Making the invisible hand visible: Managers and the allocation of workers to jobs

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Abstract

Why do managers matter for firm performance? This paper provides evidence of the critical role of managers in matching workers to jobs within the firm using the universe of personnel records from a large multinational firm. The data covers 200,000 white-collar workers and 30,000 managers over 10 years in 100 countries. I identify good managers by their speed of promotion and leverage exogenous variation induced by the rotation of managers across teams. I find that good managers cause workers to reallocate within the firm through lateral and vertical transfers. This leads to large and persistent gains in workers' career progression and productivity. My results imply that the *visible hands* of managers match workers' specific skills to specialized jobs, leading to an improvement in the productivity of *existing* workers that outlasts the managers' time at the firm.

Keywords: managers, internal labor markets, career trajectories, worker productivity

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> "[M]odern business enterprise took the place of market mechanisms in coordinating the activities of the economy and allocating its resources. In many sectors of the economy, the visible hand of management replaced what Adam Smith referred to as the invisible hand of market forces."
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> — Chandler, A.D., 1977. *The Visible Hand: The Managerial Revolution in American Business.*

1. Introduction

Economics studies how to allocate scarce resources. Traditionally, labor economics focused on the labor market, rather than looking inside the "black box" of firms, within which most workers are allocated to jobs. In firms, managers take the place of the price mechanism in directing the allocation of resources (Coase, 1937). In particular, they shape the allocation of workers to jobs through *internal labor markets* (Doeringer and Piore, 1985). Understanding the managers' role in the allocation of workers to jobs is key to understanding why differences in management across and within firms explain an important share of the persistent differences in productivity (Gibbons and Roberts, 2013).

The idea that there are gains from the division of labor with people specializing their efforts across tasks is an old one and among the cornerstones of economics (Smith, 1937). Yet, the matching of workers to jobs as a way to reach an organization's objectives has received little attention. Managers, acting as gatekeepers in internal labor markets (the *bosses*), can play an essential role in facilitating the discovery of workers' unique skills and hence their effective utilization through job allocation.

This paper documents how managerial skill shapes workers' allocation to jobs and future career outcomes and whether this ultimately determines firm productivity. I consider a setting that allows the study of workers' career trajectories both horizontally - through lateral moves - and vertically - through promotions. This is the internal labor market of a large multinational firm (MNE).

Studying the role of managers within internal labor markets requires tackling three steps. The first is access to "insider" firm data, which also combines cross-sectional granularity with a sufficiently long time dimension. Second, estimating the added value of managers has proven challenging as measures that identify good managers independently of workers' outcomes are hard to come by. Third, to analyze the impact of managers on workers, one needs to pin down the manager's contribution to the worker's outcomes, which necessitates plausibly exogenous assignment of managers to workers.

With respect to the data, I bring together a rich collection of high-granularity administrative records from a multi-billion euro multinational firm. The data reveal the organization's inner workings over several years and cover the universe of managers and workers in the MNE: more than 200,000 workers and 30,000 managers over the span of 10 years in 100 countries.

To address the first identification step, I identify successful managers based on managers' own promotion speed, as a revealed preference measure of the firm. I build on the literature on internal labor markets documenting fast track careers inside organizations (Baker et al., 1994a) by focusing on the age at promotion from worker to manager and defining a binary measure to classify managers as "high-flyers" and "low-flyers". This results in 26.2% of managers being singled out as high-flyers, and is a strong predictor of ex-post managerial performance. A key feature is that it is defined ex-ante—before the manager supervises the worker—mitigating concerns about reverse causality or confounding shocks that might jointly affect both the manager and the worker outcomes. The results are robust to using alternative age thresholds as well as alternative definitions of high-flyers based on firm tenure at promotion.

To tackle the second identification step, I leverage managers' lateral rotations across teams that are outside of the control of the worker and conduct an event-study analysis exploiting the worker first manager rotation. These rotations are part of the requirement for the managers' career progression and anecdotal evidence and empirical tests indicate that they are orthogonal to workers' characteristics. An example can illustrate the empirical strategy. Consider two teams each managed by a low-flyer manager. One of these teams then transitions from a low-flyer manager to a high-flyer manager, while the other team transitions from a low-flyer manager to a different low-flyer manager. As both teams are affected by a manager transition, this design nets out the effect of the transition (Cullen and Perez-Truglia, 2023). Hence, the results can be summarized in the effects of (i) *gaining a good manager*, i.e., switching from a low- to a high-flyer manager, and (ii) *losing a good manager*, i.e., switching from a high- to a low-flyer manager, relative to switching managers but without changing manager type. I compare the outcomes of the employees each month leading up to the manager transition date and each month after the transition.[1]

First, gaining a good manager causes significant worker reallocation to different jobs inside the firm through lateral transfers; seven years after the first manager transition event, lateral moves are 40% higher. Examples of lateral moves include transfers such as from customer service to logistics, from merchandising to sales, or from product development to quality. High-flyer managers not only increase the rate of lateral moves within the firm, but also shape their nature. In particular, while these moves show no systematic pattern in direction, they involve meaningful shifts in task content. By matching the occupation titles at the MNE with those from O*NET, I document that workers exposed to a high-flyer manager are more likely to move occupations across task groups (e.g., from cognitive to routine, and vice versa) and to make larger task-distance changes — for example, from computer service to manufacturing engineer, or from logistician to customer service.

Second, gaining a good manager results in an improvement in worker performance and long-run career progression. Seven years after the manager transition, workers earn a salary that is 13% higher. In addition, using sales productivity data from field sales workers in 15 countries, I show that good managers raise actual worker performance, rather than inflating pay for the same performance. Three years after gaining a high-flyer manager, workers' sales performance increases by 0.347 standard deviations.

These effects are *asymmetric*. Gaining a good manager has positive effects while losing one – comparing the high-to-low transition group with the high-to-high group – has no corresponding negative effects. This indicates that there are long-term benefits of a one-time exposure to a good manager: the gains from a high-flyer manager persist even after a down-

[1] Having panel data over several years is essential to be able to evaluate the returns of a worker-job match as they may not manifest immediately. I keep following the workers even if they change managers again, irrespective of whether the worker remains or not with the manager of the first transition.

grade in manager quality. In terms of organizational design, these asymmetries indicate that it suffices to expose each worker to a high-flyer once as a low-flyer manager cannot spoil away the benefits of a good match created by a high-flyer manager.

I present evidence that sheds light on how managers shape worker outcomes through the allocation channel and helps address competing explanations. Combining the results on lateral reallocation with those on pay progression, a mediation analysis reveals that 64% of the higher salary can be explained by lateral job changes. This likely understates the full contribution of the manager's allocation role, as it excludes vertical transfers – which, by definition, include salary increases – and does not capture gains from workers remaining in their current job (rather than changing jobs) due to it being a good match for them.

In terms of manager behavior, time-use data show that high-flyer managers spend 19% more time in one-on-one meetings with subordinates, and engage more in communication and multitasking—suggesting a more involved, coordination-intensive management style. In line with this, data on managers' skills reveal that high-flyer managers are more likely to have strengths in strategy and talent management skills compared to project management.

In terms of worker behavior, the firm's internal mobility platform data indicate that workers exposed to high-flyer managers are more inclined to explore new roles, teams and skill sets. They participate more in flexible, short-term projects outside their core teams, which offer a low-risk way to experiment. Complementing the quantitative findings, in-depth interviews reinforce these patterns: workers describe good managers as mentors who guide career development, offer structured feedback, foster autonomy, and create opportunities aligned with employees' individual skills and aspirations.

Heterogeneity analyses provide additional support for the allocation channel, showing that the gains from high-flyer managers are strongest when conditions are most conducive to effective talent matching—such as when managers work in the same office as the employee or operate in environments with more diverse job roles. Effects are also larger for younger workers, who are still learning about their skills and fit. Importantly, the benefits are not concentrated among high performers: even workers with low baseline pay growth see comparable gains, consistent with high-flyer managers improving allocation across the board by uncovering and deploying hidden talent.

The evidence does not support alternative productivity channels such as motivating, monitoring, or teaching. The findings of higher task distance, the persistence of the results and the asymmetric career effects are difficult to reconcile with short-term, contemporaneous channels such as motivation or oversight effects. The lateral moves patterns are also hard to reconcile with high-flyer managers mainly teaching workers how to become more productive on the job as that would lead to the opposite prediction on workers' lateral moves.[2] Moreover, I find that pay dispersion increases within teams gaining a high-flyer, suggesting that productivity gains reflect better matching rather than uniform upskilling.

The findings on worker performance also cannot be explained by high-flyer managers engaging in worker selection out of the firm (Fenizia, 2022). I observe no impact on exit from the firm, and this is not disguised by heterogeneous effects on exit by baseline worker performance: there is no impact on exit for either the high or low performers at baseline. Hence, the higher rate of internal transfers points to high-flyers finding suitable re-deployments inside the firm. Relatedly, I find no evidence that workers' lateral or vertical moves occur within the managers' pre-existing networks and prior locations, nor that workers follow their managers as they move within the firm. If anything, subordinates of high-flyer managers are less likely to move into roles connected to the manager's prior colleagues. Combined with the result on higher worker sales productivity, these results cast doubt on explanations rooted in favoritism and personal networks, or information advantages.

Overall, these findings suggest that good managers can achieve a more productive workforce by creating better matches between the present labor pool and specialized jobs in the firm. In so doing, they have a long-lasting impact on workers' trajectories that outlives their time overseeing the workers. This allocation mechanism offers firms a resource-neutral lever for productivity — especially when compared to more resource-intensive interventions such as hiring, firing, or formal training programs.

[2]I show this formally with a conceptual framework that captures task-specific human capital and learning about innate talents. I allow good managers to increase both the learning around task talent (allocation channel) and the speed of job-specific learning by doing (teaching channel). I show that the two channels have opposite predictions on job transfers and that the data is consistent with the allocation channel being the main driver behind the productivity results.

A major question in labor economics is how workers match to jobs and how that determines wages and their evolution over time. Extensive research on labor markets has studied job mobility *between* firms (e.g., Jovanovic, 1979; Rosen, 1986; Acemoglu and Autor, 2011; Card et al., 2013; Chade et al., 2017; Card et al., 2018). Yet, wage growth and job mobility also happen *within* firms as examined by a literature on internal labor markets, largely theoretical and descriptive (e.g., Waldman, 1984; Topel and Ward, 1992; Baker et al., 1994a,b; Gibbons and Waldman, 1999; Kahn and Lange, 2014; Pastorino, 2024; Huitfeldt et al., 2023). This is the first paper to study the role of managers in the allocation of workers to jobs within internal labor markets and document how this affects workers' careers in the long run.

My findings also advance our understanding of the impact of individual managers on firm and worker outcomes (e.g., Bertrand and Schoar, 2003; Bandiera et al., 2007; Lazear et al., 2015; Bandiera et al., 2020; Frederiksen et al., 2020; Hoffman and Tadelis, 2021; Metcalfe et al., 2023; Adhvaryu et al., 2023, 2022). Compared to the widely studied CEOs, this paper focuses on middle managers at the middle of the firm hierarchy. I contribute to this growing strand of research by uncovering the matching of workers to jobs as an important mechanism that determines managers' long-run impacts on workers' careers. In terms of management practices, this study puts the emphasis on managerial policies governing the allocation of workers to jobs within firms, an area largely overlooked by previous research, yet aligned with recent evidence highlighting the importance of economic decision-making skills (Deming, 2017; Caplin et al., 2023; Weidmann et al., 2024).[3]

More broadly, by providing micro-level evidence on the role of managers in the efficient assignment of workers to jobs, this study speaks to the research on the misallocation of productive inputs and its consequences for growth (Hsieh and Klenow, 2009) particularly on the mismatch between workers and jobs and its consequences for workers' careers and aggregate output (Hsieh et al., 2019).

The remainder of the paper is organized as follows. Section 2 describes the institutional

[3]The managerial practices analyzed by previous literature focus on workers' incentives via pay for performance, promotions, and monitoring (Bloom and Reenen, 2011). The tools of monetary and career incentives have also been widely examined theoretically and empirically by a prominent strand of research in organizational economics (Holmström, 1979; Lazear and Rosen, 1981; Lazear, 2000; Bandiera et al., 2007, 2013; Bertrand et al., 2020).

background and Section 3 delves into the data. Section 4 introduces the research design centered around manager rotations and discusses its validity. Section 5 presents the main results and Section 6 discusses additional evidence corroborating the allocation channel. Section 7 discusses alternative channels and external validity. Section 8 concludes.

2. Institutional context

2.1. Firm overview

I collaborate with a private consumer goods multinational with offices in more than 100 countries worldwide.[4] It has a workforce of about 120,000 workers each year, of which approximately 60,000 are white collars, and its turnover in 2020 was over €50 billion. I collect novel data on the full population of white-collar and management employees and construct a panel dataset that links workers to their managers and tracks workers' career progression inside the firm (see Appendix Figure A.1 for an overview of the data sources).

The company is organized into a hierarchy of work-levels (WL) that goes from WL1 to WL6 (C-Suite) (see Appendix Figure A.2 for a graphical visualization of the hierarchy). Employees with a work-level above one are considered performing managerial roles (WL2+). Moreover, within each work-level, there is a further vertical differentiation of workers through salary grades. A salary grade increase entails a permanent change in salary but not a major change in job responsibilities while a work-level promotion would also entail a considerable change in job responsibilities (usually less execution and more strategy and planning). The firm has the same organizational structure across all countries, functions, and over time. Appendix Figure A.3 shows that average tenure, age, and work-level shares have remained very stable over the years of the panel.

Table I describes the sample, which consists of the universe of white-collar workers from January 2011 to December 2021. This results in $224,117$ distinct regular full-time workers in 118 countries ($10,083,638$ worker-month observations). Supervisors (i.e., those that super-

[4] I have a portfolio of papers based on the collaboration with the same MNE, each examining a different dimension of the firm's organization and policies. These currently include Minni (2024); Ashraf et al. (2025a,b).

vise at least one worker) comprise 21% of the sample, although only 14% of the sample is in managerial roles (i.e., has a work-level above one).

Panels (a) and (b) of Table II present summary statistics for the main variables. Women represent 44% of employees, 39% of workers are aged between 30-39 and the large majority of workers are in work-level 1 (80%). The workers have homogeneous levels of human capital as applications require a college degree, and most employees have degrees in either economics and business administration (48%) or STEM (30%). Tenures at the firm are long, with an average of 8.5 years, highlighting the importance of internal career progression for employees' long-term income. Teams (i.e., a group of workers reporting to the same supervisor) are small with an average of 5 workers per team, although team size increases over a manager's seniority, with top managers overseeing on average 8 workers.

Because I am interested in career progression to higher-level positions, I focus on white-collar employees. Blue-collar workers have very limited career progression opportunities as well as horizontal job differentiation (87% of blue-collar workers are machine operators). Moreover, the organization of work in factories is different from offices; blue-collars are supervised by white-collar front-line workers (denoted as first-line managers) instead of employees in actual managerial positions and teams can be as large as 80 workers.

The workers and workplace practices at the firm are comparable to those of other large European manufacturing firms. I consider European-wide statistics from the European Company Surveys (van Houten et al., 2020). On average, in firms with more than 250 workers, the gender share of the workforce is 40%, age is 41 years and tenure is 9.8 years. Moreover, the typical large firm would have at least 4 hierarchical levels. As of June 2022, the most common job in the MNE in the United Kingdom was a Product Developer in the R&D function with an average annual salary of GBP 39,190 (around EUR 45,930), very much in line with Glassdoor's average salary of GBP 39,313 for product developers in the United Kingdom.[5]

[5]See Glassdoor's page for Product Developer in the United Kingdom.

2.2. Internal labor market and middle managers

Workers typically explore internal job opportunities by applying through an internal talent marketplace platform, where roles across teams are openly advertised. Managers play a critical role in this process, as they regularly engage in one-on-one meetings and quarterly reviews with workers, offering coaching, feedback, and explicit recommendations for promotions and lateral transfers (in line with other organizations, see for e.g. Frederiksen et al., 2020; Haegele, 2024).

Managers' recommendations for worker lateral moves and promotions are formally discussed and evaluated in dedicated talent forums, with the aim to ensure a structured, transparent process rather than informal placements. Managers formally review their subordinates' work every quarter, where they also identify priority skills and development areas for each worker, but the overall performance rating is annual. They are also encouraged to have weekly 1-1 meetings with each worker to re-assess priority and check status.[6]

Qualitative evidence from focus groups of workers at the firm indicates that frequent 1-1 meetings with the manager tend to go hand-in-hand with good managers. In 2020, employees reported in the annual global pulse survey at the MNE that their manager was among the top three areas of importance to them, further underscoring the relevance of this relationship in the workplace.

In terms of the managers' own performance assessment, they are explicitly incentivized to enhance their teams' capabilities, as captured by the firm's guideline to "develop and magnify the power of people". Their periodic evaluation is structured around seven "standards of leadership" and one of these is to be a "talent catalyst" who "coaches individuals and teams to realize their full potential". The firm uses 360-degree evaluations for the performance appraisal process: a manager receives written evaluations from both superiors and subordinates on each of the indicators, which are then reviewed by their own respective manager to decide on an overall (numerical) performance rating for each year, in turn used to determine the annual bonus.

[6] The firm HR guidelines to managers encourage check-ins with subordinates about priorities, capacity and resources, and wellbeing and development, on a weekly basis.

These firm policies are in line with managers' job responsibilities among white-collar employees in other companies (Clifton and Harter, 2019). In these higher-skilled, knowledge-based jobs, production is often complex and multi-faceted and firms care about both current performance and future performance, i.e., workers' "potential" and career paths (Benson et al., 2022).[7]

3. Data

The main variables in the analysis are obtained from the personnel records of the organization, which provide monthly snapshots of the workers worldwide. I assemble rich panel data by combining the global HR records with the organizational chart, the payroll and performance data, and the annual surveys. Appendix Figure A.1 illustrates the various data sources and the time periods for which they are available. Table II presents the summary statistics for the main variables.

3.1. Personnel records

The global personnel records keep track of demographic variables of interest (age, gender, tenure, education), and give a monthly snapshot of the workers' hierarchy levels, functions, and job titles (from which promotions and lateral moves can be constructed). It is also recorded if a worker has been made redundant (involuntary exit) or has decided to quit the job for alternative employment or other activities (voluntary exit).

In terms of the types of jobs, there are 16 functions in the MNE, with the biggest six being Sales, HR, R&D, Supply Chain, Finance, and Marketing. Within each function, there are multiple sub-functions (for example, in the finance function one can be working in the tax sub-function or in the M&A sub-function). Typically, a sub-function would have roles spanning from work-level 1 to work-level 4, so workers do not have to change sub-function to move up the job ladder as it is possible to advance vertically within a given sub-function. The

[7]The study population is knowledge-based workers as opposed to lower-skilled workers, who have been the subjects of most of the empirical personnel papers.

median size of a sub-function is 240 workers, the 10th percentile is 16 workers and the 90th percentile is 2103 workers. Appendix Figure A.4 shows that lateral moves are common in every sub-function and that this is also true for salary grade increases.

