does not imply a 0% probability of being exposed.

prior projects as $P_{itp}(\text{ever exposed}) = 1 - \Pi_{s=1}^{t}\left(1 - P_{isp}(exposed)\right)$. We use this measure to instrument our main explanatory variable $Exposed_{it}$ in Equation 5.

Instrument validity For this measure to be a valid instrument for exposure status, it must affect promotion prospects only through actual exposure and not through other channels. We argue that this condition is likely satisfied because the project-specific exposure probabilities are independent of the two main potential sources of endogeneity. First, these probabilities are independent of potentially endogenous matching between workers, projects, and managers during the considered time window, as they only reflect manager availability. Second, the fraction of available top managers is likely uncorrelated with worker characteristics, as it is determined by the quasi-exogenous timing of project end and start dates, and we exclude the worker's most recent manager. If all individual components meet the validity criterion, the aggregated exposure probability also satisfies the validity condition.

The validity condition would be violated if the skill composition of available managers around a specific project directly affected workers' promotion prospects. Such a violation might occur if the fraction of top managers correlates with the general availability of promotion opportunities in the company. To address potentially correlated time trends, we include year fixed effects in one specification and find that the results are unaffected. Another potential source of endogeneity could arise if workers' retention decisions depend on the quality of the manager pool. For instance, high-quality workers with higher promotion rates might be more likely to stay when facing a high-quality pool of managers, potentially creating a direct positive correlation between promotion rates and exposure probability. In Section 5.4, we examine evidence of differential dropout and its potential implications for the IV results. Through a bounding analysis, we demonstrate that differential dropout likely plays a limited role in driving the observed treatment effect.

Results Table 7 presents the results of the instrumental variable regressions. The first-stage regressions show strong relationships across all specifications. In our preferred specification, a one percentage point increase in the instrument increases the probability of actual exposure by 0.88 percentage points (column 1). This is highly statistically

Table 7: Instrumental variable regressions

	Exposed to top managers (1)	Promotion (2)	Exposed to top managers (3)	Promotion (4)	Exposed to top managers (5)	Promotion (6)
Cumulative exposure rate	0.888***		0.860***		0.887***	
	(0.031)		(0.028)		(0.029)	
Exposed to top managers		0.093*		0.167***		0.090*
		(0.049)		(0.050)		(0.049)
Outcome mean	0.492	0.270	0.492	0.272	0.492	0.270
# Observations	8,475	8,475	8,569	8,569	8,359	8,359
Project Order FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Project FE	Yes	Yes	No	No	Yes	Yes
Year FE	No	No	No	No	Yes	Yes

Notes: **Table 7 confirm the effects of exposure to top managers on promotion rates using instrumental variable estimation.** We instrument exposure to top managers with the fraction of projects led by a top manager in 90-day window around the start of a given project. Columns 1,3 and 5 show the results of first stage regression of exposure to top managers on the fraction of projects led by a top manager in the relevant time window. Columns 2,4 and 6 show the instrumental variable regression results. Columns 1 and 2 show results with project fixed effects. Columns 3 and 4 show results without project fixed effects. Columns 5 and 6 further add in fixed effects indicating the starting year of project. Standard errors in parentheses are clustered at individual and project level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

significant ($se = 0.3 percentagepoints$), thus alleviating concerns about weak instruments. Other specifications show similarly strong first-stage relationships (columns 3 and 5).

The estimated effect of exposure to top managers broadly aligns with our difference-in-differences results. Our preferred specification estimates that exposure increases promotion probability by 9.3 percentage points ($p < 0.01$, column 2), slightly lower than the difference-in-differences estimate of 12.8 percentage points. This increases to 16.7 percentage points when project fixed effects are excluded ($p < 0.01$, column 4), somewhat bigger than the corresponding difference-in-differences estimate of 10.1 percentage points. Finally, Controlling for year fixed effects hardly affects the coefficient estimate (column 6), suggesting that time trends in the availability of top managers do not confound our results. Using instrumental variable estimation in the sample of early career workers defined in Section 4.3 also yields estimates that are broadly comparable to the difference-in-differences results (Table C3).

4.5 Employee perceptions of treatment effects

Next, we compare the estimated effects with employee perceptions. We conducted a survey of project managers and team members in the second half of 2024. Details of the survey design and sampling approach are described in Appendix Section H. The sample includes 1,488 current employees, of whom 178 are past or current project managers. Table H1 presents summary statistics for the survey respondents.

We measure employees' perceptions of how exposure to top managers affects foremen by asking them to estimate promotion probabilities for two hypothetical workers on their next project: one randomly exposed to a top manager and one not exposed. We focus on foremen to reduce respondents' cognitive load of averaging across hierarchies and because this provides our most credible difference-in-differences result. Figure H1 shows that the median respondent predicts a 20 percentage point impact from being assigned a top manager (mean: 18.6 percentage points). Only 23.5% of respondents predict zero or negative impact.

Employees' estimates are somewhat lower than our estimated 30 percentage point impact on foremen (column 1, Table C1). One potential explanation for this discrepancy is that the difference-in-differences estimator aggregates across multiple follow-up projects. The impact on promotions for just the next project is 25 percentage points (column 2, Table C2), which is substantially closer to the median employee belief.

We then inform respondents about our estimated treatment effect and ask whether they find the effect size plausible. Figure H3 shows the distribution of responses. Only 8% of respondents rate the effect size as *implausible* or *extremely implausible*. Among these skeptical respondents, 58% believe the true difference should be higher than our reported result. 72% of respondents consider the effect size *plausible* or *extremely plausible*, while the remaining respondents rate it as *neither plausible nor implausible*. We conclude that our estimated impact of top managers on promotions aligns with employees' beliefs.

5 Transmission of Managerial Skills

In this section, we present evidence indicating that high-quality managers primarily influence subordinates through the transmission of managerial skills. Although we cannot directly observe workers' skills, three lines of evidence support this skill transmission mechanism. First, we demonstrate that treatment effects on promotions concentrate among workers on the management track, where managerial skills are most crucial. We also find that top managers substantially influence promotions to positions requiring managerial skills. Second, using performance-based bonus payments, we show that exposed workers outperform non-exposed workers on subsequent projects. Finally, survey results reveal that both project managers and team members identify skill transmission as the predominant mechanism. These findings collectively support the hypothesis that managerial skill transmission drives the observed effects.

5.1 Effects are concentrated in management track

We examine promotion patterns across workers with varying returns to managerial skills, demonstrating that workers most likely to use these skills in their careers benefit most from top manager exposure.

Our partner firm distinguishes between management and non-management track positions (Figure 1). Management track workers oversee personnel and construction site operations. These responsibilities align with project manager roles, reflected in 95% of project managers originating from this track. Non-management track workers focus on cost-controlling, procurement, and accounting, requiring specialized financial rather than managerial skills.

Track specialization occurs early and remains stable, with only 5.9% of workers switching tracks during their careers. Exposure to top managers does not influence track changes (Table E3). This career track stability suggests differential impacts of top manager exposure on worker trajectories.

Given the distinct skill requirements and track stability, improvements in managerial skills should yield greater benefits for management track workers compared to their non-management counterparts.

Table 8 shows that treatment effects concentrate among management track workers. Examining heterogeneous treatment effects based on workers' track at first exposure to top managers, we find that management track workers experience a 16.1 percentage point increase in promotions ($p < 0.01$). This effect exceeds that of non-management

Table 8: Effects by career track at first exposure

	Dependent variable: promotion					
	Baseline	Excl. Project FE	Exposure Project	Excl. Always-treated	Year FE	4-layer Hierarchy
	(1)	(2)	(3)	(4)	(5)	(6)
Exposed to Top Manager	0.161***	0.139***	0.154***	0.173***	0.155***	0.155***
	(0.026)	(0.025)	(0.033)	(0.030)	(0.026)	(0.025)
Exposed to Top Manager	-0.115***	-0.131***	-0.115***	-0.115***	-0.116***	-0.118***
* Non-management Track	(0.039)	(0.039)	(0.039)	(0.040)	(0.039)	(0.039)
Effect on Non-management	0.0461	0.00758	0.0395	0.0579	0.0399	0.0373
Track	(0.036)	(0.035)	(0.040)	(0.038)	(0.037)	(0.036)
Outcome mean	0.270	0.272	0.270	0.253	0.270	0.266
# Observations	8475	8569	8475	5828	8359	8475
# Projects	1305	1392	1305	1149	1291	1305
# Individuals	2275	2284	2275	1568	2259	2275
Project order FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Project FE	Yes	No	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	Yes	No

Notes: **Table 8 shows that the effects of top managers on workers' promotion rates are driven by workers on the management track.** The outcome variable is a dummy indicating a promotion relative to the previous project. *"Exposed to Top Manager"* means whether he has been exposed to a top manager at any time before the current project. Workers can be exposed to top managers either on a position on the management track or on the non-management track. *"Exposed to Top Manager"* show the estimates of top managers' effects on workers on the management track. The interaction of *"Exposed to Top Manager"* and *"Non-management Track"* shows the estimate of the difference of top manager effects between workers on the non-management track and workers on the management track. Columns 1-6 correspond to columns 1-6 in Table 5. Standard errors in parentheses are clustered at individual and project level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

track workers by 11.5 percentage points ($p < 0.01$), as the latter group shows only an insignificant 4.6 percentage point increase. The difference between groups remains robust across specifications, ranging from 11.5 to 13.1 percentage points (columns 2 to 6, all $p < 0.01$).

These findings indicate that top manager exposure benefits only those workers who can utilize enhanced managerial skills. Workers whose positions require minimal managerial skills, both currently and in the future, show no significant career advancement effects.

Promotion to senior managerial positions Consistent with previous evidence, exposed workers show higher promotion rates to senior managerial positions where managerial skills are crucial (Table B2). Exposure to top managers increases project manager promotion probability by 6.4 percentage points, representing a 114% increase over the baseline promotion rate ($p < 0.01$). The effect on department manager promotions is similar in absolute terms (5.9 percentage points, $p < 0.01$, column 3) but smaller in relative terms (53% of the sample mean). We find no significant effect on promotions to supervisor positions, the second-lowest hierarchy level. These positions combine technical and project management skills, focusing on oversight of specific project components. These patterns indicate that top manager effects are strongest for positions requiring substantial managerial skills.

5.2 Impacts on worker performance

If managerial skills are transmitted, exposed workers should demonstrate increased productivity on subsequent projects. We test this by analyzing the performance-based component of end-of-project bonus allocations.

The individual allocation of end-of-project bonuses depends on two factors, with 70% determined by workers' initial project "deposits". For each project, central management sets the total required deposit amount, while project managers determine individual team members' contribution requirements. These allocations primarily reflect seniority, though individual liquidity constraints may influence decisions. These deposits create dual incentives:[17] First, deposits are forfeited if the project fails to meet its profit target. Second, when projects meet or exceed profit targets, 70% of the end-of-project bonus is distributed proportionally to individual deposit shares.

The remaining 30% of the end-of-project bonus is allocated based on relative project performance, as jointly assessed by the project team with unanimous agreement required. Company policy stipulates that team members should receive equal shares of the performance bonus if all perform equally well. We measure relative performance as the deviation from this equal performance benchmark:

[17] While deposits average 17,900 RMB (2,600 USD) and significantly impact individuals, they represent only 0.2% of average contract volume and do not meaningfully contribute to project finance. See Table D1 for summary statistics.