I also observe the job titles detailing a worker's exact job within the sub-function. There are almost 1,000 horizontally differentiated job titles within the firm among work level 1 employees, and, on average, there are two distinct job titles in a team supervised by the same work-level 2 manager. These are some examples of job titles: Logistic Specialist; Supply Planning Admin; HR Recruiting Specialist; Occupational Health Admin; Field Sales Specialist; Vice President Brand Development.

3.2. Organizational chart

The organizational chart indicates the manager each individual worker reports to, where workers reporting to the same manager belong to the same team. Because these data capture team assignments over many years, I am also able to construct indicators of managers' formal ties to other units at the firm by measuring whether they have previously worked with anyone in that unit.

3.3. Performance and productivity

I complement these admin data with payroll data, which include employees' earnings, and bonus payments measured in euros in all countries. Pay, which is available from 2016 onward, captures differences in performance across workers and there is considerable variation in pay within a given job in a specific office-month pair, where the median standard variation in pay is around €6,000 (for the whole distribution see Panel (a) in Appendix Figure A.5).

Practically, there are three ways in which workers with the same job title can earn different salaries: the salary grade, which is positively associated with sales productivity (as shown in Panel (b) of Appendix Figure A.5); the salary band, which ranges from 80% to 120% of target pay based on market benchmark data; and the annual bonus, the variable pay that averages 10% of fixed pay for work-level 1 workers.

In addition, I collect information from the firm's talent management system which includes worker evaluations, such as performance ratings that are set annually by the manager, as described in sub-section 2.2. Salary increases and promotions are the main metrics to assess performance within the firm. The manager is the main decision-maker after taking into account the views of all the colleagues who have interacted with the worker (360-degree reviews). The decision process is designed to be as fair as possible and to limit manager bias; the manager has to justify any salary increase, transfer, or promotion decision against a set of objective criteria to the rest of their colleagues in talent forums dedicated to this discussion. The performance assessment is done in the same way in every function and office so that comparisons can be made between workers in different jobs and offices.

I complement the performance data with two independent sources of productivity data. The first is sales bonus data at the worker-month level for the field sales population in 15 countries from January 2018 until December 2021 (5,604 employees).[8] The worker sales bonus is based on reaching targets each month set by the country demand planning teams in the Supply Chain function. Some examples of sales targets include growth of sales, product placement, on-shelf availability, additional exhibitions, and number of orders vs. total visits each month. Appendix Figure A.5 Panel (b) shows that there is a positive relationship between sales bonus and future salary grade increase.

The second is operational data at the establishment level: output per worker (tons per FTE or Full-Time Equivalent), a common metric of productivity in manufacturing firms, and costs per unit of output (operational costs per ton).[9] Both of these measures are at the establishment-year level and the company shared all data available for every establishment globally (around 150 sites) over 2019-2021. Because of changing reporting requirements, the costs per ton data could only be shared for the main product category (there are three product categories in total).

[8] While most of the data come from the global personnel records, sales data is managed independently in each of the countries and the data needs to be separately collected on a country-by-country basis by liaising with the countries' local sales teams. A second data challenge is that the field sales teams are increasingly being outsourced to contractors.

[9] The operational costs are predominantly made up of labor and energy costs and they do not include the cost of raw materials.

3.4. Digital platforms

In 2018, the firm introduced two platforms aimed at fostering an internal talent marketplace. The first is denoted as a learning platform and works as a talent tool combining learning and development, skill analytics, and career mobility. Workers can use the platform to do workshops, search for internal jobs and share learning/job opportunities (Cowgill et al., 2021). The data available tracks the workers' activities in the company such as the number of completed courses, number of posted skills, and number of items shared with colleagues. I use this data to infer managers' skills and workers' engagement in learning and development activities.

The second platform is a tool that enables workers to apply for short-term projects inside the company but outside their current team, which are denoted as flexible projects. These projects can vary in duration but typically range between one to six months and entail one or two days per week of work on the flexible opportunity. The rationale underlying this initiative is rooted in two objectives: to allow workers to engage in small projects to experiment with different jobs, expand and test their skills, as well as to fill new positions in real-time in response to quickly changing market needs.

Finally, for managers, I have access to time use data, which is at weekly frequency spanning over the entire 2019, and contains a random sample of around 600 work-level 2 managers across different countries and functions. This allows me to investigate different time use patterns across managers.

3.5. Employee surveys

I conduct additional secondary analysis using individual responses to four global annual surveys that the company ran in 2017-2020. Each September, all workers are invited to the survey; the response rate is around 60%. The survey is designed to measure the "pulse" of the workers across the globe, gathering data on how the organization is perceived by the workers themselves and on their job satisfaction and well-being (questions are on a 5-point Likert scale). Respondents are broadly similar to non-respondents in terms of demographics;

they generally tend to be slightly older and higher up in the hierarchy (I provide additional details in the Supplementary Materials).

3.6. External datasets

I supplement the firm data with other sources of external data. Specifically, I use O*NET dataset 29.1 to measure occupation-level task intensity (National Center for O*NET Development, 2024). The Occupational Information Network (O*NET) is a comprehensive database of worker attributes and job characteristics, which is administered by the U.S. Department of Labor, Employment and Training Administration. In particular, I identify relevant descriptors following Deming (2017) to construct the task intensity measure for each occupation, and match the O*NET occupations to MNE job titles. A complete description of the data is in Appendix D.

In addition, I use the Restrictive Labor Regulations Index from the World Economic Forum. The WEF Restrictive Labor Regulations Index is based on an annual survey administered to a representative sample of around 15,000 business executives in 150 countries. It includes measures related to labor-employer relations, wage flexibility, hiring and firing practices, labor taxes, attraction and retention of talent.

4. Empirical strategy

My analysis revolves around the causal effects of high-flyer managers on the subsequent career progressions of their workers. For example, I want to measure whether workers have differential career paths after transitioning from a low- to a high-flyer manager. To estimate these manager effects I would ideally randomize employees to their managers. As this type of experiment is not feasible, I instead exploit naturally occurring exogenous rotations in manager assignments within the organization. I first describe how I identify high-flyers and the manager transitions, and then specify the research design and the formal econometric framework for the event-study analysis.

4.1. High-flyers

I construct an empirical measure for good managers based on managers' own speed of promotion, building on the notion of fast track promotions studied by the literature on internal labor markets (Rosenbaum, 1984; Baker et al., 1994a; Bernhardt, 1995; Prendergast, 1998; Gibbons and Waldman, 1999). This body of papers has shown, both empirically and in models with learning and assignment, that wage changes and promotion rates inside organizations are serially correlated. In particular, employees who are promoted quickly to one level tend to be promoted sooner to the next, and higher-ability employees climb the ladder faster.

The key metric I consider is age at promotion to manager. In particular, I define high-flyer managers as those who achieve work-level 2 at a relatively younger age (time-invariant). I only look at work-level 2 managers since the focus of the paper is on middle managers, who represent the predominant segment of the managerial workforce in large firms (see Figure I Panel (a) for the distribution of work-levels at different tenure years). I consider worker age instead of tenure as the former is a better proxy of labor market experience.

Empirical definition of high-flyer managers. Because of data confidentiality, I only observe 10-year age groups. To obtain a continuous age measure from the original discrete age bands, I adopt the following two-part procedure. For the subset of employees who transition from one age bracket to another age bracket (e.g., from 30-39 to 40-49), I can precisely infer their age based on the timing of the transition. For the remaining employees who remain in the same age bracket throughout, I first calculate the earliest and latest possible birth months consistent with their age bracket and observation window. Then, I take the midpoint of this interval to estimate their birth month, from which I derive a continuous age.

Figure I Panel (b) plots the distribution of age at promotion. I define a fast promotion as being promoted by age 30, resulting in 26.2% of the managers in the sample being classified as high-flyers. To establish robustness of different potential high-flyer measures, in sub-section 5.4, I compare the baseline event study results with those that are obtained using different high-flyer measures. The results remain unchanged whether I use different age thresholds to define high-flyer managers, or an alternative tenure-based measure.

Demographics and performance correlates. In terms of demographics (Panel (a) of Table III), high-flyer status is positively correlated with being female and having a degree in economics and the social sciences; which is consistent with positive selection into corporate jobs for women and negative selection for those who have a STEM major. High-flyers are more likely to have been developed internally as they are 14.5 p.p. less likely to be mid-career recruits.

The intuition behind this measure is that the speed at which a worker progresses the corporate ladder is a holistic metric of performance, which reflects the extent to which the firm values the manager's work and is symptomatic of leadership potential. I validate this intuition empirically by showing that the high-flyer status is significantly positively correlated with other measures of performance. Panel (b) of Table III shows that the high-flyer manager status is positively correlated with a number of ex-post performance metrics (taken after these employees are promoted from work-level 1 to work-level): managers' future salary growth, probability of promotion to work-level 3, performance ratings, and workers' anonymous upward feedback on the managers' leadership.

Comparison to other studies. The approach in this paper is to study how high-flyer managers, who are recognized as particularly productive by the firm, impact their subordinates' outcomes. Previous studies have based their measure of manager quality directly on worker outcomes or on worker assessments of their manager (Lazear et al., 2015; Frederiksen et al., 2020; Hoffman and Tadelis, 2021). I adopt a different, yet complementary, approach by identifying the managers that the firm recognizes as high-performers and then looking at their impacts on workers. An advantage of this alternative technique is that it avoids issues of circular reasoning whereby good managers are defined on the same outcomes that are then used to estimate their effects. It is also a metric defined ex-ante, before the manager supervises the worker, thus addressing concerns of reverse causality or of common shocks impacting simultaneously the manager and the worker's performance.

It is worth highlighting how promotion speed can easily be applied to other contexts as a holistic metric of performance to single out talented leaders: the data requirements are not particularly stringent and are not context-specific. Any organization typically establishes a career ladder for its employees and worker age is easily observable and verifiable.

As with any proxy, there is scope for measurement error. For example, fast promotions might be an imperfect measure of managerial quality due to the Peter Principle (Benson et al., 2019). These measurement issues would lead to downward bias in the results and hence to underestimating the impact of high-flyer managers on worker outcomes.

4.2. Manager transitions

I leverage the naturally occurring rotation of work-level 2 managers between teams to conduct an event-study analysis following a manager transition. In an ideal experiment, I would randomize workers with different skills to managers of different qualities and then measure the effects on the workers' career progression in subsequent years. As it would be unfeasible for most real-world companies to randomly shuffle their workers and managers, I use managerial rotations across teams that generate variation in the manager types that each worker meets and allow for causal identification of manager effects. I only consider the manager transitions that result from the reassignment across teams as part of the managerial lateral rotations. I do not include instances where the manager is promoted to a higher position or transitions that result from employee promotions to another team or employee transfers.

The firm's rotation policy. These manager rotations are not literally decided by a coin toss, but anecdotal evidence suggests that they are exogenous to workers and teams. Testimonies from executives and HR representatives suggest that these transitions are orthogonal to employee characteristics. As part of corporate strategy, work-level 2 managers are expected to gain experience in different projects and teams within a given sub-function. For this reason, managers are reassigned laterally across teams in random order to gain exposure to different teams and activities and hence broaden their managerial skills. The aim is for the managers to eventually experience all teams within a sub-function. The rotations are also used as a screening mechanism to evaluate who should progress further to work-level 3 (director level). The firm has been implementing this rotation policy for several decades.[10]

[10] The rotation of managers is a common practice in large organizations and other studies have exploited similar rotations in different organizations for their identification strategy (see e.g., Cullen and Perez-Truglia, 2023;

Endogenous mobility checks. Rather than relying exclusively on testimony that these manager rotations are orthogonal to the workers' characteristics, I evaluate this assumption by examining the parallel trajectories of employees who undergo different transitions along a wide range of outcomes using an event-study analysis (see next sub-section 4.3 for more details). Moreover, I conduct additional endogenous mobility tests where I show that an array of past team characteristics in the two years before the manager transition - including team performance, inequality, transfer rates, and team diversity - cannot predict the type of the incoming manager. To evaluate the correlation between current team characteristics and high-flyer status of future managers, I estimate the following model at the team level:

$$y_{\text{team},t} = \alpha_0 + \pi_0 \text{ High-flyer manager}_{\text{team}} + \boldsymbol{X}'_{\text{team},t}\boldsymbol{\beta} + \epsilon_{\text{team},t} \tag{1}$$

where High-flyer manager$_{\text{team}}$ denotes the quality of the future manager and controls ($\boldsymbol{X_{team,t}}$) include function, country and year fixed effects. Under the null of $\pi_0 = 0$ managers cannot impact team performance before they take charge, thus any correlation between change in manager type and past team characteristics is indicative of sorting. Table B.1 shows the results: past team-level performance and other metrics do not predict the incoming managers' quality.

Since the identification strategy relies on manager transitions, I do an additional identification check by running a similar model as in equation 1 but allowing for different transitions to have a different impact, leaving the *LowtoLow* transition as the omitted category:

$$y_{\text{team},t} = \alpha_0 + \tau_1 E^{LtoH}_{\text{team}} + \tau_2 E^{HtoL}_{\text{team}} + \tau_3 E^{HtoH}_{\text{team}} + \boldsymbol{X}'_{\text{team},t}\boldsymbol{\beta} + \epsilon_{\text{team},t}$$

In particular, I am interested in testing the hypotheses that $\tau_1 = 0$ and that $\tau_2 - \tau_3 = 0$. Table B.2 shows the results and there is no evidence that the type of manager transition is correlated with teams' prior performance.[11]

Haegele, 2024). In addition to firms in the private sector, rotation policies are also used in large public organizations such as the World Bank and the United Nations. In the Supplementary Materials I provide additional details on the manager rotations at this firm.

[11]The statistically significant coefficients in Table B.2 can be due to chance as I am testing 24 hypotheses. Applying the Bonferroni correction to account for multiple hypothesis testing, the significance threshold is adjusted

Addressing concerns of common shocks. By design, the empirical strategy tackles potential concerns that common shocks to a unit drive both manager promotions and worker outcomes. Two features of the design are particularly important in this respect. First, the measure of high-flyer manager is defined ex-ante, before the manager interacts with the worker (see subsection 4.1). Second, manager quality is assessed in a different unit from the one where the manager is later assigned. Together, these features help alleviate concerns that the determination of high-flyer status may be correlated with shocks affecting the worker's unit.

To further support the identification strategy, I complement this design-based argument with empirical tests that directly address the role of potential confounding shocks. In Appendix Table B.3, I leverage establishment-level productivity data to examine whether the share of high-flyers correlates with local performance trends (establishment-level output and costs). I do not find evidence of such a correlation. This helps assuage concerns of high flyers simply reflecting establishments' past positive shocks as a lagging indicator.

I extend this analysis in Appendix Table B.4 to the function-country level, to address concerns of common shocks at function level. While comparable productivity data are not available at this level, I proxy local shocks using employment growth among entry-level employees and the ratio of total bonus to total pay, which captures overall KPI achievement. Again, I find no evidence that the share of high-flyers reflects lagged responses to positive shocks. These findings provide additional reassurance that the estimated effects are not driven by unobserved, correlated shocks at the establishment, or function level.

4.3. Event study design

The analysis focuses on the first manager transition observed for each worker and tracks their outcomes for up to ten years following the event with the objective to estimate the long-run effect of manager quality on career trajectories.

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to $\alpha = 0.05/24 \approx 0.0021$. Under this threshold, none of the coefficients remain statistically significant.

Event-study specification. The event-study data comprises $29,423$ transition events, involving $29,423$ unique workers and $14,616$ unique managers.[12] Events occur every year but the majority of them take place in the first three years of the panel (2011-2013) since I only consider the first manager transition. They affect workers in every function and country.

Let y_{it} be an outcome of interest, where the subscripts i and t denote employees and year-month, respectively. The main outcomes analysis are the number of lateral transfers, number of salary grade increases, and performance metrics such as salary and sales bonus. I specify the model below:

$$y_{it} = \sum_{j \in J} \sum_{s \neq -1,-2,-3} \beta_{j,s} D^{j}_{i,t+s} + \boldsymbol{\alpha}_i + \boldsymbol{\xi}_t + \epsilon_{it} \tag{2}$$

where s indexes the months relative to a change in manager, $\boldsymbol{\alpha}_i$ is worker FE to control for permanent differences in worker productivity[13], $\boldsymbol{\xi}_t$ comprises of year-month FE, and D^j denote the event-study indicators for the periods leading up to and following a transition event $j \in \{LtoH, LtoL, HtoL, HtoH\}$. For instance, $LtoH$ denotes a transition from a low- to a high-flyer manager. Standard errors are clustered at the manager level.

The event-study window spans from 24 months before the event to 84 months after the event. In the event-study graphs, I average the monthly coefficients to the quarterly level for ease of presentation; the months -1, -2, and -3 are all taken as the omitted category in event studies as the quarter -1 estimate. Some outcome variables, e.g., the number of work level promotions, can only be defined after the manager transition event. Since there are no pre-event measurements for these variables, equation 2 is modified to include only post-event periods, and month 0 is taken as the omitted category.

Interpreting event-study estimates. To isolate the impact of a change in manager type from a change in manager more generally, I always compare employees undergoing manager transitions where one of those transitions results in a change of manager type and the other does not. Hence, the estimates of interest are the differences between types of transitions:

[12]As I only consider the first transition event experienced by a worker, the number of unique workers is the same as the number of transition events.

[13]The worker fixed effects also account for different starting points (initial age or workforce experience) and the time fixed effects then account for the variables increasing by the same amount for each worker.

$\hat{\beta}_{LtoH,s} - \hat{\beta}_{LtoL,s}$ (i.e., transitioning from a low-flyer manager to a high-flyer manager, relative to transitioning from a low-flyer manager to another low-flyer manager) and $\hat{\beta}_{HtoL,s} - \hat{\beta}_{HtoH,s}$, where s indicates the time since (or until) the transition date.

The key assumption is that, prior to the transitions, employees were on the same career trajectories irrespective of their upcoming transition. The event-study framework provides a further intuitive check of the identifying assumption: I can assess the evolution of the outcomes in each month before the date of the transition to confirm whether the trends were truly parallel before the event date.

Robustness. In sub-section 5.4, I report a series of robustness exercises to the event-study estimates including restricting the sample to only new hires, for whom I can tell for certain that this is their first manager change at the firm, and accounting for cohort-specific effects. In this setting, contamination from effects from other periods such as cohort-specific effects is not an issue as the firm's policies and organizational structure remained unchanged for the 10-year period, as described in Section 2. Consistent with this, re-estimating the event study using the interaction-weighted estimator developed by Sun and Abraham (2021) yields nearly identical estimates as the two-way fixed-effect estimates.

Worker exit and count outcomes. For the exit outcomes (quits and layoffs), I estimate the following cross-sectional regression:

$$y_i^P = \sum_{j \in J} \beta_j D_i^j + \boldsymbol{X}_i \boldsymbol{\alpha}_i + \varepsilon_i \tag{3}$$

where y_i^P is a set of outcome variables indicating whether the employee left the firm voluntarily or involuntarily within P years after the transition event, D_i^j are event indicators for $j \in \{LtoH, HtoL, HtoH\}$ ($LtoL$ group is omitted as the reference group), and $\boldsymbol{X_i}$ are fixed effects of event date, the interaction of office and function, as well as the interaction between age band and gender, all taken at the time of event. Standard errors are clustered at manager level. I report $\hat{\beta}_{LtoH}$ for the effect of gaining a high-flyer manager, and report $\hat{\beta}_{HtoL} - \hat{\beta}_{HtoH}$ for the effect of losing a high-flyer manager.

Finally, since some outcomes are count variables, such as the number of salary increases and the number of transfers, I also estimate the model in equation 2 using a Poisson quasi-maximum likelihood model. The estimator is consistent in the presence of high-dimensional fixed effects and can be used to model non-negative dependent variables without the need to specify a distribution (Correia et al., 2020):

$$\mathbb{E}(y_{it} \mid \boldsymbol{X}_{it}) = exp\left(\sum_{j \in J} \sum_{s \neq -1,-2,-3} \beta_{j,s} D^{j}_{i,t+s} + \boldsymbol{\xi}_t + \boldsymbol{\alpha}_i + \epsilon_{it}\right) \tag{4}$$

5. Managers and workers' careers

In this section, I document the effects of gaining a high-flyer manager on the workers' lateral and vertical moves, exit from the firm, and career progression. Then, in Section 6, I show the results of the transition in the opposite direction, i.e., losing a high-flyer manager, and provide additional evidence indicating that the job-allocation margin is a quantitatively important channel underlying the observed impacts of high-flyer managers.

5.1. Worker lateral moves and exit

Figure II presents the effect of gaining a high-flyer manager based on the econometric model discussed in Section 4: it compares the effects on the number of lateral moves when transitioning from a low to a high-flyer manager (*LtoH*) relative to transitioning from a low to another low-flyer manager (*LtoL*). Panel (a) shows the evolution of the number of lateral moves in each of the 8 quarters (2 years) leading up to a manager transition and the 28 quarters (7 years) after the manager transition.

Figure II shows that, prior to the event date, the differences in the coefficients are statistically indistinguishable from zero. This evidence indicates that the assumption about parallel trends holds. After the transition date, Panel (a) shows that the evolution of lateral moves starts to gradually diverge between the *LtoH* and *LtoL* workers. The moves increase up to 20 quarters after the manager transition and then level off at the new higher level. At 28 quarters after the manager transition, the number of lateral moves are 0.10 higher in the *LtoH* group than the *LtoL* group (or a 40% increase, p-value < 0.05). The effects of gaining a high-flyer on the number of lateral moves come from many workers making at least one lateral move, rather than few workers making many lateral moves. This is shown in Panel (c) of Figure III, which plots the probability of making at least one lateral move since the manager transition.

As the average duration of a manager's assignment to a team is two years, it might seem unusual that workers' lateral moves can occur several years after the initial high-flyer exposure. Some institutional context can clarify. Conversations with HR managers indicate that the time from when an employee begins exploring internal opportunities to when a move is completed can vary — in some cases happening quickly, but in others taking up longer timelines, especially job transitions involving more complex or cross-domain moves. This range helps explain the dynamics of Figure II where the effect on lateral moves becomes significant around 5 quarters after the manager transition, continues to rise until roughly 20 quarters later, and then levels off. The slower adjustments are most relevant for longer-distance moves, such as cross-functional transfers, which motivates the following analysis.

Task changes. To better understand the nature and direction of lateral mobility following a manager change, I first decompose job moves by organizational boundaries—within team, within function, and across functions—and then examine whether these transitions involve meaningful shifts in task content using measures of task distance and occupational classification based on cognitive, routine, and social task profiles.

In Panel (a) of Figure III, I decompose the overall increase in lateral transfers by whether they occur within the team, outside of the team but within the same function, or across functions. The figure shows a clear and sustained increase in lateral mobility following the transition to a high-flyer manager across all types of moves. The largest contribution comes from moves across teams within the same function. However, both within-team and across-function transitions also rise - suggesting that high-flyer managers facilitate a broader reallocation of workers across the organizational structure, not limited to one specific margin. The figure further shows that cross-functional moves take the longest to materialize, with effects becoming significant only after quarter 13, reflecting their broader scope and the greater procedural hurdles they might entail. Within-team moves also emerge slowly, reaching significance after quarter 10—a pattern consistent with the fact that teams typically include only two distinct job titles.

To further unpack the nature of these reallocations, I isolate task-distant lateral transfers. Following Deming (2017) and Cortes et al. (2023), I identify questions that are related to an occupation's cognitive, routine, and social task intensity from O*NET questionnaires. This provides raw intensity measures of each occupation over these three tasks. I then match job titles inside the MNE to the O*NET occupation titles, allowing me to assign percentile ranks to each occupation based on the empirical distribution of all MNE employees. To analyze job transitions, I take two complementary approaches.

First, I calculate a composite measure of task distance between the origin and destination jobs using the angular separation across these three tasks as in Gathmann and Schönberg (2010). This task distance ranges from 0 to 1, where 0 indicates identical skill sets and 1 indicates completely distinct ones. Additional details on how the outcome variable is constructed are provided in Appendix D. As the main outcome, I use the cumulative task distance an individual experiences over time. The corresponding event study results are shown in Panel (b) of Figure III, which shows that, after the manager change, cumulative task distance gradually increases, becoming statistically distinguishable from zero approximately 7 quarters after the change and continuing to rise thereafter. These dynamics are consistent with the greater adjustment costs that likewise underlie the slow emergence of cross-functional moves. Overall, these patterns suggest that manager changes are followed by a gradual shift in the types of tasks employees perform, leading to increasing divergence from their original task profile over time.

Second, to identify transition patterns across the three task groups, I classify a job as cognitive, routine, or social job based on the highest intensity measure. Next, I track the workers' occupations at the time of their first manager transition event, and then 2 and 7 years after, and construct a transition matrix with each entry representing the fraction of workers doing that transition. Figure IV shows the heatmap for the difference between $LtoH$ and $LtoL$ transition matrices. It can be seen that, for $LtoH$, there are more off-diagonal transitions for cognitive and routine tasks, a sign of broader lateral mobility across different task domains over time and diversification in $LtoH$ trajectories. For social occupations, the effect of high-flyer managers appears to operate more within-domain: $LtoH$ workers are more likely to remain within social jobs compared to their $LtoL$ counterparts. This stronger diagonal effect may reflect the fact that social occupations are the most prevalent in the sample, comprising 43% of workers at the time of the manager transition, compared to 31% in cognitive and 26% in routine occupations.

Worker exit. I also examine whether there is an effect on worker exit from the firm. Figure II Panel (c) and (d) show that there is no impact on worker exit – both on voluntary (quits) and involuntary (layoffs) exits. Moreover, in sub-section 6.3, I show that there are no heterogeneous effects by whether the worker is an under- or over-performer in terms of pay growth at baseline. As I find a higher rate of job transfers but no evidence of higher firm exit, this suggests that high-flyer managers are not kicking out workers from the firm but rather they are finding alternative suitable deployments inside the organization.

5.2. Worker career progression and productivity

In the previous sub-section, I presented evidence that high-flyer managers cause higher job reallocation to the workers they supervise through lateral transfers. In this sub-section, I show that they also have a positive persistent impact on the career progression of their workers.

Salary. Figure II Panel (b) compares the effects on the number of salary grade increases when transitioning from a low to a high-flyer manager ($LtoH$) relative to transitioning from a low to another low-flyer manager ($LtoL$). Prior to the event date, the differences in the coefficients are statistically indistinguishable from zero. In contrast, after the transition date, the evolution of salary increase rates starts to gradually diverge between the $LtoH$ and $LtoL$ workers. At 28 quarters after transitioning to a high-flyer manager (relative to transitioning to another low-flyer manager), the salary grade rates are 0.17 higher ($p < 0.05$).

This corresponds to a salary that is 13% higher: Panels (a)-(c) of Figure V show the salary estimates (pay plus bonus), as well as the pay and bonus estimates separately. The bonus increases by 116%, but it should be considered that bonus is only roughly 10% of fixed pay for work-level 1 workers.

The gap in overall pay is economically large: in the U.S. it represents $11,962 in annual salary, on average.[14] An alternative way of illustrating the magnitude of this effect is to consider that a 13% higher salary corresponds, on average, to the salary increment a work-level 1 new hire would accumulate over seven years of employment.

Promotions. In Panel (d) of Figure V, I look at work-level promotions, which in this case entail transitioning from a work-level 1 position to a work-level 2 managerial position. Seven years after transitioning to a high-flyer manager (relative to transitioning to another low-flyer manager), the number of work-level promotions is 0.02 higher or 31% increase ($p < 0.05$). The work-level promotions manifest after the manager transition and start to show significant effects from 3 years onwards.

Sales productivity. So far, I have interpreted higher worker pay growth as evidence of higher productivity. By leveraging sales performance data from the subset of field sales workers, I can provide further evidence in favor of this interpretation. Specifically, I have sales bonus data on 5,604 employees in 15 countries over 2018-2021. Field sales workers are paid a variable sales bonus according to what they achieve relative to their targets each month.[15] The data is high-frequency as sales performance is tracked monthly, but it is relatively noisy. The results are shown in Figure VI. Compared to LtoL workers, LtoH workers' standardized sales bonus is 0.347 standard deviations higher 12 quarters after the event ($p = 0.052$).

[14] To quantify how influential high-flyers are for workers' careers, one can also compute how they affect the present value of the workers' lifetime income. Assuming that careers last another 30 years (since most workers are in their late 20s or early 30s) and using a discount rate of 5% (I follow Frederiksen et al. (2020) for this assumption), a two-year exposure to a high-flyer manager is associated with an increase in the presented discounted value (PDV) of pay of 167.6% of average annual pay.

[15] Some examples of sales targets include growth of sales; product placement; on-shelf availability; additional exhibitions; and the number of orders vs. total visits each month.

5.3. Asymmetric effects, losing a high-flyer

So far, I analyzed the impact of gaining a high-flyer manager. I now look at the reverse transitions, i.e., losing a high-flyer manager (moving from a high-flyer to a low-flyer manager compared to moving to another high-flyer manager). Figure VII shows that there is no differential impact when losing a high-flyer manager, the estimates are close to zero and statistically insignificant. In particular, the point estimates do not exhibit a detectable downward trend, which would be expected if losing a high-flyer manager had the opposite effect of gaining a high-flyer manager.[16] Hence, the high-flyer manager results are asymmetric: compared to gaining a high-flyer (Figure II), losing a high-flyer does not lead to similar findings in the opposite direction, such as lower salary growth and transfers (see Figure VIII for a formal test of asymmetries).

This evidence conveys two key points. First, there are dynamic benefits of a one-time exposure to a high-flyer manager (which lasts two years on average): the impact endures even after transitioning to a low-flyer and there is no additional impact of having a second high-flyer manager.[17] Second, these findings reinforce the interpretation of the allocation channel as, once a worker has found the right job match, the gains cannot be erased by transitioning to a low-flyer manager. If high-flyers were mainly motivating or monitoring workers to exert higher effort, we would expect to see symmetric effects so that, upon transferring from a high- to a low-flyer manager, there is a negative impact on the worker's career progression (compared to transferring from a high- to another high-flyer manager).

[16]Because of the reduced number of $HtoH$ transitions (by virtue of the definition of a high-flyer manager that categorizes less than one third of managers as high-flyers), the number of observations is insufficient to estimate the impacts beyond the 20th quarter (five years post manager transition). Hence, the x-axis of these plots ends at the 20th quarter.

[17]It is helpful to consider this result in light of the identification strategy that relies on manager rotations. A threat to the validity of the strategy is potential non-random assignment of managers to teams. A profit-maximizing firm may want to design rotations to maximize output, which may cast doubt on the firm's rationale for having rotations in random order. Yet, my results suggest that the optimal policy would be close to random assignment as it would entail assigning managers to teams to maximize the chance that each worker gets exposed to a high-flyer manager at least once. This is because, as the asymmetric effects make evident, a one-time exposure to a high-flyer has a persistent effect on a worker's career.

5.4. Robustness

In this sub-section, I report a series of robustness exercises to the event-study estimates. In addition, in the Supplementary Materials, I report the results of a placebo exercise where I reproduce the analysis, but instead of focusing on high-flyer managers as the relevant characteristic of managers, I focus on a characteristic that I know ex-ante should not be relevant: whether the manager's "position number" (generated automatically by the HR system when hiring a worker) is even or odd.

Different definitions of high-flyer managers. I conduct robustness checks using alternative age cutoffs. The results are shown in Appendix Figure A.7. The blue lines present the baseline event study results, while the red ones present the results using different age-based high-flyer measures. In particular, I make the criterion for high-flyer managers to be more or less stringent by using continuous age 28 or 32 as the threshold. I also use the original (non-imputed) coarse age band variable to construct the high-flyer measure. As can be seen from Figure A.7, results are very similar when adopting different high-flyer definitions.

Tenure is also a natural and intuitive metric to capture a worker's speed of progression within the firm. In Appendix Figure A.6, I use an alternative high-flyer definition based on tenure at promotion to work-level 2. The tenure-based high-flyer manager definition is constructed as such: a manager is defined as a high-flyer manager if their minimum tenure when they are in work level 2 (middle management position) is ≤ 5. It is clear from the figure that the key patterns hold under tenure-based definitions as well.

I ultimately adopt age at promotion to work-level 2 as the primary proxy for high-flyer managers as age serves as a more comprehensive proxy for labor market experience than firm tenure. Variation in age more accurately reflects differences in cumulative labor market exposure and labor market experience, whereas tenure captures experience only within the current firm and would overlook prior relevant employment history.

Cohort dynamics. I can also run the event study using the interaction-weighted estimator developed by Sun and Abraham (2021). Appendix Figure A.8 presents the results, which remain very similar. As discussed in Section 2, in this setting, cohort-specific contamination is unlikely to bias the results, as the firm's policies and organizational structure remained stable over the 10-year period under study.

Restricting the event-study to new hires. Throughout the paper, I am only considering the first observed manager transition. However, as my data is only available from January 2011, some workers may have experienced other manager transitions before then. If so, my estimates are averaging the effects on workers who have different histories in terms of manager transitions. This should not cause bias in my estimates as long as each transition event is independent, which follows from the managers' rotations. I show that my results are robust to only considering new hires, identified as those workers whose minimum tenure in the data is strictly less than 2 years. I retain 64% of events. Panels (a) and (b) of Appendix Figure A.9 show that the event studies limited to new hires have very similar results.

Poisson model for count data. Panels (c) and (d) of Appendix Figure A.9 show the event-study graphs when using a Poisson model as in equation 4 for the count variables: lateral transfers and salary grade increases. The figures report the first differences in the exponentiated coefficients and so they should be interpreted as the differences in the incidence rate ratios. For example, Panel (d) of Appendix Figure A.9 indicates that workers gaining a high-flyer manager have a rate of salary increases 1.4 times greater, five years post-transition (where $\hat{\beta}_{LtoH,20} - \hat{\beta}_{LtoL,20} = 0.334$, and $e^{0.334} = 1.40$).

6. Evidence for the allocation channel

The results in Section 5 show higher lateral transfers and career progression for workers gaining a high-flyer manager. In this section, I provide evidence indicating that matching workers to jobs is a quantitatively important mechanism underlying the observed impacts of high-flyers on workers' careers.

6.1. Linking job moves to performance

A story by a worker from the firm illustrates the proactive "match-making" role that managers can play. In this case, the manager recognized the worker's passion for environmental sustainability and recommended the worker for a lead role in the firm's new green initiative. This opportunity not only aligned with the worker's personal values but also served as a pivotal step in the employee's progression toward a strategic leadership role.

To formally analyze the role of lateral moves behind the increase in salary, I perform a mediation analysis following the method by Imai et al. (2010a) and Imai et al. (2010b). The underlying intuition is that the treatment effect of high-flyers on outcome Y (salary) can be decomposed as operating through the mediator M (lateral move):

$$\frac{dY}{d\text{High-Flyer}} = \frac{\partial Y}{\partial M}\frac{\partial M}{\partial \text{High-Flyer}} + R \tag{5}$$

where R is the part of the treatment effect which cannot be attributed to the mediator. The actual implementation is based on an algorithm that calculates the average mediation and direct effects by simulating predicted values of the mediator or outcome variable, which are not observed, and then calculating the appropriate quantities of interest: average mediation, direct effects, and total effects. I take the number of salary grade increases in the 28th quarter as the outcome, Y, and the number of lateral moves in the 16th quarter as the mediator, M.

I find that lateral transfers contribute 64% of the total effect of high-flyers on the number of salary increases.[18] It is plausible to assume that 64% is a lower bound for the importance of the job matching channel. By using lateral moves as the instrument to proxy for job matching, the analysis misses the gains of (i) workers who do not change jobs because they are in good matches already, (ii) vertical transfers (which are also about job allocation but are left out as they involve a salary raise by definition), (iii) any task-allocation decision that does not involve a job change, such as the assignment of short-term projects.[19]

[18] Results do not change for small changes to the time horizons or when using the approach by Gelbach (2016) and Heckman and Pinto (2015).

[19] As is typical in the literature, the results of the mediation analysis should be interpreted with caution. Drawing causal conclusions requires making strong assumptions about the source of variation of the mediator. Still, they provide a practical estimate of the quantitative importance of lateral transfers in explaining the salary effect.

6.2. Managers and workers' skills and behavior

Insights from individual qualitative interviews conducted with workers at the firm highlight some key behaviors exhibited by effective managers. Workers report that good managers actively support career development by initiating conversations about growth opportunities, providing constructive feedback through structured one-on-one meetings, encouraging autonomy, and giving employees space to take initiative. Rather than simply assigning and supervising tasks, these managers act as mentors—engaging with employees about their interests and aspirations. For example, one worker describes how their manager recognized an interest in graphic design during a routine project presentation and subsequently arranged for them to take the lead on the design component of a future campaign—an opportunity that aligned closely with the employee's skills and long-term goals.

I find support for these qualitative insights in quantitative measures that track the behavior of managers and workers. Specifically, I draw on time-use and skills data to assess how high-flyer managers differ from their peers in how they allocate their time and what types of skills they possess. I then turn to workers and examine whether employees under high-flyer managers behave differently in terms of career engagement using internal job search data.

Manager behavior. Table IV draws on time-use data from Microsoft covering a random sample of 600 work-level 2 managers across multiple functions and countries. The data show that high-flyer managers spend 0.63 more hours per week in one-on-one meetings with subordinates (a 19% increase relative to low-flyer managers). They also send more emails, have fewer uninterrupted one-hour blocks, and engage in more multitasking (e.g., sending emails or messages while in meetings). These patterns are consistent with the idea that high-flyer managers facilitate better worker-job allocation by maintaining denser and more responsive communication with their teams and operating as active coordinators.

In addition, I use data on managers' skills from a new platform gradually introduced in 2018 where employees can post skills acquired, and these are in turn certified by their supervisor. As employees can post multiple skills, I reduce the dimensionality of the data by implementing a 3-topic Latent Dirichlet Allocation (LDA) algorithm. Each topic represents a probability distribution over the skill descriptions. The three topics are illustrated in the word clouds in Panels (b)–(c) of Appendix Figure A.10. Based on visual inspection, they broadly correspond to project management, strategy, and talent management skills.