Table 9: The effect of top managers on workers' performance

	Share bonus		Relative performance	
	(1)	(2)	(3)	(4)
Exposed to Top Manager	0.835*	1.950***	1.865*	1.524*
	(0.505)	(0.561)	(1.076)	(0.815)
Outcome mean	7.601	7.693	0.323	0.345
# Observations	2658	2666	2658	2666
# Projects	292	299	292	299
# Individuals	924	925	924	925
Project order FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Project FE	Yes	No	Yes	No

Notes: **Table 9 shows that top managers positively affect workers' performance.** Columns 1 and 2 show effects on workers' shares of the end-of-project bonus. Columns 3 and 4 show effects on a measure of workers' performance relative to other workers on the same project defined in Equation 7. *"Relative performance"* measures the share from a discretionary 30% of the final project bonus that workers receive in excess of a distribution proportional to their pre-project deposit share. Standard errors in parentheses are clustered at the individual and project level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

$$perf_{i,p} = \left(\frac{indiv\_bonus_{i,p} - 0.7 * deposit\_share_{i,p} * project\_bonus_p}{0.3 * project\_bonus_p} - \frac{1}{N_p}\right) * 100 \qquad (7)$$

In this equation, $indiv\_bonus_{i,p}$ represents the total bonus amount individual i receives on project p, while $project\_bonus_p$ denotes the total bonus amount paid to the project team. The term $deposit\_share_{i,p}$ represents i's share of the project deposit, and N_p describes the number of project team members. The measure $perf_{i,p}$ captures individual i's relative performance on project p in terms of percentage point deviations from an equal distribution of the performance-related bonus. Positive values indicate a higher share of the performance-related bonus relative to other team members, with each point representing a one percentage point deviation above the equal distribution benchmark.

Our dataset contains individual deposits and bonus payments for 925 individuals across 299 projects.[18] The main promotion effects remain robust in this bonus data subsample (Table D2). Figure D1 displays the distribution of this performance measure.

[18]Data is unavailable for other projects due to ongoing projects (926), unpaid bonuses (54), or incomplete firm records (113).

Table 9 demonstrates that top manager exposure increases workers' bonus payments. The total bonus share increases by 0.84 percentage points from a 7.6 percentage point mean ($p < 0.1$, column 1). The relative performance measure shows a 1.87 percentage point increase for exposed workers ($p < 0.1$, column 3), indicating they receive a bonus share that exceeds the equitable distribution by this margin. Results remain qualitatively similar when excluding project fixed effects (columns 2 and 4).

Management track workers drive this performance increase. Table D3, column 3 shows that management track workers receive a 2.08 percentage point larger share of performance-related bonuses ($p < 0.1$), compared to a 1.2 percentage point increase for non-management track workers. Without project fixed effects, this difference increases to 2.15 percentage points and becomes significant ($p < 0.1$).

These findings suggest that top manager exposure enhances workers' performance on subsequent projects, consistent with the acquisition of productive management skills during exposure. Together with our previous results, this evidence supports managerial skill transmission as the key mechanism through which top managers influence workers' career trajectories.

5.3 Employee perceptions of mechanisms

Workers and managers also perceive the transmission of managerial skills as the most important factor. In the same survey of firm employees described in Section 4.5, we elicit respondents' perceptions of the underlying mechanisms. Specifically, after presenting our preferred treatment effect estimate to respondents, we ask them to select all relevant mechanisms from a list of plausible mechanisms. We then ask them to rate each selected mechanism's relative importance in explaining the observed treatment effect. Figure H4 shows the percentage of respondents ranking each factor as the most important.

The transmission of managerial skills is perceived to be the most important mechanism by a wide margin. 73% of respondents perceive the transmission of managerial skills as the most or joint most important factor. This is substantially more than any other mechanism. 38% of respondents perceive network effects as the most important mechanism, which we discuss in Section 5.4. 30% of respondents identify the transmission of technical skills as the most important factor, which we discuss in Section 5.4. Other channels only are ranked first 4% of the time.

The perceived importance of managerial skills is even higher among project managers, with 87% selecting it as the (joint) most important mechanism. They also are less likely to rate networks (15%) and technical skills (19%) as most important. The responses of non-managers are close to the average responses, given that only 12% of respondents are or have been project managers. The difference between project managers and lower-ranked employees suggests that non-project managers might have misperceptions about the role of project managers for promotions.

Survey respondents perceive the nature of transmitted skills to be relatively broad. We ask respondents what kinds of managerial skills good project managers transmit to team members if they select the transmission of managerial skills as one potential mechanism. We ask them to select all skills that they think top managers transmit. 94% of manager respondents and 86% of non-manager respondents select at least one of the *leadership skills*, including decisiveness, problem-solving, and the ability to quickly and accurately respond to changes in the external environment (Figure H5). *Team management skills* (92% for managers and 79% for non-managers) and *relationship management skills* (67% for managers and 67% for non-managers) are the second and third most selected categories. Finally, 70% of managers and 60% of non-managers select other skills, such as project planning and team member selection and evaluation, as being skills that are transmitted by top managers. Overall, survey respondents agree that the transmitted managerial skills cover a wide range of personnel, project, and relationship management.

5.4 Alternative mechanisms

While our evidence points to the transmission of managerial skills as the key mechanism, there are other potential pathways through which top managers might affect subordinates' promotion rates.

Differential dropout and screening One explanation consistent with our findings is that top managers retain higher-quality workers more effectively than other managers (Fenizia, 2022). These managers might recommend the dismissal of low-performing workers to central management or actively work to retain high-performing employees. Such practices would increase the average quality of exposed workers observed in subsequent projects. While we find evidence of differential retention patterns supporting this theory, these effects explain only a small portion of our main results.

To assess retention effects, we examine how top manager exposure influences subsequent worker retention. We analyze this using a binary indicator for whether a project was a worker's final observed project, conditional on project completion by 2020. We exclude post-2020 worker-project observations due to incomplete retention data for this period.

Table 10 indicates that exposed workers are 5.9 percentage points less likely to work on subsequent projects (column 1, $p < 0.01$).[19] This effect concentrates among workers in the bottom 75% of the value-added distribution, whose retention rate decreases by 8.4 percentage points (column 2, $p < 0.01$). Workers in the top quartile show no significant change in attrition (column 2, beta= 1.3 percentage points, $p = 0.64$).[20] The difference between groups is statistically significant ($p = 0.044$). These patterns suggest top managers more effectively identify underperforming workers and facilitate their departure from the firm, though our data cannot distinguish between dismissals and voluntary separations.[21]

To assess whether top manager screening explains promotion effects, we perform a bounding analysis in the spirit of Lee (2009). Specifically, we impute promotion rates for workers who departed after top manager exposure, which would weaken our result. Our conservative approach assumes these workers remained for one additional project without promotion, artificially reducing the treatment group's promotion rate. This worst-case assumption overcompensates for differential post-exposure dropout (Table 10, column 3). Under this approach, estimated treatment effects decrease by 6.3 percentage points to 12 percentage points (Table 10, column 4).[22] While differential post-exposure dropout exists, these results indicate it explains only a small portion of top managers'

[19] We exclude project fixed effects from this estimation as the outcome is unrelated to current project selection.

[20] We use pre-exposure observations to estimate worker value added, as these measures may be endogenous to top manager exposure.

[21] The lower-than-average quality of departing workers suggests they are unlikely to outperform retained peers, though we cannot observe their subsequent careers outside the firm.

[22] Similar patterns emerge when limiting exposed workers to one post-exposure project (Table G2, columns 1 and 2). Assuming workers stay three additional projects without promotion - the mean post-exposure tenure for those remaining at least one project - reduces treatment effects by 13% (Table G2, columns 3 and 4). Balancing dropout rates by assuming one additional project without promotion for some departed exposed workers shows an even smaller 4.7% reduction (Table G2, columns 5 and 6).

Table 10: Differential drop out and bounding analysis

	Effect on drop-out rate		Bounding analysis	
	Dropout (1)	Dropout (2)	Dropout (3)	Promotion (4)
Exposed to Top Manager	0.059***	0.084***	-0.069***	0.120***
	(0.016)	(0.0240)	(0.005)	(0.020)
Exposed to Top Manager * Top 25% Worker		-0.070**		
		(0.035)		
Effect on Top 25% Worker		0.013		
		(0.029)		
Outcome mean	0.107	0.116	0.031	0.248
# Observations	8569	4442	9591	9495
# Projects	1392	1040	1411	1323
# Individuals	2284	1068	2486	2477
Project order FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Project FE	No	No	No	Yes

Notes: **Table 10 shows the effect of exposure to top managers on workers' retention and the degree to which it contributes to our main result.** Columns 1 and 2 show the impact of being exposed to top managers on retention as measured by a dummy indicating that a worker dropped out of the sample after a project. Column 1 shows the average effects of being exposed to top managers. Column 2 shows that the effects differ between workers in the bottom three quartiles and the top quartile of workers based on their value-added. Columns 3 and 4 show the results of a bounding analysis that assumes that all workers who dropped out directly after the exposure project stayed on for one more project without being promoted. Column 3 shows that this reverses the differential dropout effect. Column 4 shows that our main treatment effect on promotion rates is robust to correcting for differential dropout in this way. Standard errors in parentheses are clustered at both individual level and project level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

promotion effects.

Improved networks Improved access to networks may be another potential mechanism: high-quality managers might enhance workers' professional networks, leading to increased promotions (Cullen and Perez-Truglia, 2023). However, two of our findings challenge a pure network-based explanation. First, to explain the heterogeneity by management and non-management track the effects on workers' networks must also be higher for workers on the management track. We have no indication that this would be the case in our context. Second, if promotions stemmed solely from enhanced networks, we would not expect improved worker performance. Yet our data shows significantly better performance among exposed workers. Finally, only 15% of project managers perceive access to networks as the most important mechanism (Figure H4). While these results do not rule out that top managers increase promotions through access to professional networks, they suggest they are unlikely to be the primary driver of the observed effects.

Transmission of technical skills Managers could also affect promotion rates through the transmission of technical skills, including engineering, safety supervision, and cost control skills. Two findings contradict this explanation. First, promotions concentrate among management track workers, where managerial skills carry the highest value. Second, we find no effect on supervisor promotions - an intermediate position requiring both technical and managerial skills (Table B2, columns 5 and 6). If technical skill transmission drove results, we would expect increased promotions to positions demanding these skills.

The evidence indicates that mechanisms beyond managerial skill transmission play a limited role. While these alternative mechanisms may contribute to treatment effects, they appear secondary to managerial skill transmission in explaining how top manager exposure influences promotion rates.

6 Alternative Measures of Manager Quality

In this section, we demonstrate the robustness of our results across different definitions of high-quality managers. We examine the sensitivity of our findings to the binary classification of manager quality, address the role of missing values, and replicate our analysis using non-value-added measures of manager quality.

Functional form assumptions Our main measure of manager quality defines top managers as those with value-added above the 60th percentile. Figure G1 motivates this non-linear definition. Columns 1 and 2 of Table G3 support this approach: a standardized continuous measure of manager quality shows no significant relationship with future promotions. A one standard deviation increase in manager quality is associated with less than a 1 percentage point increase in subordinates' promotion probability on their next project ($p = 0.736$).

However, our results remain both qualitatively and quantitatively robust when using thresholds between the fifth and eighth decile to define top managers (columns 3 to 10, Table G3). The point estimates remain highly significant and similar in magnitude across all thresholds. These findings confirm important non-linearities in the effect of manager quality while demonstrating that our results are not sensitive to the specific threshold choice.

Conceptually, this non-linearity suggests a minimum threshold of managerial ability is required to boost workers' career trajectories. This finding aligns with a model of managerial skill transmission and threshold-based promotions. If the firm promotes workers whose skills exceed a certain threshold, and managers transmit skills reflecting their own ability, we would expect to observe such non-linear effects of manager quality. The effect does not increase when using stricter definitions of top managers (columns 7 to 10, Table G3), suggesting that the promotion threshold is absolute rather than relative to other workers. This interpretation is consistent with the firm's promotion process: central management makes promotion decisions based on annual employee assessments using scored indicators, with objective thresholds determining promotion eligibility.

Missing manager value-added We cannot estimate value-added for a subset of managers ($N = 20$) in our data. These managers have one or zero finished projects, primarily because they joined late in the sample period. The fixed-effects estimation of manager value-added requires at least two observations per manager. In our main specification, we classify these managers as non-top managers. However, our results remain robust when treating their top manager status as missing instead (Table G4). The treatment effect estimates maintain similar magnitude (between 10 and 14 percentage points) and high statistical significance ($p < 0.01$). This robustness check confirms that our results do not depend on assumptions about manager quality for those with few finished projects.