As the LDA algorithm returns a skill distribution for each manager over the three topics that sums to one, I estimate seemingly unrelated regressions using the topic shares as outcomes, with project management as the reference category. Panel (a) of Appendix Figure A.10 present the results. High-flyer managers are significantly more likely to report skills related to strategy and talent management compared to low-flyer managers, thus reinforcing the view of high-flyers being better positioned to allocate and develop talent within their teams. In the Supplementary Materials, I also document that workers under a high-flyer manager are more likely to report higher manager effectiveness in the annual engagement surveys run by the company.

Worker behavior. Table V examines worker behavior by analyzing data from the firm's flexible project program and from the internal learning platform. Workers who gain a high-flyer manager are significantly more engaged in the flexible projects initiative: they are 9.7% more likely to complete their profile on the platform, 15.4% more likely to apply to project roles, and they apply to 50.5% more projects overall. These short-term projects, which take place inside the company but outside the worker's current team, are designed precisely to allow greater career and organizational agility by allowing workers to explore different career paths. Additionally, data from the internal talent-matching platform show that workers who gain a high-flyer manager post 0.66 more skills (a 10.0% increase), suggesting that these workers become more proactive in signaling and developing their capabilities.

6.3. Heterogeneous effects

To further probe the allocation mechanism, I examine heterogeneous treatment effects by extending the model in equation 2 to allow the effects to vary with characteristic H_i:

$$y_{it} = \sum_{j \in J} \sum_{s \neq -1} \beta_{j,s} D^{j}_{i,t+s} + \sum_{j \in J} \sum_{s \neq -1} \beta^{H}_{j,s} D^{j}_{i,t+s} \times H_i + \boldsymbol{\xi}_t + \boldsymbol{\alpha_i} + \epsilon_{it} \tag{6}$$

where all the variables are defined as in equation 2. Let H_i be a dummy variable that indexes for example, younger workers, then β identifies the effect of high-flyers on older workers while β^H identifies the differential impact between younger and older workers. Thus, β^H tests for the presence of heterogeneous treatment effects and it is the main coefficient of interest. Since the high-flyer managers appear to have the largest impact on worker outcomes in the 20th quarter, the display of the heterogeneity analysis focuses on worker heterogeneous outcomes (β^H) in that quarter.

I explore a number of dimensions of heterogeneity on the four main outcomes: lateral moves, salary grade increases, work-level promotions, and worker exit. First, I investigate workers and managers' characteristics: manager tenure, manager and worker being in the same office, manager and worker sharing the same gender, and worker age. Second, I consider characteristics concerning the environment in which they operate: office size, number of different jobs in the office, and country labor laws as measured by the Restrictive Labor Regulations Index from the World Bank. Third, I look at worker baseline performance and team baseline performance in terms of average pay growth in the two years preceding the manager transition: above and below the median and top 10% versus bottom 10%.

Worker and manager characteristics. Panel (a) of Table VI shows that the effects are strongest for managers with higher tenure, workers that are in the same office as their manager, and younger workers, while they largely do not seem to be different based on whether the manager shares the same gender as the worker. It is helpful to interpret these heterogeneous effects through the lens of the allocation channel. Conditional on having a high-flyer manager, a higher manager tenure in the firm tends to correlate with more information regarding job opportunities and career paths at the firm, as well as with higher general experience in managing workers. Second, the worker being in the same office as the manager facilitates interactions and observation by the manager. The larger effects for younger workers make sense when thinking that these workers have just started operating in the labor market: they have a lot to discover about their skills and fit and, relatedly, they have not accumulated yet a lot of job-specific experience.[20]

Environmental characteristics. Panel (b) of Table VI shows that the gains are larger for bigger offices, offices with a larger number of different jobs, and countries with stricter labor laws. The heterogeneous effects along these dimensions also corroborate the allocation channel: small offices or offices with a smaller number of different jobs have less job variety and hence there is less scope for worker-job reallocation, and stricter labor laws impose constraints on hiring and firing, making reallocation of existing talent to jobs particularly crucial.[21]

Worker and team performance. Panel (c) of Table VI displays no evidence of heterogeneity in terms of worker and team performance, indicating that high-flyers are not disproportionately benefiting higher or lower-performing workers. Going back to the allocation channel, in a world where workers have horizontal differentiation in task-specific skills, it pans out that high-flyers impact both high and low performers. In both cases, there could be instances of misallocation, which the high-flyer manager uncovers.

7. Discussion

7.1. Alternative channels

Manager bias, social connections, and information. I interpret the lateral moves and career effects as the causal impact of high-flyer managers improving worker-job match and performance, rather than merely boosting pay. Three facts argue against bias or network favoritism. First, productivity rises: exposure to a high-flyer increases monthly sales productivity by 0.347 SD twelve quarters after the event (Figure VI). Second, workers under high-flyers are more likely to move outside the manager's prior network (in terms of subfunctions/branches/peers) and less likely to remain with the same supervising manager, inconsistent with a pure infor-

[20]The framework in Appendix C clarifies this trade-off between finding a better job match and losing previously accumulated job-specific human capital.

[21]The heterogeneous effects by labor laws echo the findings of Fenizia (2022) on good managers having large impacts on the efficiency of the public sector despite the lack of many of the tools available to private sector firms such as hiring, firing, and promotions.

mation or "plug-in to my network" channel (Appendix Table B.5). Third, homophily does not appear to drive the results: effects do not vary by manager–worker gender match (Table VI, panel a). A leniency-bias story would also require the bias to be correlated with high-flyer status; if uncorrelated, it is differenced out by the design.

Manager teaching, motivating, or monitoring workers. The empirical evidence also points away from teaching, transmitting higher motivation to work, or monitoring. (i) Lateral moves, including the task distant moves and out-of-team moves, cannot be easily reconciled with these other channels (see Panel (a) and (b) of Figure III).[22] (ii) The effects are asymmetric—losing a high-flyer does not mirror gains—whereas motivation/monitoring would predict symmetry. (iii) Pay dispersion rises when teams move from low- to high-flyer managers, inconsistent with uniform effort-raising (Appendix Figure A.11).[23] (iv) Exits do not increase, thus gains are unlikely to be driven by higher general human capital (Figure II, panels (c) and (d)). (v) Employee-survey outcomes, such as "going the extra mile," do not differ, offering little support for an aspirations/effort story (see Section 3 in the Supplementary Materials).

In terms of talent hoarding, if high-flyer status is uncorrelated with hoarding, it cannot account for the findings—consistent with Haegele (2024), which finds no link between hoarding and manager characteristics. If high-flyers hoard more, my estimates are a lower bound because hoarding suppresses lateral and vertical moves. If they hoard less, we should see heterogeneity by baseline performance (low-flyers retaining stars and shedding low performers), which I do not observe (Panel (c), Table VI). Workers who make a lateral move also do not differ in engagement-survey responses, reducing "escape from hoarding" concerns (see Section 3 in the Supplementary Materials). Asymmetric career effects upon losing a high-flyer manager are also in contradiction with a hoarding explanation.

Institutional factors. Congestion effects – where subordinates benefit simply from their manager's promotion (Bianchi et al., 2023) – are not supported by the data since workers are no

[22] This is also discussed more formally in Appendix C with a framework, which shows how these other channels would have opposite predictions on lateral moves.

[23] To shut down effects due to changes in team composition, I keep the team constant at the time of the manager transition, regardless of whether a worker continues to work under the manager of the transition or changes manager after some time.

more likely to inherit their manager's role (Appendix Table B.5), and promotions are determined at the sub-function level, not the team. In addition, high-flyer managers do not create new jobs or eliminate existing ones at higher rates, indicating that they are reallocating workers across pre-existing roles rather than changing the opportunity set (see Appendix Table B.6).

Together, these findings support the interpretation that high-flyer managers improve worker careers by efficiently matching talent to roles, rather than through bias, favoritism, or institutional artifacts.

7.2. Managers' outcomes

Given the value that high-flyer managers bring to the firm, a natural question is the extent to which these managers are "rewarded" by the multinational. On average, a high-flyer manager has a 12.0 percentage point higher increase in salary over a 12-month period compared to a low-flyer manager (from Panel (b) of Table III, which shows that the monthly salary growth is 1.0 percentage point higher). As the average annual increase in salary for low-flyer managers is 10.8%, this estimate is economically meaningful: being a high-flyer manager more than doubles the salary growth rate.

A related question is: for high-flyer managers, how much cost does the firm incur in higher manager salaries relative to the benefits of more productive workers? To answer this, I retrieve the company's 2019 income statement from the Orbis database to get operating profits per employee as an indicator of the company's overall profitability per employee. I also take the average salary of low-flyer managers in 2019 from the company's payroll data. Both values are kept confidential to preserve the anonymity of the firm. In addition, I consider that: (1) high-flyer managers receive an additional 12.0 percentage point salary raise each year relative to low-flyers (Panel (b) in Table III), (2) workers are 0.347 S.D. more productive when exposed to a high-flyer manager (Figure VI), which is roughly a 16% increase relative to the LtoL worker mean and (3) average team size for work-level 2 managers is 5 workers. Hence, I compute the cost-benefit ratio as:

$$\frac{\text{Cost}}{\text{Benefit}} = \frac{\%\Delta\text{Manager wages}^{\text{High-flyers}} \times \text{Average manager wages}^{\text{Low-flyers}}}{\%\Delta\text{Worker productivity} \times \text{Operating profits per empl.} \times \text{Team size}}$$

I find that the firm pays out roughly \$0.21 in higher manager salaries for each \$1 in benefit from higher worker productivity. Hence, the extra pay that high-flyer managers receive is well worth the return to the firm from more productive employees.

7.3. External validity

In terms of context, my results are most directly comparable to those of Lazear et al. (2015), which use company data on technology-based services workers, and of Frederiksen et al. (2020), which use data on the performance system of a Scandinavian service sector firm. They estimate supervisor fixed effects and find them to be large. For instance, in Frederiksen et al. (2020), worker performance increases by 30% when assigned to a 1 standard deviation higher-rated supervisor. Moreover, Weidmann et al. (2024) develops a lab experimental measure of managerial contributions and finds that a 1 standard deviation in managerial skill improves team performance by 0.22 S.D.

My estimates are aligned with these benchmarks: upon switching from a low to a high-flyer manager, sales performance increases by 0.347 S.D. four years later (16% higher) and pay is 13% higher from five years onwards. The aforementioned studies, however, only investigate the short-run effects of managers due to the limited duration of the interventions, thus they cannot speak to persistence. By contrast, in this paper, I track workers' *career trajectories* over time and document that the impact of high-quality managers is both substantial and persistent.

While the results pertain to only one firm, and the magnitude of the effects may vary in other contexts, the mechanism of managers harnessing workers' unique skills by directing them to their most suitable career path is of general application. Moreover, three features of my environment suggest that the patterns documented here are likely present both in other firms and in other countries. First, I study the entire population of workers in the firm, rather than a sub-sample. Second, the firm is similar to other manufacturing firms in terms of its workforce composition as well as its organizational design (sub-section 2.1). Third, the firm is present in more than 100 countries worldwide, suggesting that the results are not country-specific.

In studying the internal labor market of a multinational firm, I extend the grasp of economic analysis to questions of importance to today's large companies. This is particularly relevant when considering that, across the OECD countries, large firms with over 250 workers represent only 1% of enterprises but account for a staggering 40% of manufacturing employment.[24] Modern business enterprises feature rich and complex internal labor markets characterized by a multiplicity of horizontally differentiated jobs as well as vertical layers (Topel and Ward, 1992).[25] Within these, firms rely on managers to determine the allocation of workers to jobs and to steer workers' careers so that they can reach their potential in the organization (Drucker, 2001; Conaty and Charan, 2010).[26] The scale of these internal transitions is notable: data from the Current Population Survey in the US over the past two decades shows that internal job transitions account for approximately 30-35% of the rate of employer-to-employer (EE) transitions (Bagga, 2024).

8. Conclusion

Managers are at the heart of organizations, within which they determine the allocation of resources, and thus are fundamental in the theory of the firm (Coase, 1937; Chandler, 1993). Their importance can also be seen in the latest empirical trends: globally, the managers' share of wages is 38% (ILO, 2019). And yet, empirical evidence studying the long-term impact of

[24]Based on OECD Structural and Demographic Business Statistics. Moreover, Autor et al. (2020) documents extensively how large firms have gotten bigger over the last five decades across high-income countries. For example, the share of U.S. employment in firms with more than 5,000 employees rose from 28% in 1987 to 34% in 2016.

[25]Topel and Ward (1992) highlight: "Large organizations encompass transitions that would otherwise occur between smaller ones. This "internal labor market" means that careers develop within the firm, though there may be no less mobility among tasks in large organizations".

[26]Organizations such as General Electric, Procter and Gamble, LG, and Novartis have been heavily investing in building effective people management strategies to develop and allocate employees to the positions they are best suited for.

individual managers on workers' careers remains sparse.

I open the "black box" of the firm by collecting novel personnel records from a large consumer goods multinational and provide evidence that the ability of managers to match diversely skilled workers to specialized jobs inside the firm has large and persistent effects on worker performance and career paths. The impacts of a worker's exposure to a good manager extend far beyond the period circumscribed by the particular manager-worker spell. In fact, it may often be through the future career development of their workers that managers' greatest influence on firm productivity occurs. Such gains are out of a more productive allocation of workers and occur potentially at zero cost, as they do not require any firing, hiring, or training of workers.

Connecting this to the literature on the AKM framework on matched employer-employee datasets, which typically documents the lack of firm-worker match effects (Abowd et al., 1999; Card et al., 2018), my results indicate that, *within* firms, there is sorting on match effects at the worker-job level. This suggests that managers' learning, or in aggregate employer learning (Altonji and Pierret, 2001), is an important determinant of firm boundaries.

Considering managerial training and management practices, my results underscore that the allocation of workers to jobs is an important margin for improving performance. The ability to create efficient worker-job matches is particularly valuable at times when technological innovation, such as digitalization and artificial intelligence, and disruptions, such as pandemics or climate change, force widespread firm restructuring and require the reallocation of existing workers to new jobs or their replacement with workers featuring new skills. Moreover, my results imply that the most successful managers (as identified by the firm) are able to extract more value from the same managerial practices set by firm-wide policies, indicating that the effectiveness of managerial practices also depends on the managers' ability to use them.

Methodologically, instead of using surveys regarding the way managers run their operations, I analyze rich administrative firm data, unpacking the managers' impacts by looking at outcomes from within the firm. The data does not shed light on the precise skills needed for managers to enable the discovery of workers' unique aptitudes and whether managers can get trained in these or whether they are innate. Designing effective training initiatives to test this, as well as understanding if predictions by artificial intelligence can substitute for or complement human skills, are fascinating questions for future research.

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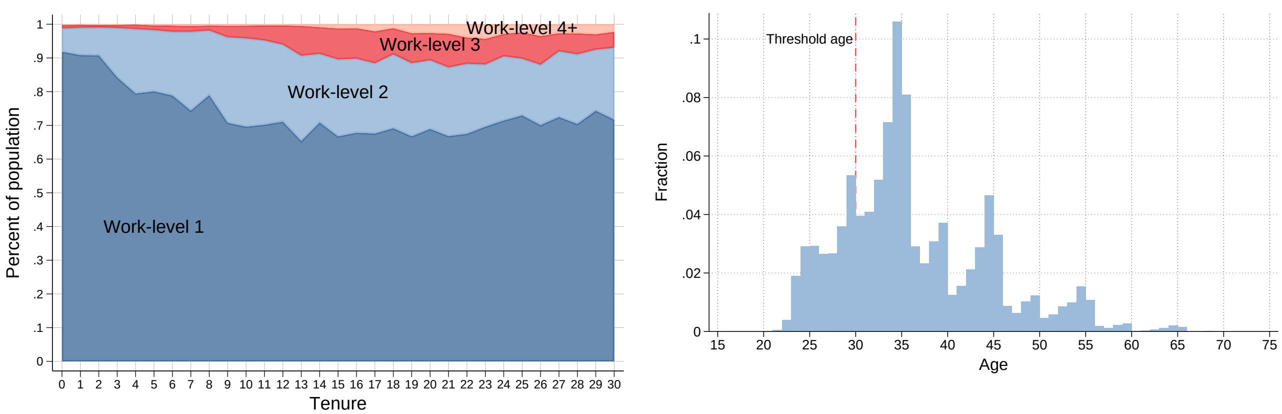
10. Figures

Figure I: Work-levels, tenure and promotion

(a) Distribution of work-levels by tenure

(b) Age at promotion: work-level 2



Notes. Panel (a) presents the cumulative distribution of work-levels at different tenure years. Panel (b) presents the distribution of the minimum continuous age when an employee is observed to be work level 2 in the data. About 26.2% managers are identified as high-flyers, i.e., the minimum continuous age first observed at work level 2 is ≤ 30.