Non-value-added based definitions of manager quality Our results remain robust across several non-value-added definitions of top managers. Table G5 presents our main results using five different proxies for high manager quality. In columns 1 and 2, we define top managers as those who have led projects with exceptionally high contract prices.[23] Similarly, we classify top managers as those who have led projects with extremely high profit (columns 3 and 4) or bonus (columns 5 and 6).

We also define top managers as recipients of personal "excellent manager" awards (columns 7 and 8). These awards, presented regularly by the National Building Industry Association, reflect manager quality as recognized industry-wide. Our final definition identifies top managers as those who have led projects receiving national awards (columns 9 and 10).[24] These national awards typically recognize well-executed large or important projects.

Treatment effect estimates range from 8.8 percentage points to 18.6 percentage points and maintain high statistical significance throughout ($p < 0.01$ for all specifications), consistent with our main specification.

Our results demonstrate robust consistency across diverse measures of management quality. While most of our measures rely on project outcomes, the results remain strong when using personal performance awards as an indicator of manager quality. This consistency across outcome-based and individual recognition measures reinforces that the observed effects stem from manager quality rather than project characteristics.

7 Conclusion

Our results highlight the critical role of high-quality managers in facilitating subordinates' career advancement within managerial teams. We demonstrate that top managers significantly enhance their subordinates' promotion rates by 12.8 percentage points (47% of the sample mean). This effect, we argue, is likely attributable to the transmission of managerial skills—a mechanism that has received limited attention in existing literature. Our findings suggest that firms benefit from these positive human capital spillovers from top managers to subordinates, which is particularly significant given that promoting workers based solely on their performance in non-managerial tasks can lead to sub-

[23] This definition reflects the firm's private information about manager quality, as key projects are typically assigned to high-quality managers due to their importance to the firm. To account for contract price increases over time, we categorize projects by starting years: 2003-2006, 2007-2010, 2011-2013, 2014-2015, and 2016-2021. Large-scale projects are defined as those ranking in the top 10 within each period.

[24] National awards encompass both nationwide and province-wide recognition. Nationwide awards from national architecture and construction associations involve fierce competition, with managers considering them career achievements. Province-wide awards, while less competitive, still indicate significant project quality.

optimal promotion decisions (Benson et al., 2019).

These findings yield important practical implications for organizations. First, when evaluating investments in managerial training, firms should consider the multiplicative effects of manager ability through positive spillovers. The direct returns to managerial ability may underestimate the total organizational benefits of such training. Second, our findings inform the optimal rotation strategies for managers and workers across projects. The diminishing returns to exposure to high-quality managers suggest that firms should consider providing more entry-level workers with opportunities to work under high-quality managers. While such increased rotation may incur costs (e.g., reduced team cohesion), our findings suggest that the substantial benefits of even limited exposure to high-quality managers should be factored into organizational decision-making.

How does the specific context of our study influence its generalizability? We examine project-based teams where managers and subordinates interact intensively on a daily basis, creating abundant opportunities for skill transmission through direct observation, mentoring, and collaborative problem-solving. This high-frequency interaction in professional teams likely amplifies the skill transmission effects we hypothesize. Moreover, our context involves promotion into skilled managerial positions where success depends heavily on leadership capabilities, strategic decision-making, and people management skills—precisely the type of human capital that can be effectively transmitted through close collaboration with high-quality managers. This differs fundamentally from settings involving progression into primarily technical or routine supervisory roles, where managerial skills may play a less central role. Organizations with more limited manager-subordinate interaction or those promoting workers into positions requiring fewer managerial skills might also experience weaker effects. Nevertheless, the core mechanism we propose – the transmission of managerial human capital through sustained professional interaction—likely operates across various organizational contexts where skilled management matters, albeit potentially with varying intensity.

This research opens several avenues for future investigation into the relationship between manager quality and subordinates' career trajectories. Future research examining these relationships across different team structures, interaction patterns, and job skill requirements would help establish the conditions under which manager quality most effectively influences subordinate career progression. Particularly valuable would be research examining whether these effects persist in contexts beyond project-based work environments, especially in settings where managers might have incentives to retain talent (Haegele, 2024b) or where managerial skills may be less central to subordinate career development. Additionally, future research would benefit from direct measurement of managerial human capital spillovers, requiring longitudinal assessment of management skills for both managers and employees, similar to the approach used by (Hoffman and Tadelis, 2021).

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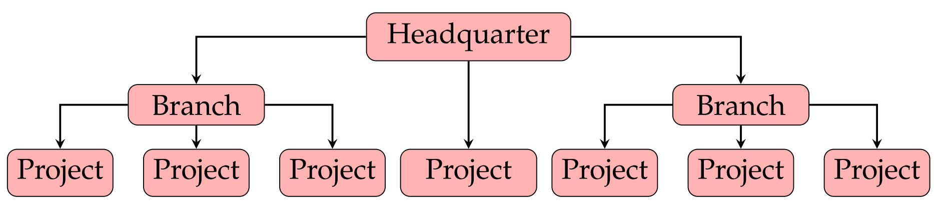
Appendix – For Online Publication

This online supplement contains eight appendices. Appendix A provides supplementary descriptions of our research background and data. Appendix B extends our main results by focusing on different levels of promotion, or multiple exposures to top managers. Appendix C contains analyses that are conducted on a restricted sample of early career workers. Appendix D show summary statistics and results that are related to deposit, bonus and relative performance. Appendix E contains top managers' effects on workers' additional outcomes, including project selection, demotion and transition of career track. We collect various heterogeneous treatment effect results in Appendix F. Appendix G lists robustness tables as mentioned in Section 6. Finally, Appendix H details our survey, including questions and results.

A Descriptions of data

This appendix provides illustrations on background and data. First, Figure A1 shows the organizational structure of the construction firm, emphasizing that our study focuses on these project management teams. Second, Table A1 shows the panel data structure. Third, Figure A2 shows the distribution of starting years of the projects and Figure A3 shows the distribution of the number of projects per individual. Finally, Figure A4 and A5 plots the evolution of hierarchies for individuals.

Figure A1: Firm structure



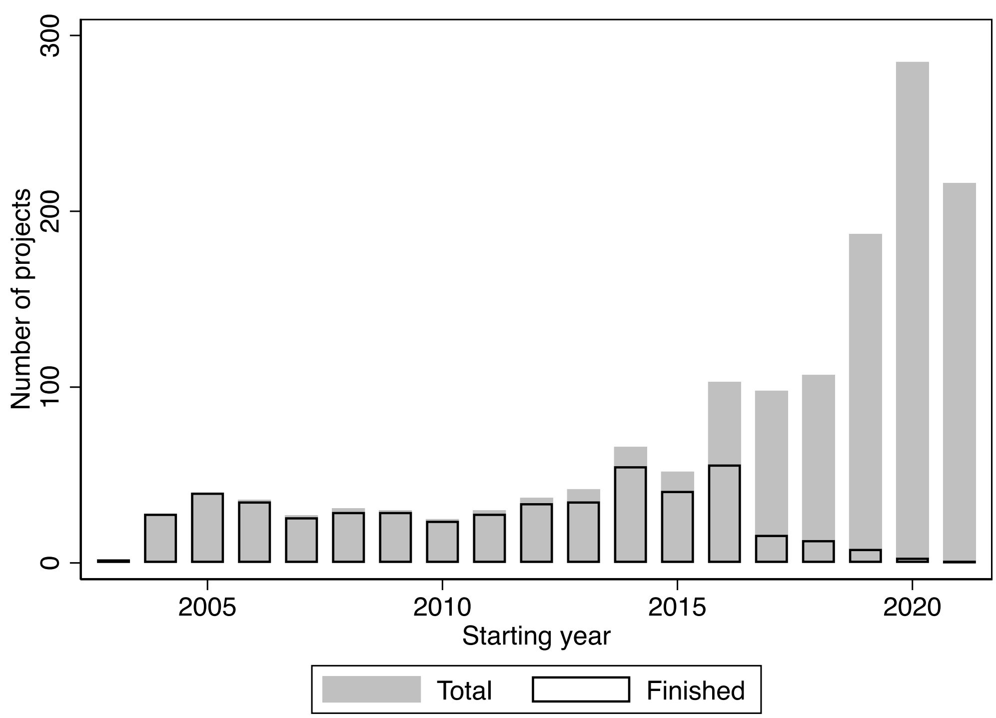
Notes: **Figure A1 illustrates the organizational structure of the construction firm.** There is a clear division of labor within the firm. The head office (of both headquarter and branch) is in charge of business affairs such as bidding for projects and signing contracts with clients. The construction work is undertaken and managed by the affiliated project teams. Our study focuses on these project management teams.

Table A1: Data structure

project ID	team year	worker ID	position	project order
P001	2009	W001	Project manager	1
P001	2009	W002	Production manager	1
P001	2009	W003	Chief engineer	1
P001	2009	W004	Production engineer	1
P001	2009	W005	Accountant	1
P002	2013	W001	Project manager	2
P002	2013	W006	Production manager	1
P002	2013	W007	Chief engineer	1
P002	2013	W004	Production supervisor	2
P002	2013	W008	Production engineer	1
P002	2013	W009	Accountant	1

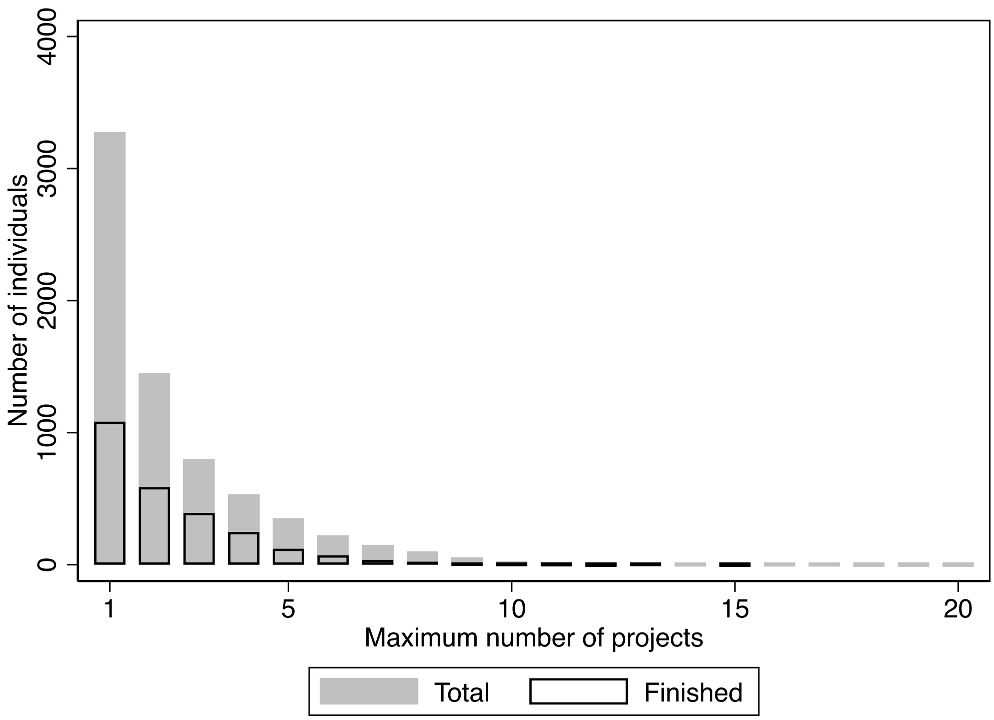
Notes: **Table A1 illustrates the panel data structure.** For each unique worker, we define *"project order"* according to the sequence of projects he has worked on. For example, worker W004 is a production engineer (Hierarchy 1) in his first project P001, and he becomes a production supervisor (Hierarchy 2) in his second project P002. Such occasion constitutes a promotion. In such a panel structure, *worker ID* is the 'panel' variable and *project order* is the 'time' variable.

Figure A2: Starting year of projects



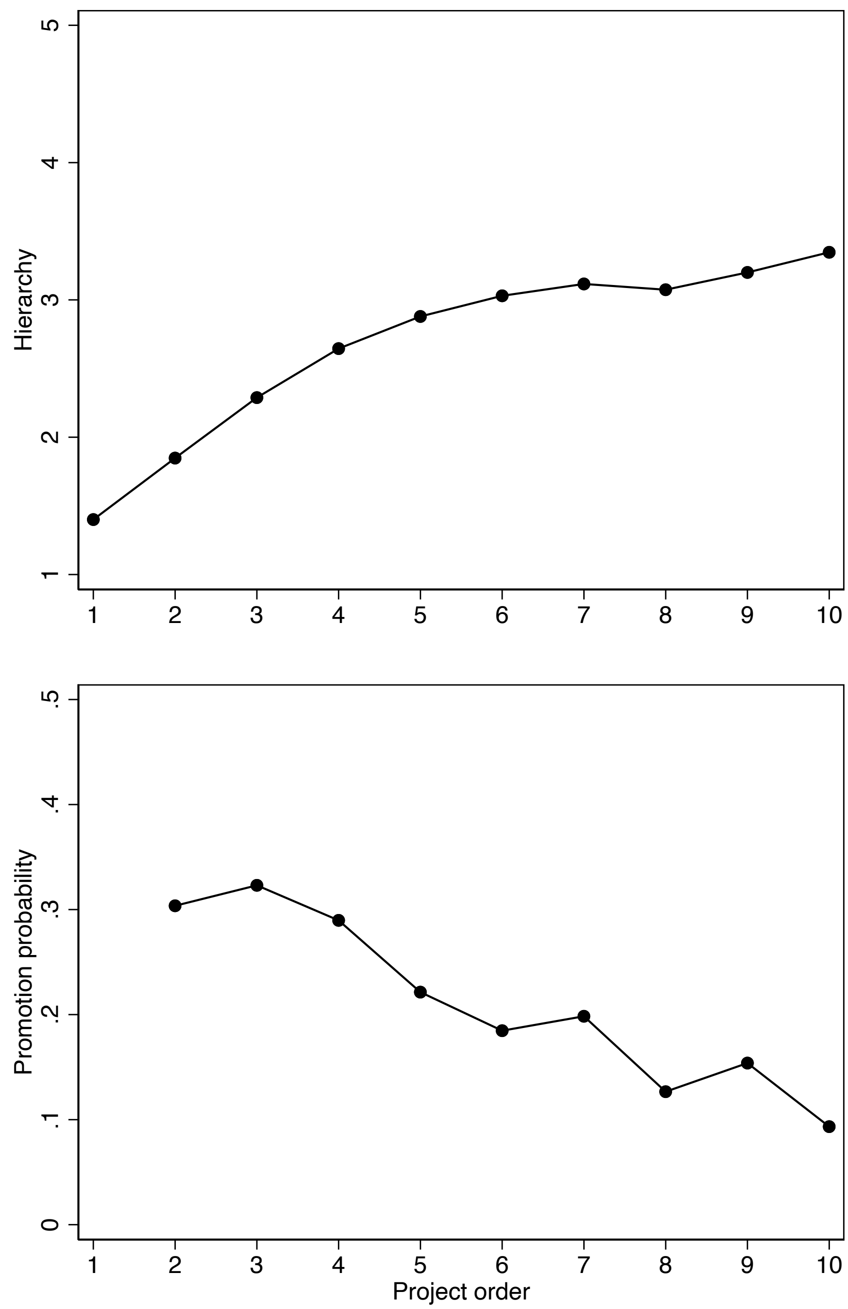
Notes: **Figure A2 shows the distribution of starting years of the projects.** We have access to data on 1422 projects in total. Among them, 503 projects are finished for which we can observe project outcomes.

Figure A3: Distribution of the number of projects each individual has



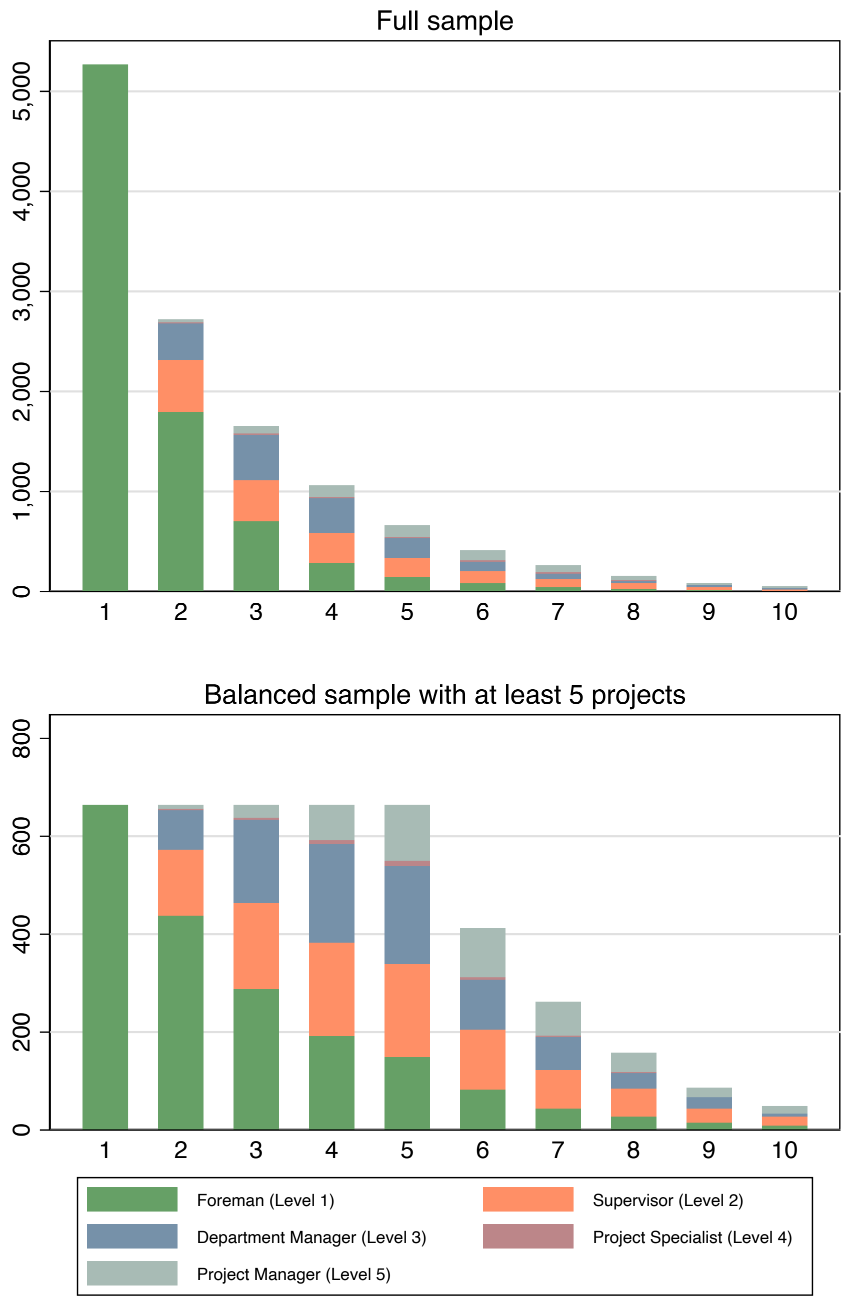
Notes: **Figure A3 shows the distribution of the number of projects each individual has in our data.** In the original data, there are 17,033 records of workers and 7,012 unique workers. Among them, 3,277 (46.7%) appear in only one project. They have to be dropped since we are studying promotion from project to project. 1,451 (20.7%) appear in only two projects. By controlling for individual fixed effects, they are also dropped from our main analysis. These result in a smaller sample of 2,284 individuals (see column 2 of Table 5).

Figure A4: Project order and career progressions



Notes: **Figure A4 shows the average career trajectories in our data.** The upper sub-figure plots the relationship between project order and hierarchy. X-axis is project order and Y-axis is the average hierarchy. The bottom sub-figure shows the average promotion probability instead.

Figure A5: Career progressions of individuals who start as a Foreman



Notes: **Figure A5 plots the evolution of hierarchies for individuals who start as a *Foreman* in our data.** X-axis is project order and Y-axis is frequency of different hierarchies. In the upper sub-figure, we include all the individuals who start as a *Foreman* in our sample. In the bottom sub-figure, we only keep those with at least 5 projects.

B Extensions to main results

This appendix shows two extensions to our main results. First, Table B1 distinguishes between one and multiple exposures and shows dynamic effects of multiple exposures. Second, instead of viewing all types of promotion as a whole, Table B2 focuses on the effects of top managers on workers' promotion to different levels.

Table B1: Multiple exposures

	Dependent variable: promotion					
	Baseline	Excl. Project FE	Exposure Project	Excl. Always-treated	Year FE	4-layer Hierarchy
	(1)	(2)	(3)	(4)	(5)	(6)
Exposed to 1st Top Manager	0.142***	0.105***	0.130***	0.137***	0.138***	0.135***
	(0.024)	(0.022)	(0.032)	(0.028)	(0.024)	(0.024)
Exposed to 2nd Top Manager	0.054**	0.055**	0.055**	0.079**	0.055**	0.045*
	(0.025)	(0.023)	(0.025)	(0.039)	(0.026)	(0.025)
Exposed to 3rd Top Manager	0.040	0.032	0.040	-0.022	0.046	0.040
	(0.036)	(0.031)	(0.036)	(0.058)	(0.037)	(0.037)
Exposed to 4th Top Manager	0.028	0.037	0.0290	-0.000	0.040	0.032
	(0.047)	(0.035)	(0.047)	(0.094)	(0.047)	(0.046)
Outcome mean	0.270	0.272	0.270	0.253	0.270	0.266
# Observations	8475	8569	8475	5828	8359	8475
# Projects	1305	1392	1305	1149	1291	1305
# Individuals	2275	2284	2275	1568	2259	2275
Project order FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Project FE	Yes	No	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	Yes	No

Notes: **Table B1 shows dynamic effects of multiple exposures.** Columns 1-6 corresponds to columns 1-6 in Table 5. *"Exposed to 1st Top Manager"* estimates the effects of first exposures. *"Exposed to 2nd Top Manager"* estimates the effects of second exposures. *"Exposed to 3rd Top Manager"* estimates the effects of third exposures. *"Exposed to 4th Top Manager"* estimates the effects of all the exposures after third exposures. Standard errors in parentheses are clustered at both individual level and project level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B2: Promotion to top positions

Dependent variable: Promotion to	Project manager		Department manager		Supervisor	
	(1)	(2)	(3)	(4)	(5)	(6)
Exposed to Top Manager	0.064***	0.061***	0.059***	0.049***	-0.005	-0.009
	(0.012)	(0.010)	(0.019)	(0.016)	(0.017)	(0.016)
Outcome mean	0.056	0.059	0.110	0.109	0.096	0.095
# Observations	8475	8569	8475	8569	8475	8569
# Projects	1305	1392	1305	1392	1305	1392
# Individuals	2275	2284	2275	2284	2275	2284
Project order FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Project FE	Yes	No	Yes	No	Yes	No

Notes: **Table B2 focuses on the effects of top managers on workers' promotion to top levels in the team.** *"Project manager"* indicates promotion to Project Managers (Hierarchy 5). *"Department manager"* indicates promotion to Department Managers (Hierarchy 3). *"Supervisor"* indicates promotion to Supervisors (Hierarchy 2). Standard errors in parentheses are clustered at both individual level and project level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C Restricted sample of early career workers

This appendix contains analyses that are conducted on a restricted sample of early career workers. Managers generally having less information about these workers as they are typically fresh university graduates. We construct this restricted sample in two ways: First, we drop never exposed individuals who did not start their career at the lowest hierarchy level. Second, we restrict the sample of treated workers to a sample of workers exposed to top managers while still being in an entry level position. These restrictions leave us wit 56% of individuals in our original sample.