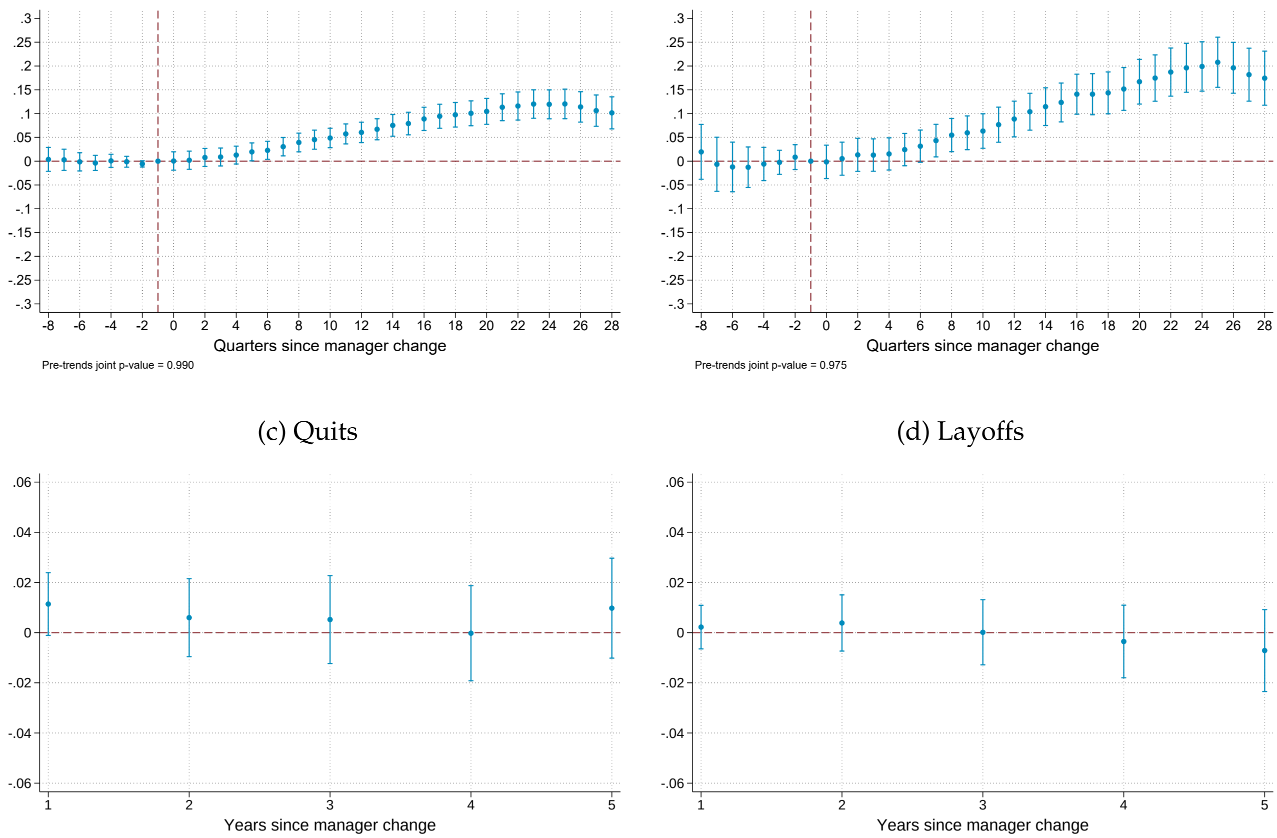
Figure II: Effects of gaining a high-flyer manager $\left(\hat{\beta}_{LtoH,s} - \hat{\beta}_{LtoL,s}\right)$

(a) Lateral moves

(b) Salary grade increases

(c) Quits

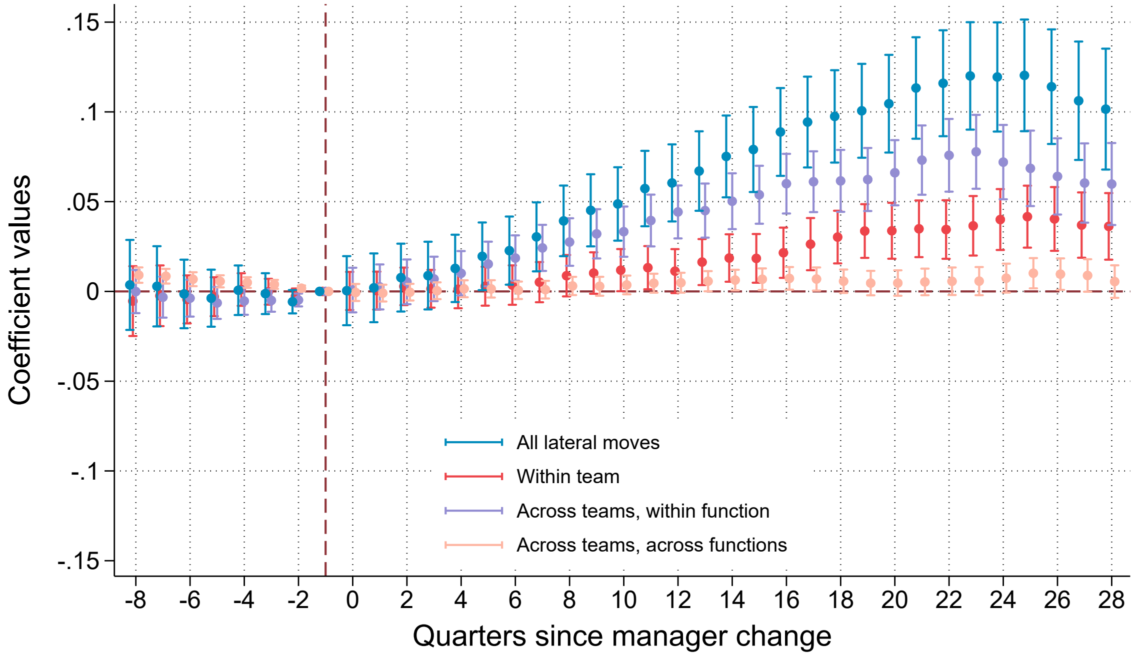
(d) Layoffs



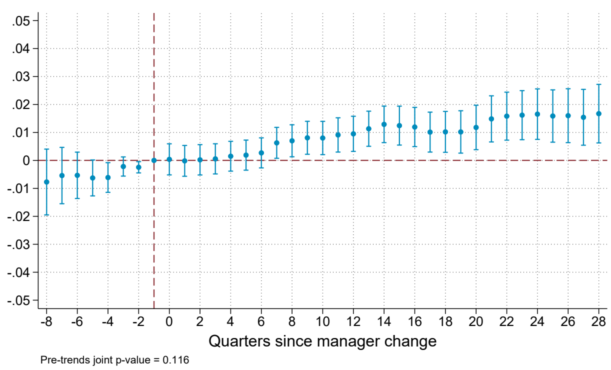
Notes. For (a) and (b), an observation is a worker-year-month, coefficients are estimated from equation 2, and are aggregated to the quarterly level for ease of presentation. The outcome variables are: number of *lateral moves*, and number of *salary grade increases*. The baseline means for the LtoL group of these two outcomes are 0.393 and 0.191, respectively. For (c) and (d), an observation is a worker, coefficients are estimated from equation 3, where controls include the fixed effects of the event time, the interaction of office and function, as well as the interaction between age band and gender. The controls are at the time of the event. The outcome variables are: whether the worker *quits* or *gets laid off* within given years after the event. All standard errors are clustered by manager and 95% confidence intervals are presented.

Figure III: Effects of gaining a high-flyer manager, lateral moves

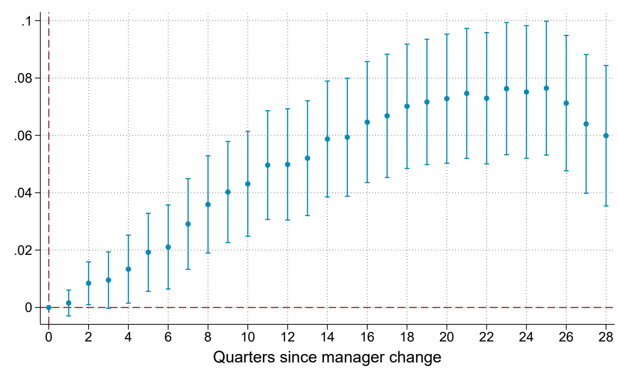
(a) Decomposing lateral moves



(b) Cumulative distance in task distance



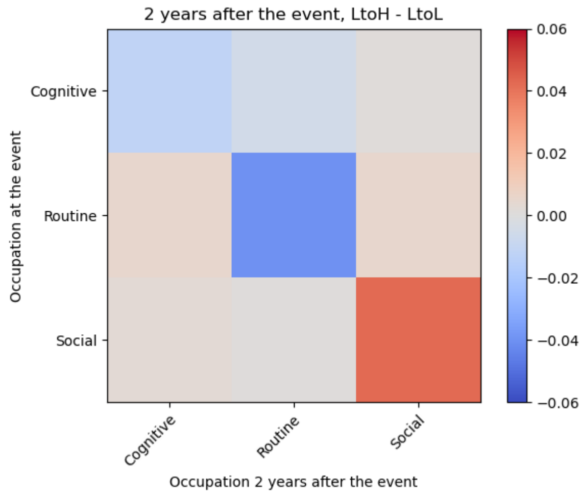
(c) Making at least one post-event lateral move



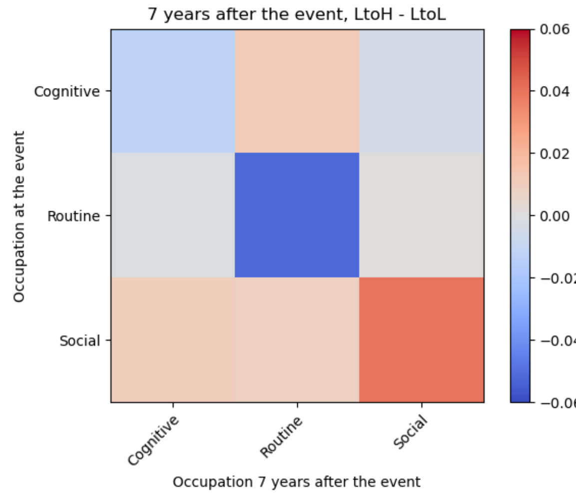
Notes. An observation is a worker-year-month. Coefficients are estimated from equation 2, and are aggregated to the quarterly level for ease of presentation. All standard errors are clustered by manager and 95% confidence intervals are presented. In panel (a), for each lateral move, it can be classified exclusively into one of three types: (i) within team, (ii) across teams, within function, and (iii) across teams, across functions. Similar to the construction of the main outcome variable, I construct the cumulative number of these different types of lateral moves, and use them as the dependent variable in event studies. This makes sure that the sum of the coefficients on the three outcomes equals the corresponding coefficients on the number of lateral moves. In panels (b) and (c), the outcome variables are the cumulative measure of task distance moves using O*NET data and the probability of at least one post-event lateral move. Task distance between any two jobs is constructed by matching the firm's job titles with O*NET occupation titles, and constructing intensity for three tasks: cognitive, routine, and social (as explained in Appendix D). The baseline mean for the LtoL group is 0.015 for this cumulative task distance measure.

Figure IV: Effects of gaining a high-flyer manager, transition matrices across task groups

(a) 2 years later

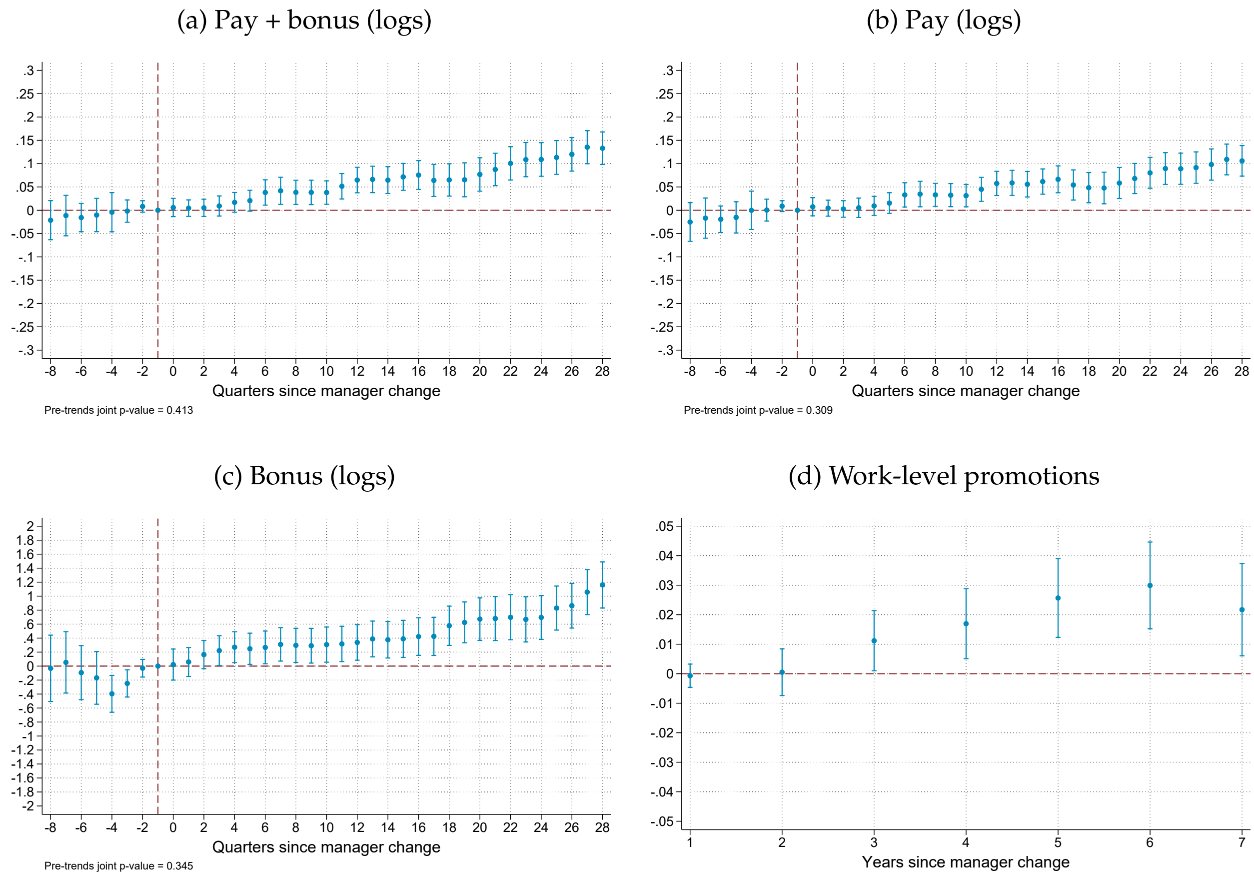


(b) 7 years later



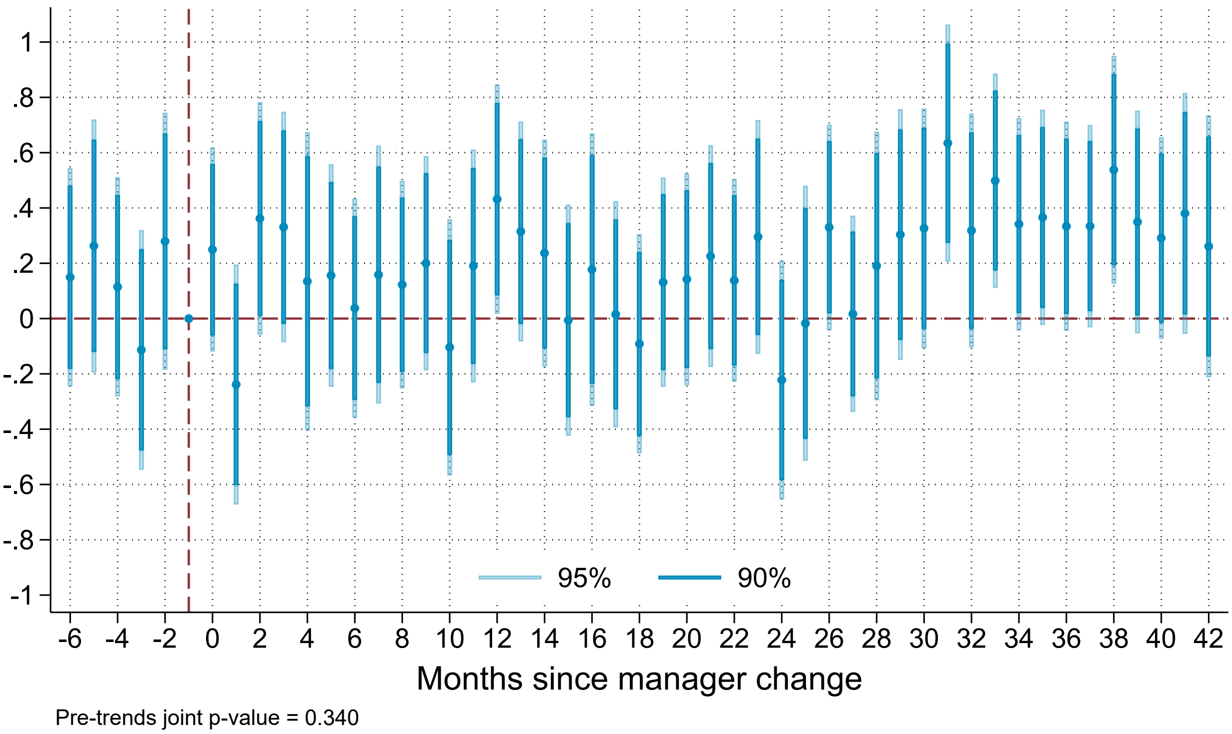
Notes. The heatmaps plot the differences in transition ratio matrices between LtoH and LtoL workers 2 (panel a) and 7 years (panel b) after the manager transition event. Separately for LtoL and LtoH workers, I construct two transition ratio matrices, where the entries denote the fraction of workers doing the transition from one occupation group to the other. A job is classified into a cognitive, routine, or social job based on the highest intensity measure. In the event month, 31% of workers are in a cognitive occupation, 26% are in a routine occupation, and 43% are in a social occupation.

Figure V: Effects of gaining a high-flyer manager on salary and promotions



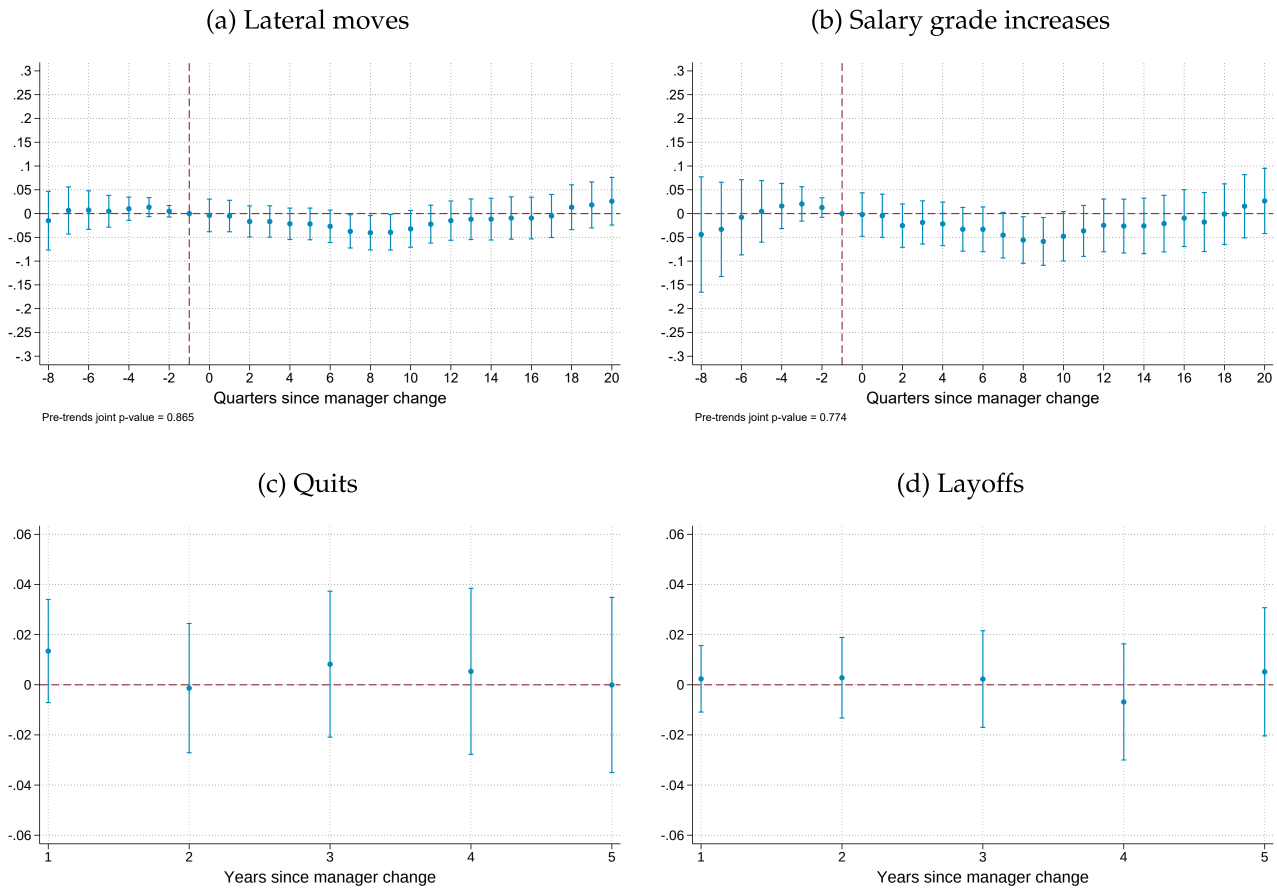
Notes. An observation is a worker-year-month. All coefficients are estimated from a single regression as in equation 2 and are aggregated to the quarterly level for ease of presentation for panels (a), (b) and (c), to the yearly level for panel (d). All standard errors are clustered by manager and 95% confidence intervals are presented. The outcome variables in the first three panels are *pay + bonus* in logs, *pay* in logs, *bonus* in logs, and the outcome variable in panel (d) is the number of *work-level promotions*. For panel (d), since I consider workers who experience the manager transition event at work-level 1, there are no pre-event promotions and only post-transition coefficients can be estimated.

Figure VI: Effects of gaining a high-flyer manager on sales productivity



Notes. An observation is a worker-year-month. All coefficients are estimated from equation 2. The outcome variable is sales bonus (s.d.), which is available for 15 countries for a subset of sales-related occupations inside the MNE. Countries for which the sales bonus data is available are India, Indonesia, Italy, Russia, Mexico, Philippines, Guatemala, Malaysia, South Africa, Nicaragua, El Salvador, Costa Rica, Colombia, Honduras, Greece. All standard errors are clustered by manager, 90% and 95% confidence intervals are presented. The 12th quarter estimate (the average of month 34, 35, 36 estimates) is 0.347 ($p = 0.052$).

Figure VII: Effects of losing a high-flyer manager $\left(\hat{\beta}_{HtoL,s} - \hat{\beta}_{HtoH,s}\right)$

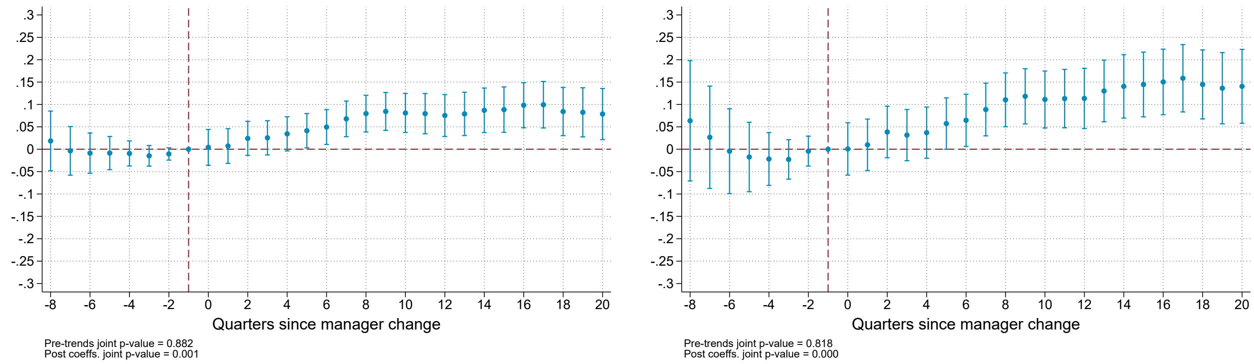


Notes. For (a) and (b), an observation is a worker-year-month, coefficients are estimated from equation 2, and are aggregated to the quarterly level for ease of presentation. The outcome variables are: number of *lateral moves*, and number of *salary grade increases*. For (c) and (d), an observation is a worker, coefficients are estimated from equation 3, where controls include the fixed effects of the event time, the interaction of office and function, as well as the interaction between age band and gender. The controls are at the time of the event. The outcome variables are: whether the worker *quits* or *gets laid off* within given years after the event. All standard errors are clustered by manager and 95% confidence intervals are presented.

Figure VIII: Test for asymmetries, gaining vs. losing $(\hat{\beta}_{LtoH,s} - \hat{\beta}_{LtoL,s}) - (\hat{\beta}_{HtoL,s} - \hat{\beta}_{HtoH,s})$

(a) lateral moves

(b) Salary grade increases



Notes. An observation is a worker-year-month. All coefficients are estimated from a single regression as in equation 2 and are aggregated to the quarterly level for ease of presentation. The outcome variables are: number of *lateral moves*, and number of *salary grade increases*. All standard errors are clustered by manager and 95% confidence intervals are presented.

11. Tables

Table I: Number of observations by workers, managers, jobs

Variable	No. unique values
Total white collar $\times$ months	10,083,638
Employee	224,117
Managers (work-level 2+)	32,473
Supervisors	47,816
Year-month	132
Standard job	2,118
Sub-function $\times$ work-level	473
Offices	2,645
Countries	118
Country $\times$ Year	1,187
Office $\times$ Year	14,769
Employee $\times$ Job	462,286

Notes. The data contain personnel records for the entire white-collar employee base from January 2011 until December 2021.

Table II: Descriptive statistics

	Mean	SD	P1	P99	N
Panel (a): gender, age and education					
Female	0.44	0.5	0.0	1.0	224,117
Share in cohort 18-29	0.25	0.4	0.0	1.0	10,083,638
Share in cohort 30-39	0.39	0.5	0.0	1.0	10,083,638
Share in cohort 40-49	0.23	0.4	0.0	1.0	10,083,638
Share in cohort 50+	0.13	0.3	0.0	1.0	10,083,638
Econ, business, and admin	0.48	0.5	0.0	1.0	14,741
Sci, engin, math, and stat	0.30	0.5	0.0	1.0	14,741
Social sciences and humanities	0.15	0.4	0.0	1.0	14,741
Other educ	0.08	0.3	0.0	1.0	14,741
Panel (b): tenure, hierarchy and team size					
Tenure (years)	8.50	8.8	0.0	35.0	10,083,638
Share in work level 1	0.80	0.4	0.0	1.0	10,083,625
Share in work level 2	0.16	0.4	0.0	1.0	10,083,625
Share in work level 3+	0.04	0.2	0.0	1.0	10,083,625
No. of months per worker	44.99	41.4	1.0	132.0	224,117
No. of supervisors per worker	3.49	3.0	1.0	13.0	224,117
No. of workers per supervisor	5.02	7.8	1.0	33.0	47,816
Panel (c): outcome variables					
Number of salary grade increases	0.60	1.0	0.0	4.0	224,117
Number of lateral moves	0.24	0.6	0.0	3.0	224,117
Number of promotions (work-level)	0.06	0.3	0.0	1.0	224,117
Monthly exit	0.01	0.1	0.0	1.0	10,083,638
Pay + bonus (logs)	10.27	0.9	8.2	12.5	4,977,935
Bonus over pay	0.20	116.2	0.0	0.6	4,977,935
Sales bonus (s.d.)	0.00	1.0	-2.0	2.2	146,831

Notes. An observation is a worker-month-year or a worker or a manager, depending on the nature of the variable. The data contain personnel records for the entire white-collar employee base from January 2011 until December 2021. In Panel (a), cohort refers to the age group, and education data is only available for a subset of workers. In Panel (b), work level denotes the hierarchical tier (from level 1 at the bottom to level 6). In Panel (c), salary information is only available since 2016 and the information on sales bonus is only available for a subset of countries.

Table III: High-flyer managers' characteristics

Variable	Low-flyers (1)	High-flyers (2)	Difference (3)
Panel (a): demographics			
Female	0.451	0.582	0.131***
	(0.498)	(0.493)	(0.000)
MBA	0.001	0.000	-0.000
	(0.026)	(0.020)	(0.656)
Econ, Business, and Admin	0.464	0.546	0.082***
	(0.499)	(0.498)	(0.000)
Sci, Tech, Engin, and Math	0.325	0.241	-0.083***
	(0.468)	(0.428)	(0.000)
Social Sciences and Humanities	0.147	0.185	0.038***
	(0.354)	(0.389)	(0.001)
Other Educ	0.070	0.039	-0.031***
	(0.255)	(0.193)	(0.000)
Mid career hire	0.277	0.131	-0.145***
	(0.447)	(0.338)	(0.000)
Panel (b): performance after high-flyer status is determined			
Monthly salary growth	0.009	0.019	0.010***
	(0.040)	(0.049)	(0.000)
Promotion work-level 3	0.080	0.093	0.013***
	(0.271)	(0.291)	(0.000)
Perf. rating (1-150)	96.431	102.733	6.302***
	(21.380)	(17.156)	(0.000)
Effective leader (survey)	4.047	4.145	0.098***
	(0.704)	(0.683)	(0.000)
Observations	24,506	8,692	33,198

Notes. The table reports means, standard deviations (in parentheses), and p-values for differences in means, which are computed using robust standard errors. *Mid-career hire* refers to managers who have been hired directly as managers by the firm (at work-level 2 instead of work-level 1). *Perf. rating* refers to the performance assessment given annually to each employee; and *Effective leader (survey)* refers to the workers' anonymous upward feedback on the managers' leadership.

Table IV: High-flyer managers' time use

Variable	Low-flyers	High-flyers	Difference
Work-week span	41.977	40.983	-0.995
	(9.512)	(10.595)	(0.336)
Meeting hours	12.759	13.140	0.381
	(4.757)	(4.491)	(0.401)
Meeting hours 1-1 with reportees	3.242	3.869	0.627**
	(2.401)	(2.666)	(0.016)
Meeting hours internal	4.821	3.628	-1.193***
	(4.618)	(4.426)	(0.008)
Meeting hours external	4.696	5.643	0.947***
	(3.273)	(3.746)	(0.009)
Emails sent	65.216	74.859	9.642**
	(36.008)	(46.765)	(0.030)
Open 1 hour block	26.927	24.787	-2.140***
	(7.574)	(8.279)	(0.008)
Multitasking hours	2.712	3.222	0.510**
	(2.081)	(2.220)	(0.020)
Observations	455	129	584

Notes. This table uses time-use data from Microsoft to document how high- and low-flyer managers use their time differently. The original dataset is at weekly frequency spanning over the entire 2019, and contains a random sample of 2000 employees from multiple work levels, gender, age, countries and functions. All variables are the average across all weeks in the year. The table shows the mean and standard deviations (in parentheses) for high- and low-flyer managers and p-values for the difference in means. P-values are calculated using robust standard errors.

Table V: Worker engagement in flexible projects and learning platform

	Profile completed (1)	Applied to any project role (2)	Number of project roles applied (3)	Number of skills (4)
LtoH	0.0458*	0.0434*	0.4818**	0.6552**
	(0.024)	(0.022)	(0.211)	(0.267)
Mean, LtoL	0.474	0.281	0.954	6.581
R-squared	0.296	0.244	0.270	0.251
N	3638	3638	3638	13526

Notes. An observation is a worker. The regression sample consists of workers in the LtoL and LtoH event groups. The regressor is whether the employee is in the LtoH event group. Controls include event time fixed effects, and the interaction of office and function fixed effects. All standard errors are clustered by manager. For columns (1)-(3), data are taken from flexible project program at the firm that allows workers to apply for short-term projects inside the company but outside their current team. Data for column (4) come from the internal talent matching platform. *Profile completed* indicates whether the profile on the platform is fully completed; *Applied to any project role* indicates whether the employee has applied to any project role through the platform; *Number of project roles applied* indicates the number of project roles the employee has applied to; and *Number of skills* is the number of skills posted on the platform.

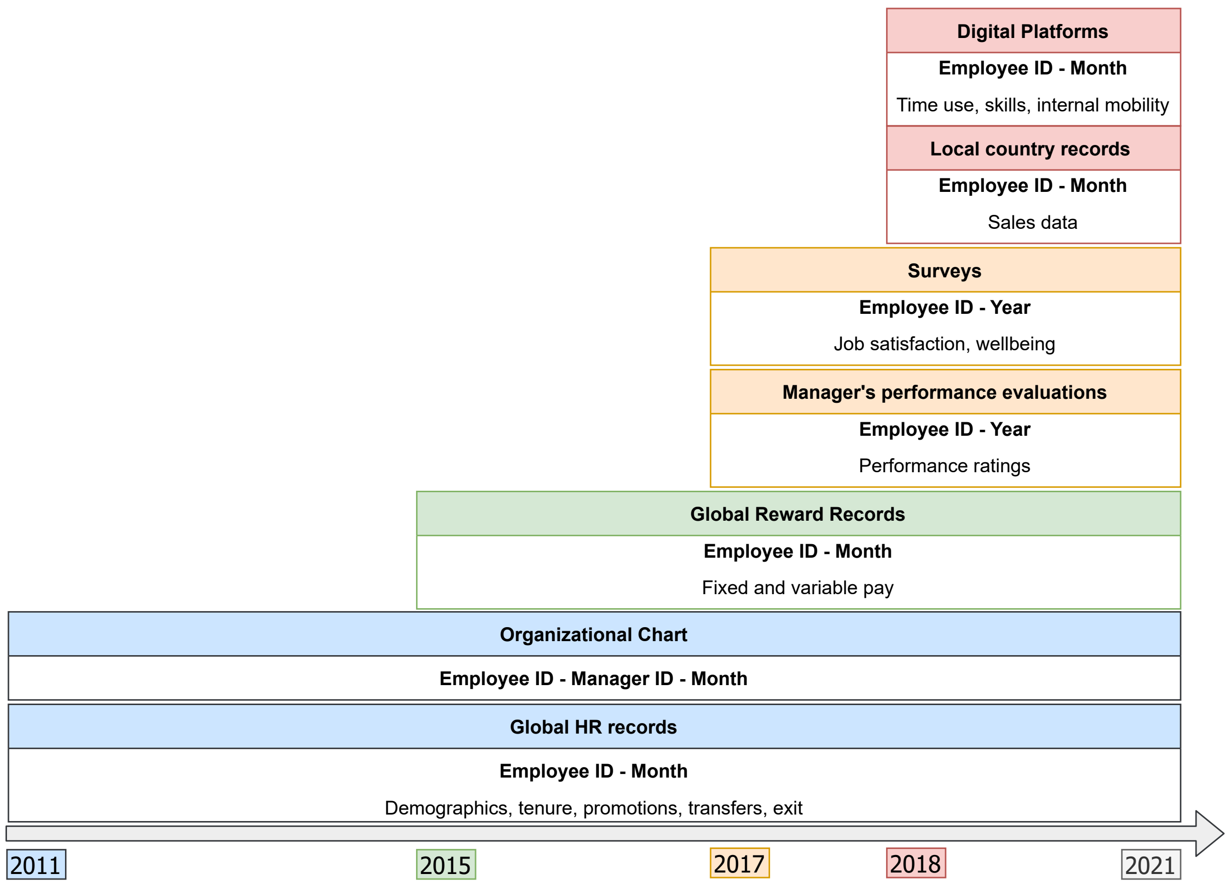
Table VI: Heterogeneous effects of gaining a high-flyer manager

	Lateral move (1)	Salary grade increase (2)	Work level promotion (3)	Exit from firm (4)
Panel (a): worker and manager characteristics				
Manager tenure, high	0.080*	0.090	0.053**	-0.017
	(0.05)	(0.08)	(0.03)	(0.02)
Same office as manager	0.182***	0.178***	0.069***	-0.037*
	(0.04)	(0.06)	(0.02)	(0.02)
Same gender as manager	0.060*	0.060	0.007	-0.005
	(0.04)	(0.05)	(0.02)	(0.01)
Worker age, young	0.080**	0.087*	0.062***	0.003
	(0.04)	(0.05)	(0.02)	(0.02)
Panel (b): office and country-wide characteristics				
Office size, large	0.173***	0.193***	0.067***	0.017
	(0.04)	(0.06)	(0.02)	(0.03)
Office job diversity, high	0.172***	0.194***	0.068***	0.006
	(0.04)	(0.06)	(0.02)	(0.02)
Labor laws, high	0.177***	0.242***	0.085***	0.016
	(0.04)	(0.06)	(0.02)	(0.02)
Panel (c): worker performance				
Worker performance, high (p50)	0.004	0.208	0.050	-0.033
	(0.12)	(0.20)	(0.07)	(0.04)
Worker performance, high (p90)	-0.092	0.273	0.002	0.020
	(0.18)	(0.29)	(0.09)	(0.11)
Team performance, high (p50)	0.023	0.250	0.036	-0.044
	(0.13)	(0.19)	(0.07)	(0.03)

Notes. An observation is a worker-year-month. Coefficients in columns (1), (2), and (3) are estimated from a regression as in equation 6 and the table reports the coefficient at the 20th quarter since the manager transition. Controls include worker and year-month fixed effects. Coefficients in column (4) are estimated from a cross-sectional regression, where the outcome variable is whether the worker left the firm within 2 years after the treatment, and where controls include the fixed effects of event time, the interaction of office and function, as well as the interaction between age band and gender. All standard errors are clustered by manager. Each row displays the differential heterogeneous impact of each respective variable. Panel (a): the first row looks at the differential impact between having the manager with over and under 7 years of tenure (the median tenure years for high-flyer managers); the second row looks at the differential impact between sharing and not sharing the office with the manager; the third row looks at the differential impact between sharing and not sharing the same gender with the manager; the fourth row looks at the differential impact between being under and over 30 years old. Panel (b): the first row looks at the differential impact between large and small offices (above and below the median number of workers); the second row looks at the differential impact between offices with high and low number of different jobs (above and below median); the third row looks at the differential impact between countries having stricter and laxer labor laws (above and below median). Panel (c): the first row looks at the differential impact between better and worse performing workers at baseline in terms of salary growth; the second row looks at the differential impact between the top 10% and the bottom 10% workers in terms of salary growth; the third row looks at the differential impact between better and worse performing teams at baseline in terms of salary growth.

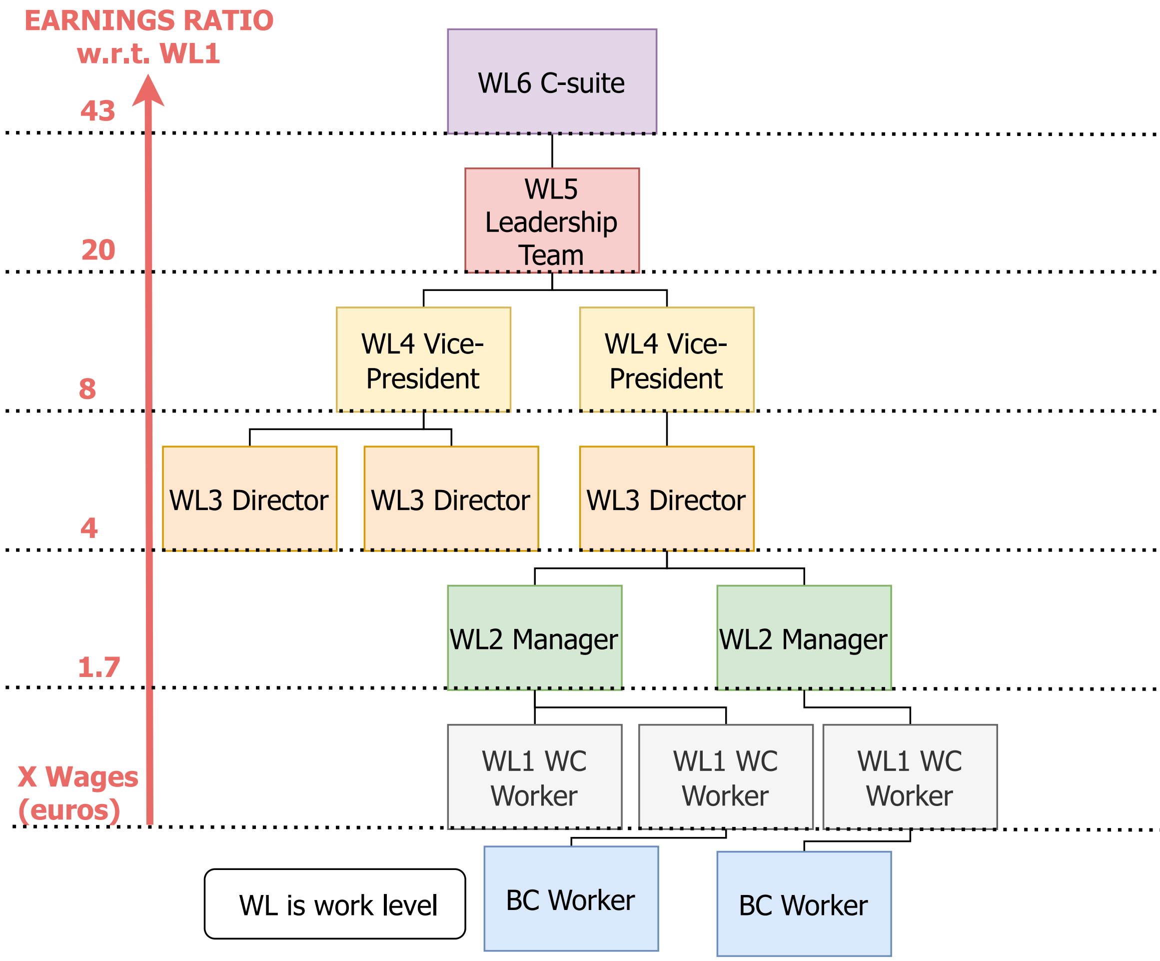
A. Appendix Figures

Figure A.1: Data sources and time periods



Notes. This figure shows the data sources collated from the multinational's records.