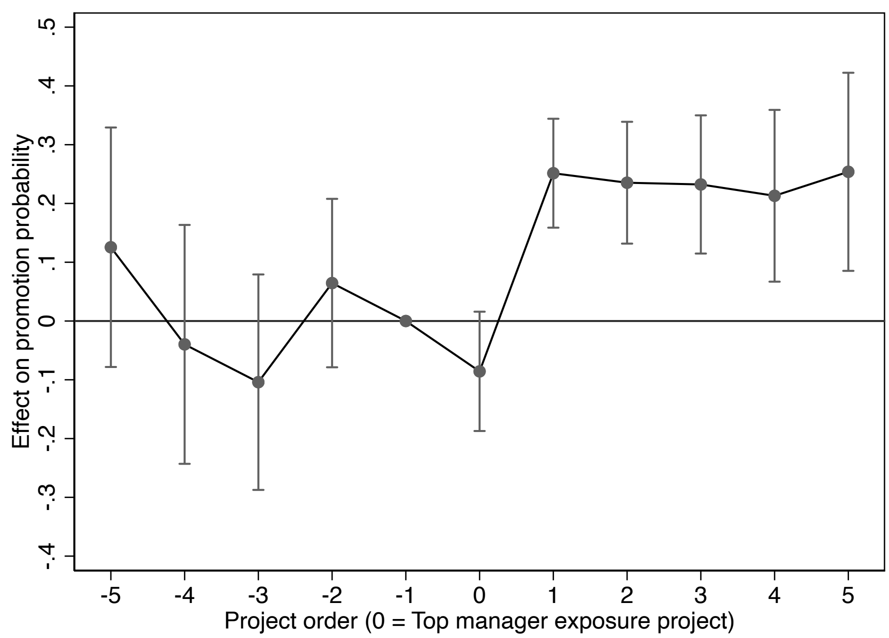
Table C1 reproduces Table 5 using this restricted sample. Table C2 shows and Figure C1 plots coefficients of dynamic effects estimated by Equation 6. Table C3 presents IV regressions on this restricted sample. These results show that our main results are robust to restricting our sample to workers for whom there is little selection.

Table C1: Effects on a sub-sample of early career workers

	Dependent variable: promotion						
	Baseline	Excl. Project FE	Exposure Project	Excl. Always-treated	Year FE	4-layer Hierarchy	C-D Estimator
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Exposed to Top Manager	0.304***	0.342***	0.246***	0.297***	0.297***	0.310***	0.430***
	(0.032)	(0.025)	(0.044)	(0.042)	(0.031)	(0.032)	(0.125)
Outcome mean	0.284	0.289	0.284	0.249	0.285	0.282	–
# Observations	4622	4896	4622	2466	4553	4622	1597
# Projects	998	1245	998	667	985	998	–
# Individuals	1277	1308	1277	696	1267	1277	–
Project order FE	Yes	Yes	Yes	Yes	Yes	Yes	–
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	–
Project FE	Yes	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	Yes	No	No

Notes: **Table C1 shows the effects of top managers using a sub-sample of early career workers.** Columns 1-7 correspond to columns 1-7 in Table 5. Standard errors in parentheses are clustered at both individual level and project level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure C1: Event plot using a restricted sample of early career workers



Notes: **Figure C1 plots coefficients of dynamic effects estimated by Equation 6, using a restricted sample of early career workers.** We normalize the exposure project to have $ProjectOrder_{ij} = 0$ and treat the treatment effect in $ProjectOrder_{ij} = -1$ as the reference point.

Table C2: Event study

	Dependent variable: promotion	
	Full sample	Foremen sample
	(1)	(2)
Project(-5)	-0.053	0.125
	(0.095)	(0.104)
Project(-4)	0.005	-0.040
	(0.074)	(0.104)
Project(-3)	-0.032	-0.104
	(0.054)	(0.093)
Project(-2)	-0.001	0.065
	(0.040)	(0.073)
Exposed to Top Manager	-0.014	-0.086*
	(0.039)	(0.052)
Project(1)	0.116***	0.251***
	(0.036)	(0.047)
Project(2)	0.103***	0.235***
	(0.040)	(0.053)
Project(3)	0.114**	0.232***
	(0.045)	(0.060)
Project(4)	0.070	0.213***
	(0.054)	(0.074)
Project(5)	0.088	0.254***
	(0.060)	(0.086)
Outcome mean	0.270	0.284
# Observations	8475	4622
# Projects	1305	998
# Individuals	2275	1277
Project order FE	Yes	Yes
Individual FE	Yes	Yes
Project FE	Yes	Yes

Notes: **Table C2 shows coefficients of dynamic effects estimated by Equation 6.** Column 1 shows results on full sample and column 2 shows results on a restricted sample of early career workers described in Section 4.3. Standard errors in parentheses are clustered at both individual level and project level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C3: Instrumental variable regressions on a sub-sample of early career workers

	Exposed to top managers (1)	Promotion (2)	Exposed to top managers (3)	Promotion (4)	Exposed to top managers (5)	Promotion (6)
Cumulative exposure rate	0.841***		0.780***		0.840***	
	(0.039)		(0.037)		(0.038)	
Exposed to top managers		0.252***		0.406***		0.239***
		(0.073)		(0.065)		(0.073)
Outcome mean	0.571	0.284	0.569	0.289	0.571	0.285
# Observations	4,622	4,622	4,896	4,896	4,553	4,553
Project Order FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Project FE	Yes	Yes	No	No	Yes	Yes
Year FE	No	No	No	No	Yes	Yes

Notes: **Table C3 confirm the effects of exposure to top managers on promotion rates using instrumental variable estimation.** We focus on the subsample of early career workers described in Section 4.3. Standard errors in parentheses are clustered at individual and project level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D Deposit and bonus

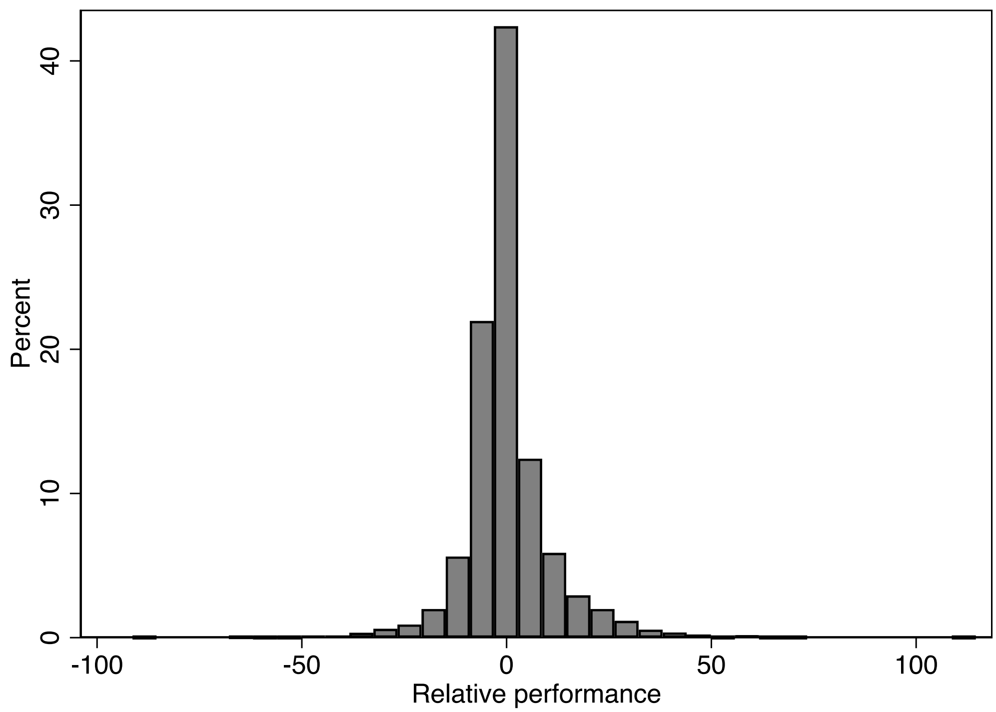
This appendix provides summary and results that are related to deposit, bonus and relative performance. Table D1 presents summary statistics of deposit and bonus. Figure D1 shows the distribution of relative performance. Table D2 shows our main effects on promotions are robust to using only the sub-sample with observed bonus data. Table D3 shows heterogeneous effects by career track of top managers on workers' deposit, bonus and relative performance.

Table D1: Summary for deposit and bonus

	Obs	Mean	SD	Min	Max
Panel A: Cash deposit					
Team deposit (10,000 RMB)	299	21.89	20.75	0.50	150
Amount of individual deposit (10,000 RMB)	2,666	1.79	2.38	0	49.50
Share of individual deposit (%)	2,666	8.38	9.26	0	100
Panel B: Bonus payment					
Team bonus (10,000 RMB)	299	284.60	310.80	0.08	1815
Amount of individual bonus (10,000 RMB)	2,666	2.05	3.29	0	54.93
Share of individual bonus (%)	2,666	7.69	9.04	0	100
Relative performance bonus	2,666	0.35	11.30	-64.88	68.52

Notes: **Table D1 presents summary statistics of deposit and bonus.** Observations are restricted to regression sample in Table 9.

Figure D1: Distribution of relative performance



Notes: **Figure D1 shows the distribution of relative performance.** This variable captures relative performance in terms of percentage points deviations from an equal distribution of the performance-related bonus. Positive values imply a higher performance-related bonus share than other team members on the same project. See Section 5.2 for more details.

Table D2: Main effects on a sub-sample with observed bonus data

	Dependent variable: promotion					
	Baseline	Excl. Project FE	Exposure Project	Excl. Always-treated	Year FE	4-layer Hierarchy
	(1)	(2)	(3)	(4)	(5)	(6)
Exposed to Top Manager	0.205***	0.102**	0.128*	0.181***	0.209***	0.201***
	(0.0479)	(0.0506)	(0.0668)	(0.0630)	(0.0466)	(0.0674)
Outcome mean	0.258	0.262	0.258	0.242	0.257	0.264
# Observations	1643	1674	1643	1218	1623	924
# Projects	263	286	263	233	260	197
# Individuals	573	583	573	427	566	350
Project order FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Project FE	Yes	No	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	Yes	No

Notes: **Table D2 reproduces Table 5, showing our main effects on promotions are robust to using only the sub-sample with observed bonus data.** Standard errors in parentheses are clustered at both individual level and project level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D3: Heterogeneous effects on deposit and bonus

	Full sample		Restricted sample with bonus data					
Dependent variable:	Share deposit		Share deposit		Share bonus		Relative performance	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposed to Top Manager	1.651***	2.029***	0.716	2.021***	1.124**	2.460***	2.076*	2.103**
	(0.369)	(0.506)	(0.509)	(0.670)	(0.542)	(0.661)	(1.127)	(0.853)
Exposed to Top Manager	-2.412***	-2.850***	-1.352**	-1.689**	-1.210**	-1.896**	-0.880	-2.150*
* Non-management Track	(0.462)	(0.607)	(0.583)	(0.760)	(0.604)	(0.756)	(1.313)	(1.280)
Effect on Non-management	-0.761*	-0.821*	-0.635	0.332	-0.086	0.564	1.196	-0.047
Track	(0.396)	(0.468)	(0.611)	(0.626)	(0.635)	(0.631)	(1.466)	(1.253)
Outcome mean	10.20	10.43	8.281	8.377	7.601	7.693	0.323	0.345
# Observations	8461	8555	2658	2666	2658	2666	2658	2666
# Projects	1304	1391	292	299	292	299	292	299
# Individuals	2273	2282	924	925	924	925	924	925
Project order FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Project FE	Yes	No	Yes	No	Yes	No	Yes	No

Notes: **Table D3 reproduces Table 9, additionally showing heterogeneous effects by career track.** Standard errors in parentheses are clustered at both individual level and project level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

E Additional outcomes

This appendix shows top managers' effects on workers' additional outcomes. Table E1 shows the effects of top managers on workers' subsequent project characteristics. Table E2 focuses on *"demotion"* rather than *"promotion"*. Table E3 shows the null effect of top managers on workers' career track.

Table E1: The effects of top managers on project selection

Dependent variable:	Led by top manager (1)	Manager quality (2)	Peer quality (3)	Contract price (4)	Team size (5)
Exposed to Top Manager	0.501***	0.594***	0.133***	0.571***	0.039
	(0.028)	(0.059)	(0.037)	(0.089)	(0.036)
Top Manager Project	0.964***	1.409***	0.489***	0.801***	0.181***
	(0.013)	(0.083)	(0.053)	(0.097)	(0.042)
Outcome mean	0.369	-0.008	-0.052	9.672	2.784
# Observations	7544	7544	12193	13723	13697
# Projects	756	756	1225	1438	1435
# Individuals	2066	2066	3321	3727	3723
Project order FE	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
Project FE	No	No	No	No	No

Notes: **Table E1 shows the effects of top managers on workers' subsequent project characteristics.** *"Top Manager Project"* is a dummy indicating whether he is exposed to a top manager in this exact project. *"Led by top manager"* is a dummy indicating whether the project manager is a top manager or not. *"Manager quality"* refers to manager value added. *"Peer quality"* refers to average peer value added (excluding project manager and the worker himself). *"Contract price"* and *"Team size"* refer to ln(contract size) and ln(team size) respectively. Standard errors in parentheses are clustered at both individual level and project level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table E2: The effects of top managers on workers' demotion

	Dependent variable: demotion					
	Baseline	Excl. Project FE	Exposure Project	Excl. Always-treated	Year FE	4-layer Hierarchy
	(1)	(2)	(3)	(4)	(5)	(6)
Exposed to Top Manager	-0.012	-0.011	0.028	-0.008	-0.008	-0.002
	(0.016)	(0.013)	(0.021)	(0.021)	(0.016)	(0.016)
Outcome mean	0.062	0.061	0.062	0.064	0.062	0.058
# Observations	8475	8569	8475	5828	8359	8475
# Projects	1305	1392	1305	1149	1291	1305
# Individuals	2275	2284	2275	1568	2259	2275
Project order FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Project FE	Yes	No	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	Yes	No

Notes: **Table E2 reproduces Table 5 , changing the outcome variable from *"promotion"* to *"demotion"*.** Standard errors in parentheses are clustered at both individual level and project level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table E3: The effects of top managers on transition of track

Dependent variable:	From non-management to management track		From management to non-management track	
	(1)	(2)	(3)	(4)
Exposed to Top Manager	0.005	0.002	0.005	0.010
	(0.008)	(0.008)	(0.008)	(0.008)
Outcome mean	0.018	0.019	0.025	0.025
# Observations	8475	8569	8475	8569
# Projects	1305	1392	1305	1392
# Individuals	2275	2284	2275	2284
Project order FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Project FE	Yes	No	Yes	No

Notes: **Table E3 shows the effects of top managers on workers' career track.** *"From non-management to management track"* is a dummy indicating whether the worker is in a position of non-management track in his previous project, and he is in a position of management track in his current project. Standard errors in parentheses are clustered at both individual level and project level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

F Heterogeneous treatment effects

This appendix collects five heterogeneous treatment effect results. We find the positive effects of top managers concentrate on workers that have lower educational attainment (Table F1), that are younger (Table F2) and less experienced (Table F3). They are also exposed to top managers at their first or second project (Table F4) and in entry-level positions (Table F5).

Table F1: Heterogeneous effects by education level

	Dependent variable: promotion					
	Baseline (1)	Excl. Project FE (2)	Exposure Project (3)	Excl. Always-treated (4)	Year FE (5)	4-layer Hierarchy (6)
Exposed to Top Manager	0.117***	0.107***	0.113***	0.132***	0.113***	0.118***
	(0.027)	(0.025)	(0.033)	(0.031)	(0.027)	(0.027)
Exposed to Top Manager	0.027	-0.018	0.026	0.016	0.024	0.011
* College degree	(0.038)	(0.037)	(0.038)	(0.040)	(0.038)	(0.038)
Outcome mean	0.272	0.273	0.272	0.255	0.271	0.267
# Observations	8372	8462	8372	5754	8258	8372
# Projects	1303	1388	1303	1148	1289	1303
# Individuals	2233	2239	2233	1538	2218	2233
Project order FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Project FE	Yes	No	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	Yes	No

Notes: **Table F1 shows heterogeneous effects of top managers on workers with different educational background.** *"Exposed to Top Manager"* estimates the effects of top managers on workers without a college degree. The interaction of *"Exposed to Top Manager"* and *"College degree"* estimates the effects on workers with a college degree compared with other workers. Columns 1-6 correspond to columns 1-6 in Table 5. Standard errors in parentheses are clustered at both individual level and project level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table F2: Heterogeneous effects by age at the beginning of the panel

	Dependent variable: promotion					
	Baseline	Excl. Project FE	Exposure Project	Excl. Always-treated	Year FE	4-layer Hierarchy
	(1)	(2)	(3)	(4)	(5)	(6)
Exposed to Top Manager	0.153***	0.097***	0.148***	0.151***	0.141***	0.146***
	(0.033)	(0.032)	(0.040)	(0.037)	(0.033)	(0.032)
Exposed to Top Manager * Above median age	-0.044	0.004	-0.044	-0.022	-0.034	-0.042
	(0.038)	(0.036)	(0.039)	(0.041)	(0.038)	(0.038)
Outcome mean	0.271	0.273	0.271	0.255	0.271	0.267
# Observations	8376	8466	8376	5754	8262	8376
# Projects	1303	1388	1303	1148	1289	1303
# Individuals	2234	2240	2234	1538	2219	2234
Project order FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Project FE	Yes	No	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	Yes	No

Notes: **Table F2 shows heterogeneous effects of top managers on workers by their age at the beginning of the panel.** We split workers into two groups based on the median age (which is 26 years old) when they enter our panel data. *"Exposed to Top Manager"* estimates the effects of top managers on workers entering the panel at 26 years old or younger. The interaction of *"Exposed to Top Manager"* and *"Above median age"* estimates the effects on workers entering the panel above 26 years old compared with other workers. Columns 1-6 correspond to columns 1-6 in Table 5. Standard errors in parentheses are clustered at both individual level and project level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table F3: Heterogeneous effects by working experience at the beginning of the panel

	Dependent variable: promotion					
	Baseline	Excl. Project FE	Exposure Project	Excl. Always-treated	Year FE	4-layer Hierarchy
	(1)	(2)	(3)	(4)	(5)	(6)
Exposed to Top Manager	0.148***	0.087***	0.143***	0.145***	0.138***	0.140***
	(0.032)	(0.032)	(0.040)	(0.037)	(0.032)	(0.032)
Exposed to Top Manager	-0.038	0.024	-0.037	-0.012	-0.029	-0.033
* Above median experience	(0.039)	(0.035)	(0.039)	(0.040)	(0.038)	(0.039)
Outcome mean	0.272	0.273	0.272	0.255	0.271	0.267
# Observations	8372	8462	8372	5754	8258	8372
# Projects	1303	1388	1303	1148	1289	1303
# Individuals	2233	2239	2233	1538	2218	2233
Project order FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Project FE	Yes	No	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	Yes	No

Notes: **Table F3 shows heterogeneous effects of top managers on workers by their working experience at the beginning of the panel.** We split workers into two groups based on the median experience (which is 3 years) when they enter our panel data. *"Exposed to Top Manager"* estimates the effects of top managers on workers entering the panel with at most 3 years of working experience. The interaction of *"Exposed to Top Manager"* and *"Above median experience"* estimates the effects on workers entering the panel with more than 3 years of experience, compared with other workers. Columns 1-6 correspond to columns 1-6 in Table 5. Standard errors in parentheses are clustered at both individual level and project level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table F4: Heterogeneous effects by project order at first exposure

	Dependent variable: promotion					
	Baseline	Excl. Project FE	Exposure Project	Excl. Always-treated	Year FE	4-layer Hierarchy
	(1)	(2)	(3)	(4)	(5)	(6)
Exposed to Top Manager	0.124***	0.0641*	0.111**	0.147***	0.123***	0.117***
	(0.037)	(0.034)	(0.052)	(0.043)	(0.036)	(0.037)
Exposed to Top Manager	0.008	0.062	0.014	-0.011	0.000	0.007
* Third project or later	(0.042)	(0.039)	(0.047)	(0.046)	(0.042)	(0.042)
Outcome mean	0.270	0.272	0.270	0.253	0.270	0.266
# Observations	8475	8569	8475	5828	8359	8475
# Projects	1305	1392	1305	1149	1291	1305
# Individuals	2275	2284	2275	1568	2259	2275
Project order FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Project FE	Yes	No	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	Yes	No

Notes: **Table F4 shows heterogeneous effects of top managers on workers by project order at first exposure.** *"Exposed to Top Manager"* estimates the effects of top managers on workers who are exposed to top managers at their first or second project. The interaction of *"Exposed to Top Manager"* and *"Above median age"* estimates the effects on workers who are exposed to top managers at their third project or later, compared with workers in the previous category. Columns 1-6 correspond to columns 1-6 in Table 5. Standard errors in parentheses are clustered at both individual level and project level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table F5: Heterogeneous effects by hierarchy at first exposure

	Dependent variable: promotion					
	Baseline	Excl. Project FE	Exposure Project	Excl. Always-treated	Year FE	4-layer Hierarchy
	(1)	(2)	(3)	(4)	(5)	(6)
Exposed to Top Manager	-0.038	-0.073***	-0.032	-0.028	-0.043	-0.050*
	(0.030)	(0.028)	(0.036)	(0.033)	(0.030)	(0.029)
Exposed to Top Manager	0.395***	0.424***	0.395***	0.400***	0.391***	0.406***
* Foreman	(0.036)	(0.032)	(0.036)	(0.038)	(0.036)	(0.035)
Effect on Foreman	0.356***	0.352***	0.364***	0.372***	0.372***	0.357***
	(0.028)	(0.022)	(0.037)	(0.033)	(0.033)	(0.028)
Outcome mean	0.270	0.272	0.270	0.253	0.270	0.266
# Observations	8475	8569	8475	5828	8359	8475
# Projects	1305	1392	1305	1149	1291	1305
# Individuals	2275	2284	2275	1568	2259	2275
Project order FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Project FE	Yes	No	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	Yes	No

Notes: **Table F5 shows heterogeneous treatment effects by a worker's hierarchy at his first exposure to top managers.** Exposed workers are exposed to top managers either in an entry-level (*Foreman*) or higher levels. *"Exposed to Top Manager"* estimates the effects of top managers on workers who are exposed to top managers when they are in higher levels than *Foreman*. The interaction of *"Exposed to Top Manager"* and *"Foreman"* estimates the effects on workers in an entry level compared with higher levels. *"Effect on Foreman"* is the linear combination of the two coefficients. Columns 1-6 correspond to columns 1-6 in Table 5. Standard errors in parentheses are clustered at both individual level and project level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

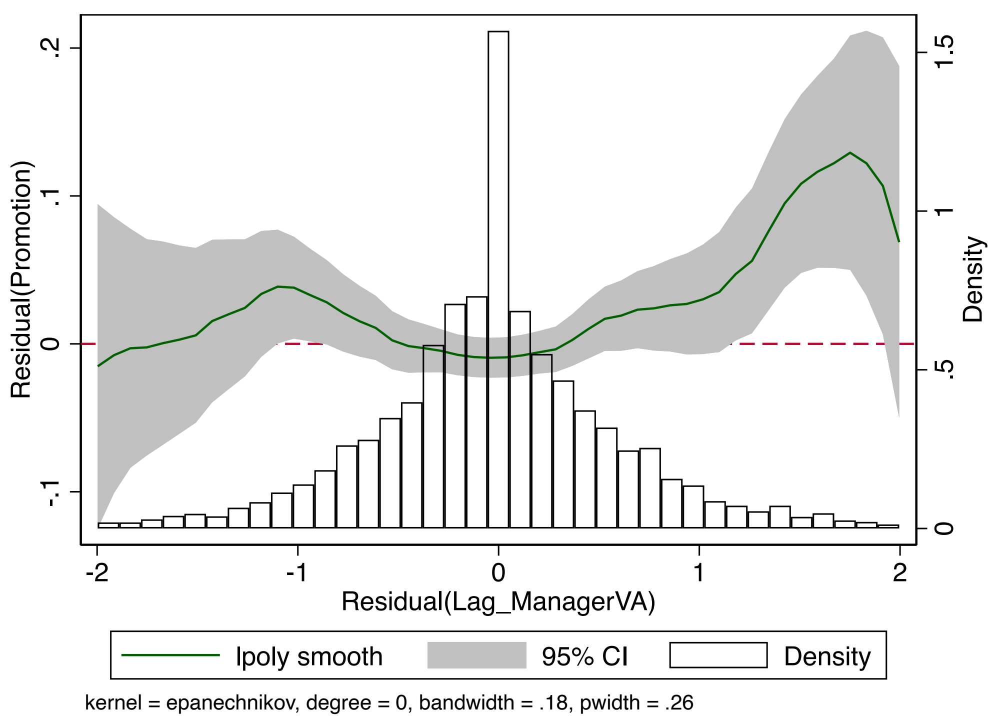
G Robustness checks

This appendix gathers robustness checks. First, we show more information on the instrumental variable in Section 4.4. Table G1 shows the IV results are robust to using thresholds between 30 and 120 days.