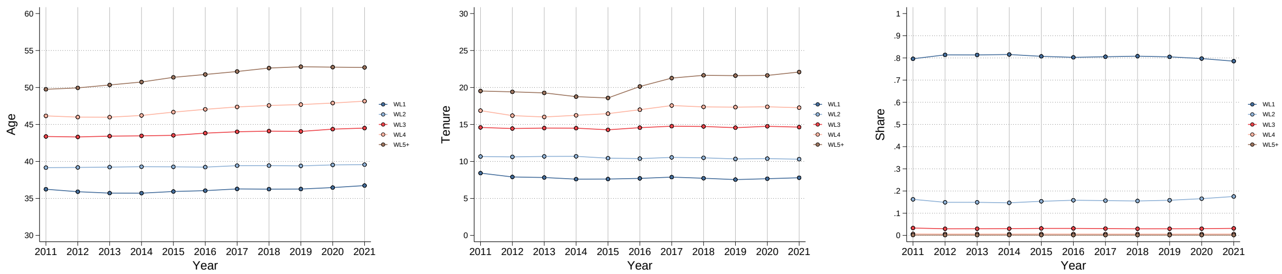
Figure A.2: Firm hierarchy



Notes. This figure shows the vertical job differentiation at the company.

Figure A.3: Age, tenure and work-level profiles over the years, by work-level

(a) Age (b) Tenure (c) Work-level shares

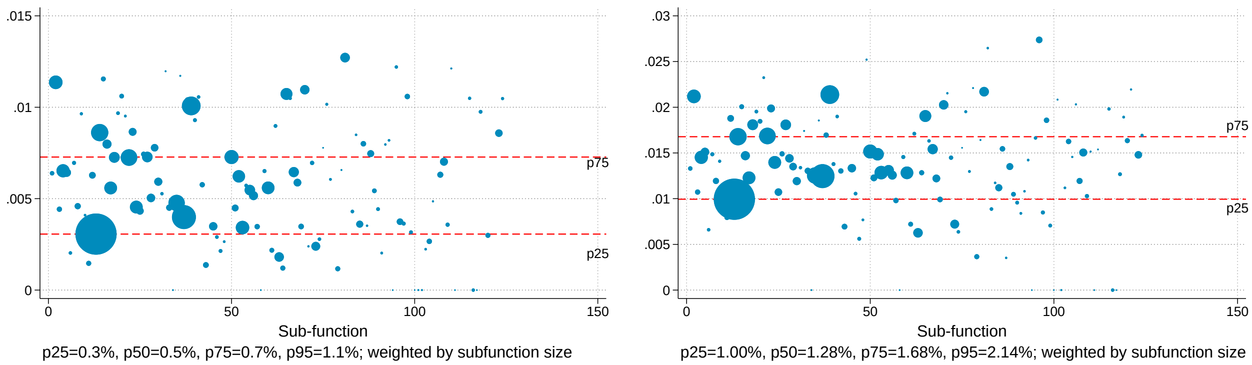


Notes. This figure shows the average age, tenure, and share of workers across work-levels over the years.

Figure A.4: Average lateral move and salary increase rates by sub-function

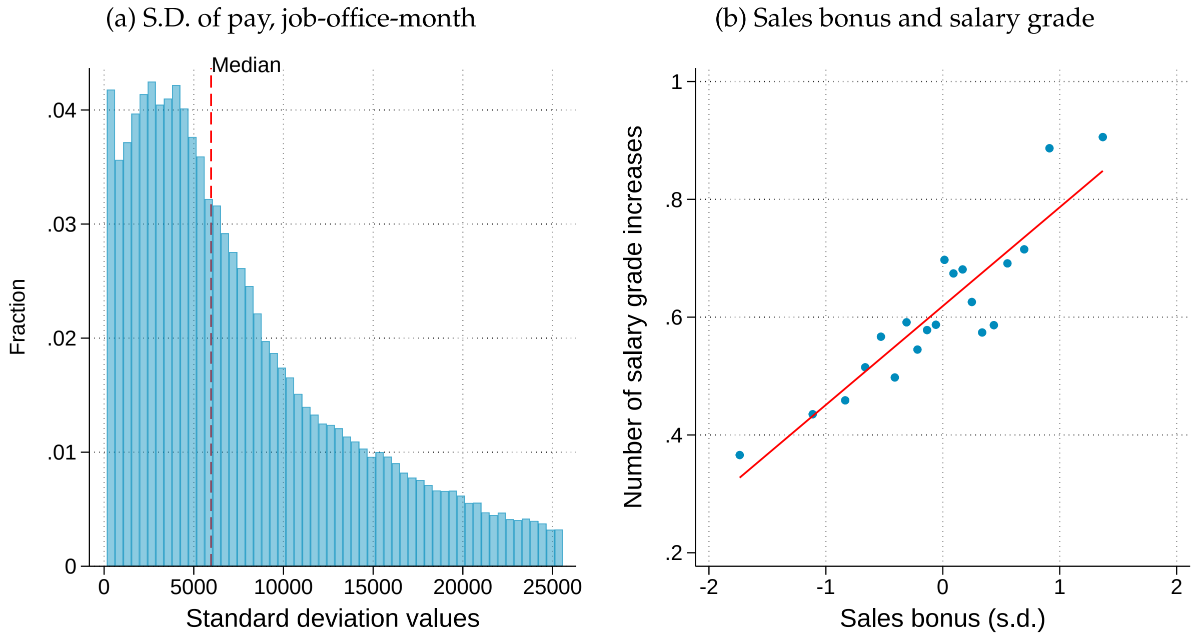
(a) Lateral move

(b) Salary grade increase



Notes. The figure reports, by sub-function, the mean monthly probabilities of (i) a lateral move and (ii) a salary-grade increase. Each circle denotes a sub-function; circle area is proportional to that sub-function's employment size. The horizontal axis indexes sub-functions. To limit the influence of extreme values—particularly from very small sub-functions—rates are winsorized at the 99th percentile.

Figure A.5: Pay, sales bonus, and salary grade increases

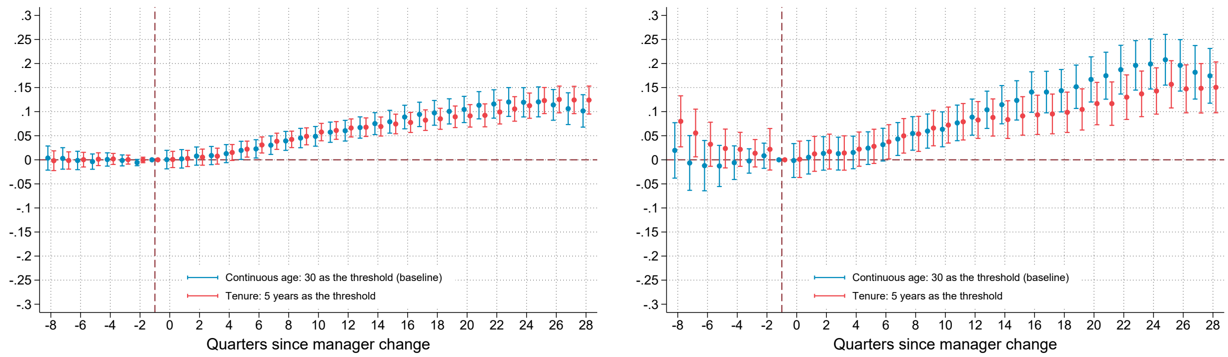


Notes. Panel (a) shows the distribution of the standard deviation in overall pay (fixed pay plus variable pay) within a given job title in an office and year-month. Panel (b) presents binned scatter plots of (standardized) sales bonus against the number of salary grade increases.

Figure A.6: Different high-flyer measures: tenure- vs. age-based measures

(a) Lateral move

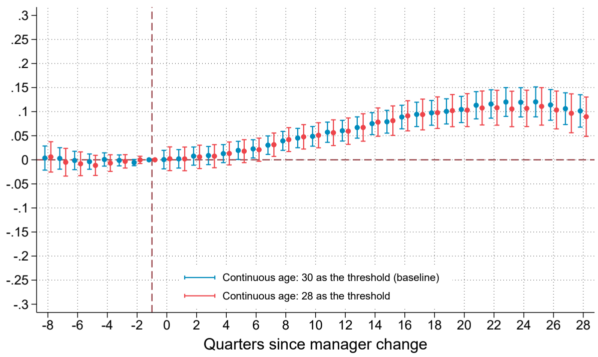
(b) Salary grade increase



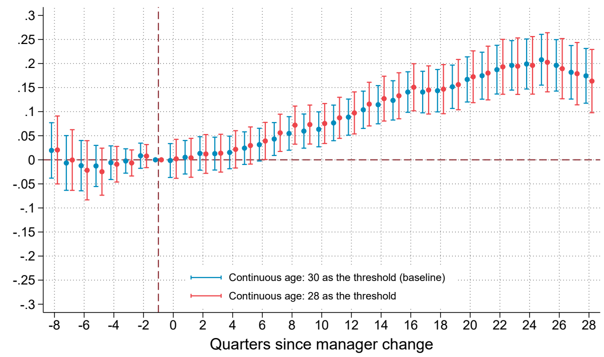
Notes. An observation is a worker-year-month. All coefficients are estimated from a single regression as in equation 2 and are aggregated to the quarterly level for ease of presentation. The outcome variables are: number of *lateral moves*, and number of *salary grade increases*. All standard errors are clustered by manager and 95% confidence intervals are presented. The blue lines report event study results using the baseline age-based high-flyer measure, i.e., high-flyer managers are defined as those whose minimum continuous age observed at work level 2 is ≤ 30. The red lines report event study results using an alternative tenure-based high-flyer measure, i.e., a high-flyer manager is defined as those whose minimum tenure observed at work level 2 is ≤ 5.

Figure A.7: Different high-flyer measures: alternative age thresholds

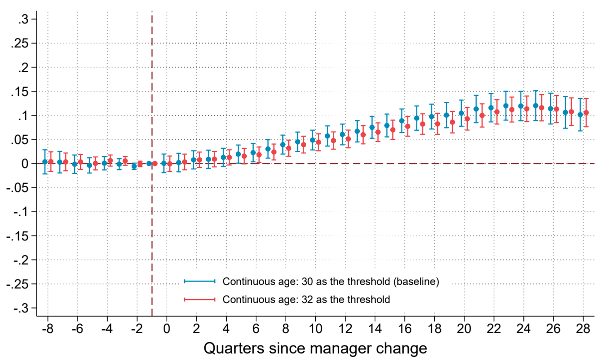
(a) Lateral move; age 28 as another threshold



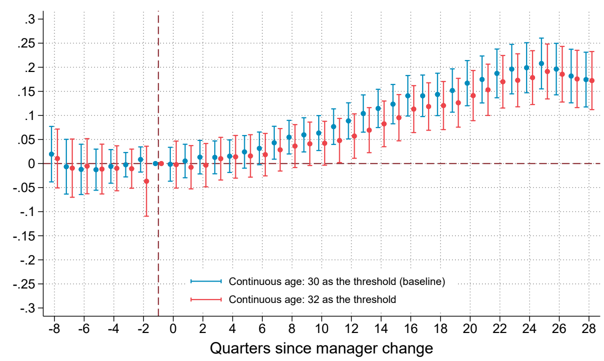
(b) Salary grade increase; age 28 as another threshold



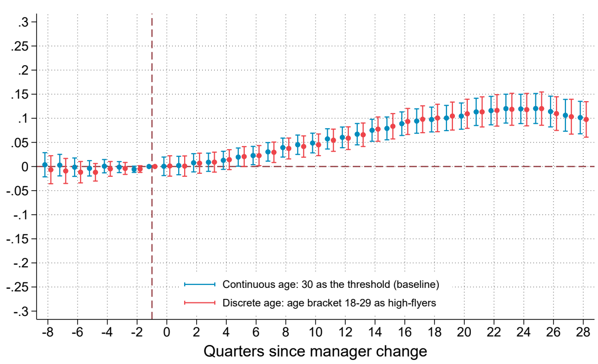
(c) Lateral move; age 32 as another threshold



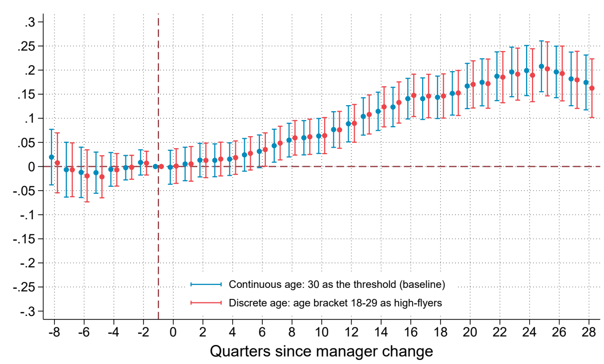
(d) Salary grade increase; age 32 as another threshold



(e) Lateral move; discrete age bracket 18-29



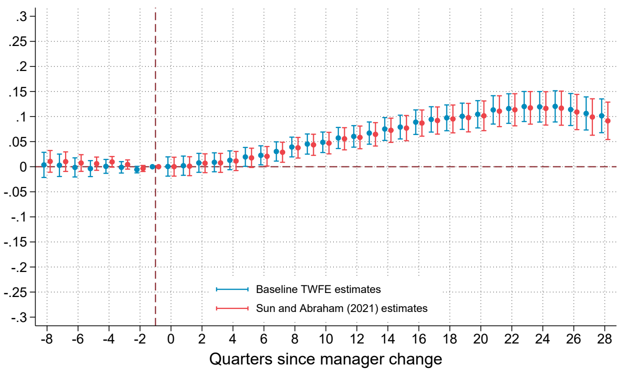
(f) Salary grade increase; discrete age bracket 18-29



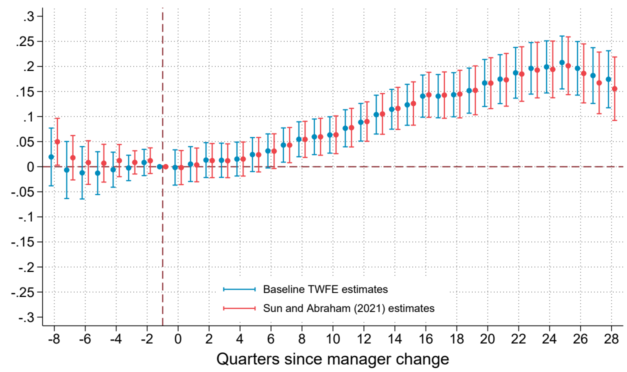
Notes. An observation is a worker-year-month. All coefficients are estimated from a single regression as in equation 2 and are aggregated to the quarterly level for ease of presentation. The outcome variables are: number of *lateral moves*, and number of *salary grade increases*. All standard errors are clustered by manager and 95% confidence intervals are presented. The blue lines report event study results using the baseline age-based high-flyer measure, i.e., high-flyer managers are defined as those whose minimum continuous age observed at work level 2 is $\leq$ 30. The red lines report event study results using alternative age-based high-flyer measures. In panels (a) and (b), high-flyer managers are those whose minimum continuous age observed at work level 2 is $\leq$ 28; in panels (c) and (d), high-flyer managers are those whose minimum continuous age observed at work level 2 is $\leq$ 32; in panels (e) and (f), high-flyer managers are those whose minimum age band at work level 2 is $18-29$.

Figure A.8: Robustness: accounting for cohort heterogeneity

(a) Lateral moves, gaining a high-flyer manager

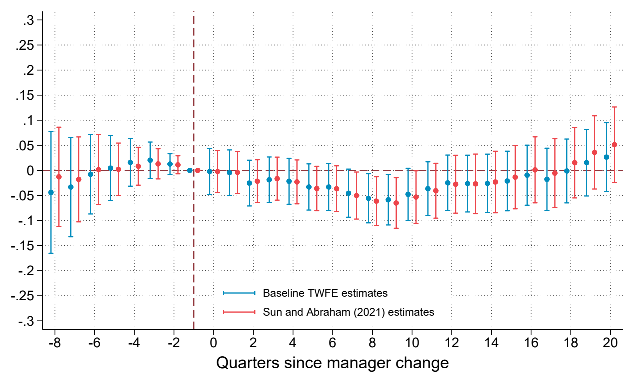


(b) Salary grade increases, gaining a high-flyer manager



(c) Lateral moves, losing a high-flyer manager

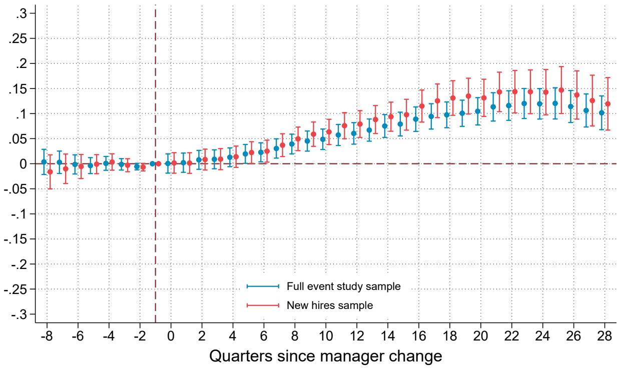
(d) Salary grade increases, losing a high-flyer manager



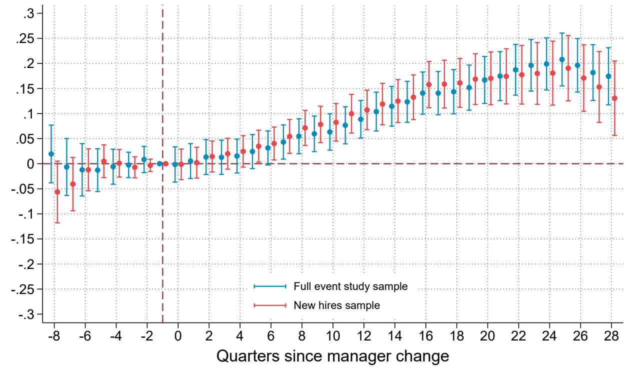
Notes. An observation is a worker-year-month. All coefficients are estimated from a modified version of equation 2. The outcome variables are: the number of *lateral moves*, and the number of *salary grade increases*. All standard errors are clustered by manager and 95% confidence intervals are presented. In all panels, the blue lines report event study results using the baseline TWFE specification as in equation 2 estimated on the full event study sample. The red lines report event study results using the interaction-weighted estimator developed by Sun and Abraham (2021) in the full sample.