Second, Table G2 performs bounding analysis under different assumptions compared with Table 10. This confirms that differential dropout after exposure to top managers, while existent, only explains a relatively small part of the observed effect of top managers on promotions.

Third, we show that our results are robust to a range of different definitions of high-quality managers. Table G3 reproduces main results using a continuous measure of manager quality and alternative thresholds to define top managers. Figure G1 shows nonlinear regression of promotion probability on lagged managers' value added. This motivates the choice of a non-linear definition of top managers. When defining *"Exposed to Top Manager"*, Table G4 treats missing manager value-added in a different way. Table G5 uses alternative definitions of top managers.

Figure G1: Nonlinear effects of managers' quality on subordinates



Notes: **Figure G1 shows nonlinear regression of promotion probability on lagged managers' value added.** First, we regress "promotion" and "lagged managers' value added" on project order fixed effects and individual fixed effects. Second, we draw the residuals and test for the nonlinear correlations. There's a positive but nonlinear effect of lagged managers' value added on promotion probability.

Table G1: Instrumental variable regressions: alternative thresholds

	30-day window		60-day window		120-day window	
	Exposed to top managers	Promotion	Exposed to top managers	Promotion	Exposed to top managers	Promotion
	(1)	(2)	(3)	(4)	(5)	(6)
Cumulative exposure rate	0.850***		0.890***		0.920***	
	(0.022)		(0.025)		(0.034)	
Exposed to top managers		0.063*		0.080*		0.062
		(0.038)		(0.043)		(0.053)
Outcome mean	0.492	0.270	0.492	0.270	0.492	0.270
# Observations	8,475	8,475	8,475	8,475	8,475	8,475
Project Order FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Project FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	No

Notes: **Table G1 shows the IV results are robust to using thresholds between 30 and 120 days.** In Table 7, we instrument exposure to top managers with the fraction of projects led by a top manager in 90-day window around the start of a given project. Here we provide results using IV defined on different time windows. Standard errors in parentheses are clustered at individual and project level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table G2: Bounding analysis under alternative assumptions

	Assumption 1		Assumption 2		Assumption 3	
Dependent variable:	Dropout	Promotion	Dropout	Promotion	Dropout	Promotion
	(1)	(2)	(3)	(4)	(5)	(6)
Exposed to Top Manager	-0.090***	0.130***	-0.055***	0.111***	-0.005	0.122***
	(0.007)	(0.025)	(0.005)	(0.018)	(0.012)	(0.021)
Outcome mean	0.047	0.229	0.025	0.198	0.073	0.262
# Observations	6234	5905	11994	11900	8970	8874
# Projects	1288	1032	1411	1323	1409	1321
# Individuals	2074	1990	2740	2733	2355	2357
Project order FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Project FE	No	Yes	No	Yes	No	Yes

Notes: **Table G2 performs bounding analysis under different assumptions.** Columns 1 and 2 limit the same of exposed workers to one project after exposure. Columns 3 and 4 assume that workers stay an additional 3 projects (the average tenure after exposure for those who stay at least one project) without being promoted. Columns 5 and 6 exactly balance dropout rates by assuming an additional project without promotions for a subset of dropped-out exposed workers. Standard errors in parentheses are clustered at both individual level and project level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table G3: Robustness: continuous measure and alternative thresholds

	Dependent variable: promotion									
	Continuous Measure		Top 50 percentile		Top 40 percentile		Top 30 percentile		Top 20 percentile	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Lag(Manager VA)	0.003	0.009								
	(0.009)	(0.010)								
Exposed to Top Manager			0.101***	0.098***	0.128***	0.101***	0.113***	0.103***	0.104***	0.070***
			(0.023)	(0.022)	(0.022)	(0.022)	(0.024)	(0.023)	(0.030)	(0.025)
Outcome mean	0.268	0.278	0.270	0.272	0.270	0.272	0.270	0.272	0.270	0.272
# Observations	5655	5900	8475	8569	8475	8569	8475	8569	8475	8569
# Projects	918	1106	1305	1392	1305	1392	1305	1392	1305	1392
# Individuals	1581	1640	2275	2284	2275	2284	2275	2284	2275	2284
Project order FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Project FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No

Notes: **Table G3 shows the results of Equation 5 using a continuous measure of manager quality and alternative thresholds to define top managers.** In columns 1 and 2, *"Lag(Manager VA)"* denotes the value added of the project manager in the worker's previous project. Columns 3-10 use a discrete approach to define top managers and show different thresholds. For example, *"Top 20 percentile"* represents defining managers with the top 20 percentile manager value added as top managers. Standard errors in parentheses are clustered at both individual level and project level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table G4: Robustness: dealing with missing manager value-added

	Dependent variable: promotion					
	Baseline	Excl. Project FE	Exposure Project	Excl. Always-treated	Year FE	4-layer Hierarchy
	(1)	(2)	(3)	(4)	(5)	(6)
Exposed to Top Manager	0.119***	0.098***	0.123***	0.144***	0.110***	0.111***
	(0.024)	(0.023)	(0.034)	(0.031)	(0.025)	(0.023)
Outcome mean	0.271	0.276	0.271	0.249	0.270	0.265
# Observations	6532	6764	6532	3885	6433	6532
# Projects	1074	1278	1074	798	1062	1074
# Individuals	1718	1753	1718	1015	1704	1718
Project order FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Project FE	Yes	No	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	Yes	No

Notes: **Table G4 reproduces Table 5, differing only in the way of treating missing manager value-added when defining *"Exposed to Top Manager"*.** Workers could be led by a manager with missing value-added. In such cases, we are not sure whether those are top managers or not. In our main analysis, we treat such cases as non-top managers. In this robustness check, we set them to missing. Standard errors in parentheses are clustered at both individual level and project level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table G5: Robustness: alternative definitions of top managers

	Dependent variable: promotion									
	Large Scale		High Profit		High Bonus		Personal Award		Project Award	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Exposed to Top Manager	0.100***	0.156***	0.140***	0.165***	0.088***	0.115***	0.120***	0.186***	0.106***	0.141***
	(0.029)	(0.027)	(0.027)	(0.025)	(0.026)	(0.025)	(0.027)	(0.026)	(0.027)	(0.025)
Outcome mean	0.270	0.272	0.270	0.272	0.270	0.272	0.270	0.272	0.270	0.272
# Observations	8475	8569	8475	8569	8475	8569	8475	8569	8475	8569
# Projects	1305	1392	1305	1392	1305	1392	1305	1392	1305	1392
# Individuals	2275	2284	2275	2284	2275	2284	2275	2284	2275	2284
Project order FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Project FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No

Notes: **Table G5 shows results using alternative definitions of top managers.** *"Large Scale"* means we define top managers based on whether he has ever led extremely large-scale projects (ranking Top 10 in a given time period). *"High Profit"* and *"High Bonus"* are defined using the same approach based on high-profit and high-bonus projects. *"Personal Award"* means we define top managers based on whether he has ever won an award for "excellent managers". *"Project Award"* means we define top managers based on whether he has ever led projects that won a national award. Standard errors in parentheses are clustered at both individual level and project level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

H Survey

We carried out a survey to current workers in this firm. We obtained IRB from Guanghua School of Management, Peking University (IRB reference code: #2024-41). We collected the responses on 16^{th} and 17^{th} of October, 2024.

After dropping repeated respondents, we have responses of 1488 current employees. Table H1 shows a summary for the respondents. 149 respondents (10%) are currently a project manager. 178 (12%) of them have ever been or are currently a project manager. 1357 (91%) of them can be matched to the HR data provided by the firm. 92% of them are male workers, with an average age of 32 years old and an average tenure of 6.6 years. 74% of them have a college degree.

Table H1: Summary for survey respondents

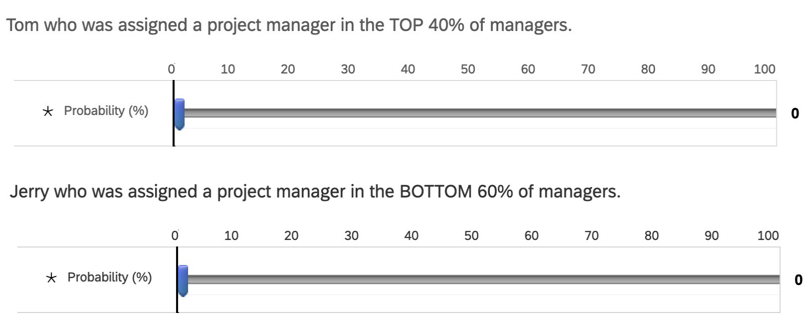
	Obs	Mean	SD	Min	Max
Hierarchy					
Hierarchy 5: Project manager	1,488	0.10	0.30	0	1
Hierarchy 3: Department manager	1,488	0.20	0.40	0	1
Hierarchy 2: Supervisor	1,488	0.10	0.30	0	1
Hierarchy 1: Foreman	1,488	0.60	0.49	0	1
Have ever been a project manager	1,488	0.12	0.33	0	1
Male	1,357	0.92	0.27	0	1
Education					
Primary school	1,357	0.00	0.05	0	1
High school	1,357	0.01	0.07	0	1
Technical college	1,357	0.26	0.44	0	1
College	1,357	0.74	0.44	0	1
Age	1,357	32.08	5.42	22	62
Tenure	1,357	6.59	4.99	2	46

Notes: **Table H1 presents summary statistics for survey respondents.** We have responses of 1488 current employees in total, 1357 (91%) of which can be matched to the HR data provided by the firm.

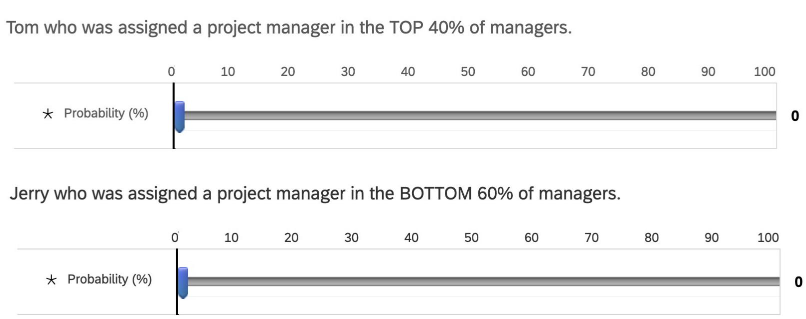
H.1 Prediction of treatment effects

In the first part of the survey, we ask respondents to predict the treatment effects of top managers on their subordinates' promotion probability. The questions are as follows.

> Consider two workers (Tom and Jerry) with the same educational background who enter the firm at the same time.
>
> They are randomly assigned to two very similar projects, as foremen.
>
> - Tom is assigned to an excellent project manager **whose ability ranks in the TOP 40%** of managers in the firm.
>
> - Jerry is assigned to a project manager **whose ability ranks in the BOTTOM 60%** of managers in the firm.
>
> They complete their respective projects and go on to work on their second project.
>
> **Q1.** What do you think? What is the likelihood of that each of the workers will be promoted to a position higher than *Foreman* on their second project?

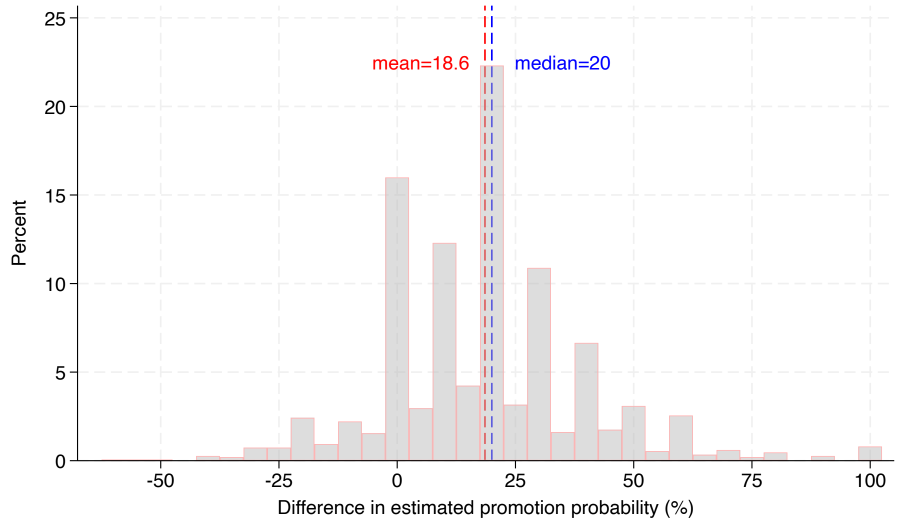


> **Q2.** What do you think? What is the probability they become a *Project Manager* throughout their career at the firm?



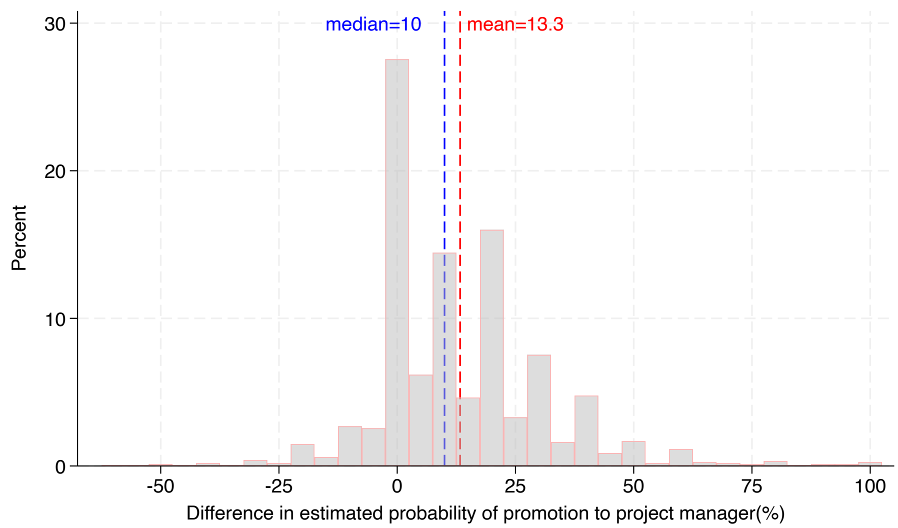
For **Q1** (**Q2**), we calculate the difference in the predicted probability of the two persons and plot the distribution in Figure H1 (H2).

Figure H1: Difference in the estimated promotion probability



Notes: **Figure H1 plots the distribution of answers to Q1 .** We subtract the estimated probability of Jerry (who was assigned to a project manager in the BOTTOM 60% of managers) being promoted from that of Tom (who was assigned to a project manager in the TOP 40% of managers), and plot the distribution of this difference.

Figure H2: Difference in the estimated probability of promotion to project manager



Notes: **Figure H2 plots the distribution of answers to Q2.** We subtract the estimated probability of Jerry (who was assigned to a project manager in the BOTTOM 60% of managers) being promoted to a project manager from that of Tom (who was assigned to a project manager in the TOP 40% of managers), and plot the distribution of this difference.

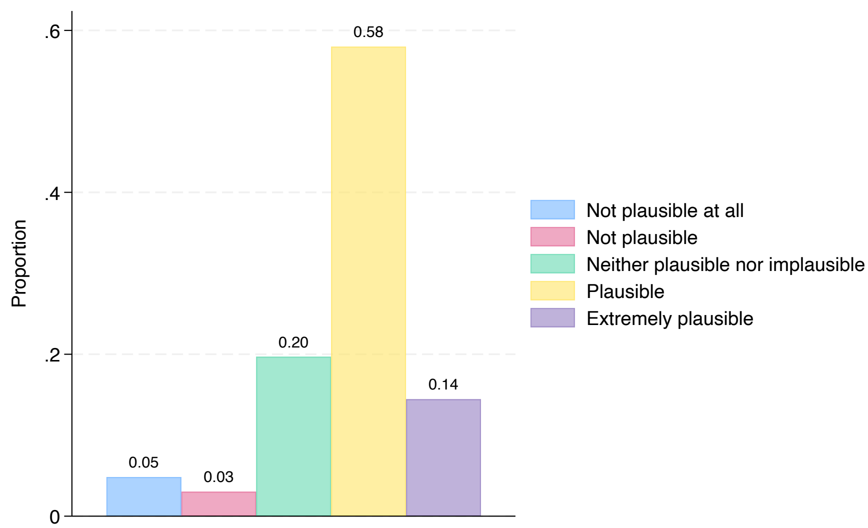
H.2 Mechanisms

In the second part of the survey, we present our main finding and ask whether the respondents perceive it as plausible. We also ask for explanations for this effect. The questions are as follows.

> We conducted research on the effect of having a project manager in the TOP 40% of managers on subsequent promotion of subordinates.
>
> We found that working for such managers increases the promotion rate of workers on the next project by 12 percentage points relative to workers who worked for managers in the BOTTOM 60%.
>
> **Q3.** How plausible do you think this result is?
>
> **Q4(a).** How do you think good managers affect the promotion rates of their subordinates? (Please select all that apply.)
>
> **Q4(b).** You selected the following mechanisms through which good managers affect promotion rates of subordinates.
>
> What do you think? How much of the effect we observe in the data does each of the mechanisms explain? (Note that the percentages have to sum to 100.)
>
> **Q5.** Which kind of management skills do managers transmit to subordinates? (Please select all that apply.)

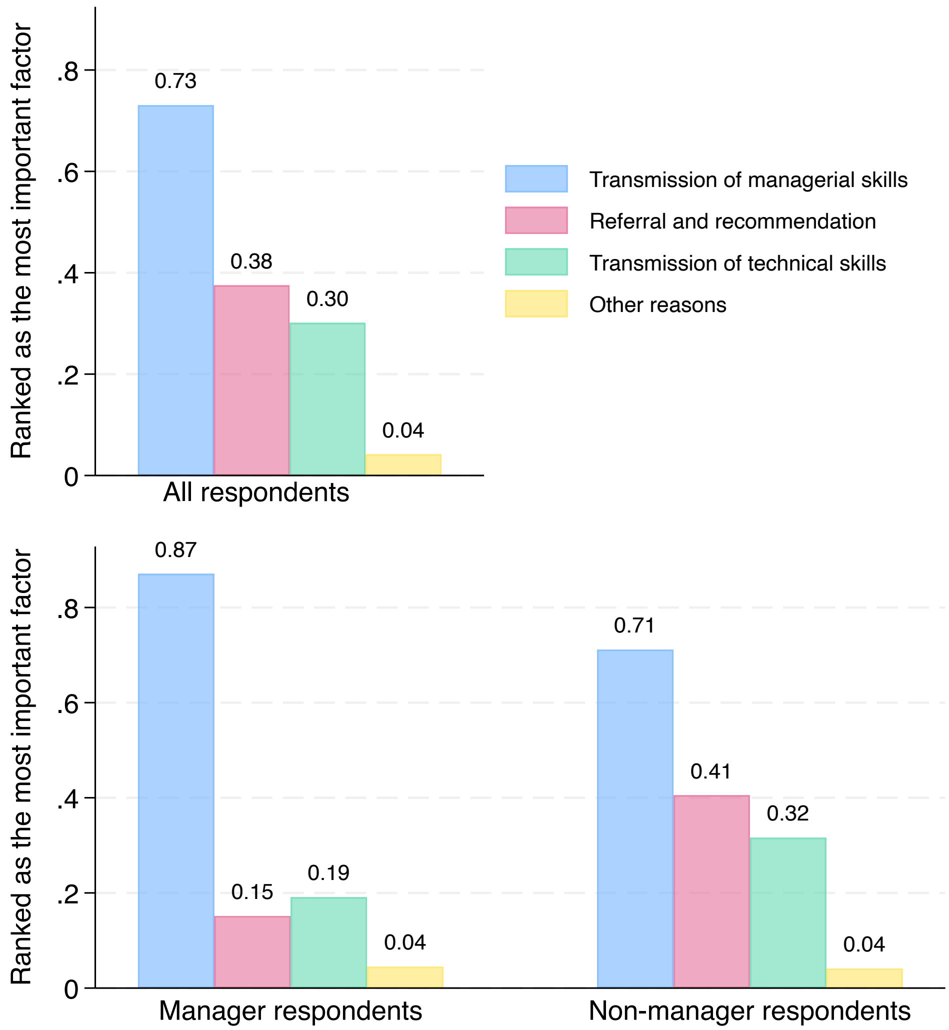
For **Q3**, we plot the answers in Figure H3. Combining **Q4(a)** and **Q4(b)**, Figure H4 plots the percentage of respondents ranking a specific factor as the most important in explaining the observed treatment effect. For **Q5**, we plot the selected answers in Figure H5.

Figure H3: Whether respondents perceive our main finding as plausible



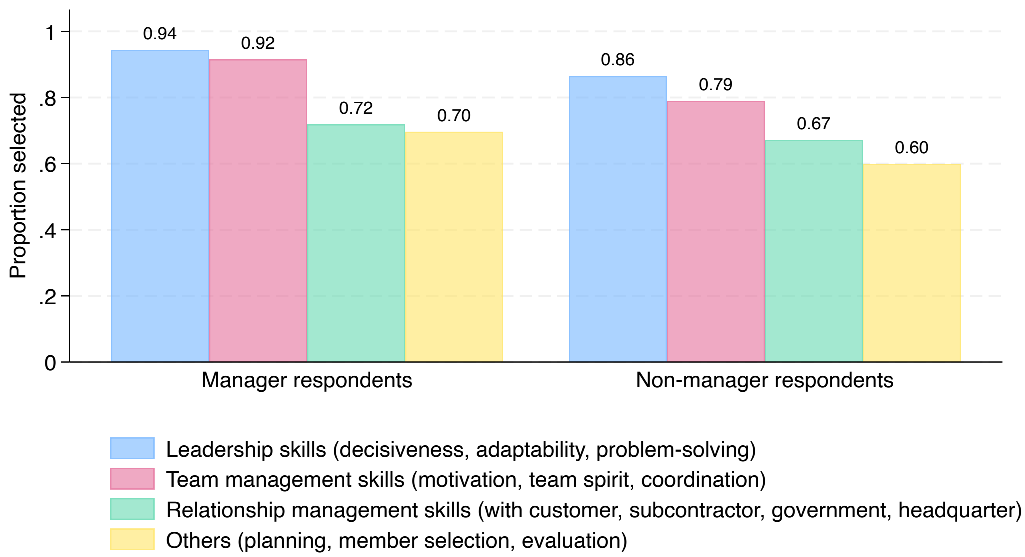
Notes: **Figure H3 shows the answers to Q3.**

Figure H4: The most important factor in explaining the observed treatment effect



Notes: **Figure H4 plots the answers to Q4.** This figure shows the percentage of respondents ranking a specific factor as the most important in explaining the observed treatment effect. In cases of ties, we treat both factors as most important. This explains why the percentages sum to more than 100%.

Figure H5: Types of managerial skills that are transmitted



Notes: **Figure H5 shows answers to Q5.** For each different type of managerial skills that can be transmitted from the project manager to his team members, we plot the fraction of respondents choosing that skill.