Figure A.9: Robustness: restricting to new hires and Poisson specification

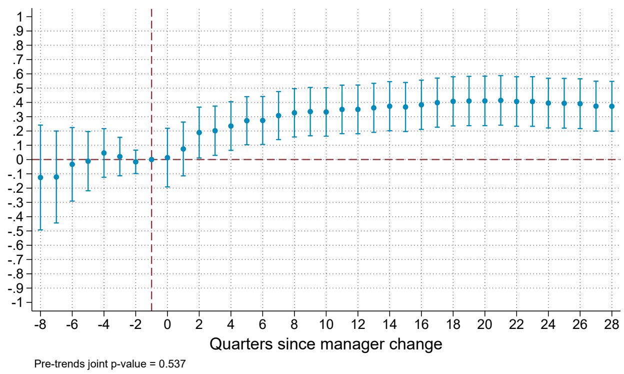
(a) Lateral moves, new hires



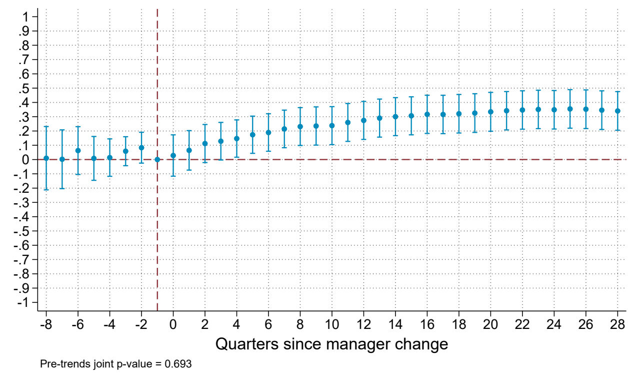
(b) Salary grade increases, new hires



(c) Lateral moves, Poisson



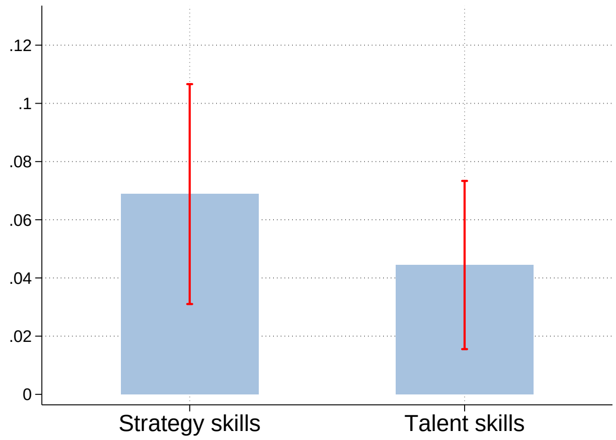
(d) Salary grade, Poisson



Notes. An observation is a worker-year-month. The outcome variables are: the number of *lateral moves*, and the number of *salary grade increases*. Standard errors are clustered by manager and 95% confidence intervals are presented. In panels (a) and (b), the blue lines report event study results using the baseline TWFE specification as in equation 2 estimated on the full event study sample, while the red lines report event study results when the sample is restricted to new hires (with strictly less than two years of tenure). In panels (c) and (d), all coefficients are estimated from a single regression using a Poisson model as in equation 4 and are aggregated to the quarterly level for ease of presentation.

Figure A.10: Skill differences between high- and low-flyer managers

(a) Mean difference



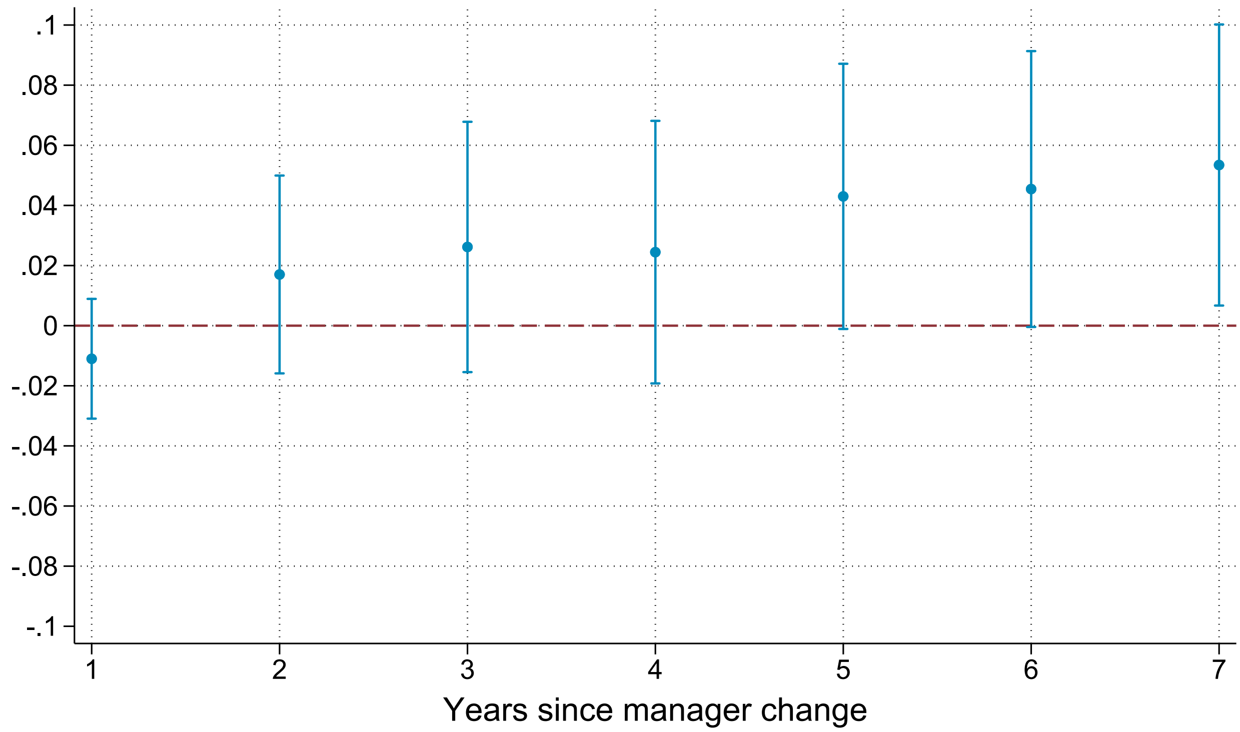
(b) Topic 1 (Project management skills)

(c) Topic 2 (Strategy management skills)

(d) Topic 3 (Talent management skills)

Notes. A 3-topic Latent Dirichlet Allocation (LDA) algorithm is implemented over managers' self-reported skills, and the corresponding word clouds are presented in the last three panels. The LDA algorithm offers a probability distribution over the three topics for each manager whose skills data is available. Panel (a) presents the mean difference and 95% confidence intervals between H- and L-type managers' distribution over these topics after running a seemingly-unrelated regression model (SUR) on the probability distribution.

Figure A.11: Effects of gaining a high-flyer manager on pay dispersion within the team



Notes. An observation is a team-year-month. All coefficients are estimated from a single regression as in equation 2 and are aggregated to the yearly level for ease of presentation. The outcome variable is the coefficient of variation in pay at the team level. The team is defined at the time of the manager transition, regardless of whether a worker continues to work under the manager of the transition or changes manager after some time. Standard errors are clustered by manager and 95% confidence intervals are presented.

B. Appendix Tables

Table B.1: Endogenous mobility checks

	Panel (a): team performance			
	(1) Pay + bonus (logs)	(2) Bonus/pay ratio	(3) Salary grade increase	(4) Vertical move
High-flyer manager	-0.0024	0.0027	-0.0002	-0.0001
	(0.025)	(0.007)	(0.001)	(0.000)
Mean, low-flyer manager	10.123	0.104	0.010	0.000
R-squared	0.706	0.262	0.013	0.002
N	14431	14431	58305	58305
	Panel (b): team mobility			
	(1) Lateral move	(2) Cross-functional move	(3) Same age	(4) Same office
High-flyer manager	-0.0003	0.0002	0.0074	0.0054
	(0.000)	(0.000)	(0.013)	(0.014)
Mean, low-flyer manager	0.003	0.001	0.309	0.790
R-squared	0.006	0.013	0.048	0.162
N	58305	58305	58305	58305
	Panel (c): team diversity			
	(1) Diversity, gender	(2) Diversity, age	(3) Diversity, office	(4) Diversity, nationality
High-flyer manager	0.0084	-0.0036	0.0099	-0.0029
	(0.008)	(0.008)	(0.010)	(0.004)
Mean, low-flyer manager	0.245	0.431	0.139	0.036
R-squared	0.094	0.107	0.160	0.212
N	58305	58305	58305	58305

Notes. An observation is a team-month. The regression sample is restricted to observations between 1 and 24 months before the manager switch. Standard errors are clustered at the manager level. Controls include: function, country and year fixed effects. In Panel (a), *Pay + bonus (logs)* is the log of the average total salary in the team; *Bonus/pay ratio* is the average bonus/pay ratio in the team; *Salary grade increase* is share of workers with a salary increase; *Vertical move* is share of workers with a work level promotion. In Panel (b), *Lateral move* is the share of workers that experience a lateral move; *Cross-functional move* is the share of workers that experience a function change; *Same age* is the share of workers that share the same age band as the manager; *Same office* is the share of workers that have the same office as the manager. In Panel (c), each outcome variable is a fractionalization index (1- Herfindahl-Hirschman index) for the relevant characteristic; it is 0 when all team members are the same and it is 1 when there is maximum team diversity.

Table B.2: Endogenous mobility checks (transitions)

	Panel (a): team performance			
	(1) Pay + bonus (logs)	(2) Bonus/pay ratio	(3) Salary grade increase	(4) Vertical move
LtoH - LtoL	0.0071	0.0081	-0.0002	-0.0001*
	(0.033)	(0.007)	(0.001)	(0.000)
HtoL - HtoH	-0.0366	0.0043	0.0007	0.0000
	(0.035)	(0.012)	(0.001)	(0.000)
Mean, LtoL group	10.165	0.103	0.011	0.000
R-squared	0.710	0.262	0.013	0.002
N	14431	14431	58305	58305
	Panel (b): team mobility			
	(1) Lateral move	(2) Cross-functional move	(3) Same age	(4) Same office
LtoH - LtoL	-0.0004	-0.0000	-0.0213	0.0204
	(0.000)	(0.000)	(0.014)	(0.016)
HtoL - HtoH	0.0007	-0.0013**	-0.0085	0.0218
	(0.001)	(0.001)	(0.027)	(0.031)
Mean, LtoL group	0.003	0.001	0.299	0.795
R-squared	0.006	0.013	0.065	0.163
N	58305	58305	58305	58305
	Panel (c): team diversity			
	(1) Diversity, gender	(2) Diversity, age	(3) Diversity, office	(4) Diversity, nationality
LtoH - LtoL	0.0039	0.0001	0.0013	-0.0008
	(0.010)	(0.010)	(0.011)	(0.005)
HtoL - HtoH	-0.0247*	-0.0124	-0.0358*	0.0072
	(0.015)	(0.016)	(0.021)	(0.006)
Mean, LtoL group	0.248	0.437	0.139	0.036
R-squared	0.095	0.110	0.161	0.212
N	58305	58305	58305	58305

Notes. An observation is a team-month. The regression sample is restricted to observations between 1 and 24 months before the manager switch. Standard errors are clustered at the manager level. Controls include: function, country and year fixed effects. In Panel (a), *Pay + bonus (logs)* is the log of the average total salary in the team; *Bonus/pay ratio* is the average bonus/pay ratio in the team; *Salary grade increase* is share of workers with a salary increase; *Vertical move* is share of workers with a work level promotion. In Panel (b), *Lateral move* is the share of workers that experience a lateral move; *Cross-functional move* is the share of workers that experience a function change; *Same age* is the share of workers that share the same age band as the manager; *Same office* is the share of workers that have the same office as the manager. In Panel (c), each outcome variable is a fractionalization index (1- Herfindahl-Hirschman index) for the relevant characteristic; it is 0 when all team members are the same and it is 1 when there is maximum team diversity.

Table B.3: High-flyer share and establishment productivity

	Output per worker in logs			Costs per output in logs		
	Current Year (1)	Lagged -1 Year (2)	Lagged -2 Year (3)	Current Year (4)	Lagged -1 Year (5)	Lagged -2 Year (6)
Share of high-flyers	0.203	0.623	0.811	-0.214	-0.361	-0.487
	(0.37)	(0.47)	(0.71)	(0.45)	(0.58)	(0.80)
Mean	5.567	5.590	5.602	5.693	5.696	5.677
R-squared	0.379	0.456	0.485	0.513	0.545	0.505
N	371	228	81	315	206	72

Notes. An observation is an office-year. Standard errors are clustered by office. Control variables include country and year fixed effects, and office size. In Columns (1)-(3), the outcome variables are current-year, and lagged (-1 and -2 year) output per worker in logs. In Columns (4)-(6), the outcome variables are current-year, and lagged (-1 and -2 years) costs per output in logs.

Table B.4: High-flyer share and function-country performance

	Monthly employment growth (WL1)			Bonus/pay ratio		
	(1) Current month	(2) Lagged -12 months	(3) Lagged -24 months	(4) Current month	(5) Lagged -12 months	(6) Lagged -24 months
Share of high-flyers	0.0586	0.0206	0.0190	-0.0123	-0.0435	0.0004
	(0.039)	(0.035)	(0.039)	(0.033)	(0.040)	(0.004)
Mean	0.045	0.005	0.005	0.156	0.160	0.169
R-squared	0.009	0.009	0.010	0.005	0.005	0.259
N	55911	50591	45327	31526	26260	21039

Notes. An observation is a function-country-month. Standard errors are clustered by function-country. Control variables include country, year-month, and function fixed effects. In Columns (1)-(3), the outcome variables are current and lagged (-12 and -24 months) work level 1 employment growth. In Columns (4)-(6), the outcome variables are current and lagged (-12 and -24 months) bonus/pay ratio.

Table B.5: Moves within manager's network

	Same subfunction or office (1)	Manager's managers (2)	Manager's subordinates (3)	Manager's same-level colleagues (4)	Same manager (5)
Panel (a): 3 years after the event					
LtoH	-0.0783***	0.0025	-0.0082**	-0.1025***	-0.0824***
	(0.020)	(0.005)	(0.004)	(0.015)	(0.013)
Mean, LtoL group	0.578	0.023	0.024	0.302	0.220
R-squared	0.054	0.042	0.045	0.055	0.060
N	11567	11518	7618	9769	12299
Panel (b): 7 years after the event					
LtoH	-0.0970***	-0.0005	-0.0176***	-0.0519***	-0.0325***
	(0.029)	(0.004)	(0.007)	(0.014)	(0.010)
Mean, LtoL group	0.505	0.012	0.022	0.126	0.069
R-squared	0.076	0.024	0.056	0.067	0.073
N	5182	5160	3331	4248	5511

Notes. An observation is a worker. The regression sample consists of workers in the LtoL and LtoH event groups 3 or 7 years after the event. The regressor is whether the employee is in the LtoH event group. Standard errors are clustered by manager. Controls include country and event time fixed effects. In column (1), for each worker, I obtain a list of his incoming manager's experienced subfunctions and offices (before the manager change event), and the outcome variable is a dummy indicating whether the worker's subfunction or office is in the list. In columns (2)-(4), I obtain different lists of his incoming manager's colleagues with whom he has worked before the event time, and the outcome variable is a dummy indicating whether the worker's manager 3 or 7 years after the event is in these lists. In column (5), the outcome variable is a dummy indicating whether the worker's manager 3 or 7 years after the event is the same incoming manager in the event.

Table B.6: Organizational structure of teams, jobs created and destroyed

	Probability of job created (1)	Probability of job destroyed (2)	Share of managerial jobs (3)
LtoH	0.0004	-0.0001	-0.0026*
	(0.000)	(0.000)	(0.001)
Mean, LtoL group	0.016	0.021	0.183
R-squared	0.133	0.434	0.635
N	1121872	1121872	1121872

Notes. An observation is a worker-year-month. The regression sample consists of workers in the LtoL and LtoH event groups. The regressor is whether the employee is in the LtoH event group. Controls include year-month fixed effects, the interaction of gender and age band fixed effects, and the interaction of function and office fixed effects. Standard errors are clustered by manager. The outcomes are the probability that a new job is created, an old job is destroyed and the share of managerial (WL2+) jobs within an office-subfunction-month.

C. Theoretical Appendix

To explain the managers' effects on workers' careers, I propose a conceptual framework linking managerial quality to worker performance through on-the-job talent discovery and learning by doing.[27] The elemental economic problem that arises with worker-job matching and on-the-job talent discovery has been well understood by economists at least since Johnson (1978) and Jovanovic (1979). The optimal solution to experimentation problems draws on the "bandit" literature, which shows how to account for the trade-off between output now and information that can help increase output in the future. There are also studies that combine experimentation in a labor market with multiple job types (MacDonald, 1982; Miller, 1984). However, these papers abstract away from the role of individual managers in revealing workers' talents. In my framework, I introduce managers' heterogeneity in quality and examine their differential impact on workers within a simple setup in which production depends on performing a variety of tasks and workers differ in their task-specific human capital.

The framework captures task-specific human capital and learning about innate talents. I use it to formally distinguish two channels of managers: matching workers' unique skills to specialized jobs inside the firm and teaching workers on the job. In the framework, good managers increase both the learning around task talent (allocation channel) and the speed of learning-by-doing or in other words the accumulation of on-the-job experience (teaching channel). I show that the two channels have opposite predictions on job transfers following a change in manager type. This is because there is a trade-off between finding a better job match and losing previously accumulated job-specific human capital. If allocation is more important than teaching in terms of what differentiates good managers from the rest, then gaining a good manager would have a positive impact on both transfers and productivity, which is what is found empirically.

[27] Friebel and Raith (2022) highlights this dual role of managers in the development and allocation of human capital in firms: they train junior employees and acquire private information about workers that is needed to allocate them to the right positions.

C.1. Model setup

Consider a firm composed of managers (b), workers (i), and occupations (o). Output in an occupation is produced by combining multiple tasks, e.g. negotiating, programming, and managing personnel (Autor et al., 2003; Gibbons and Waldman, 2004; Lazear, 2009; Gathmann and Schönberg, 2010). Workers differ in their task-specific human capital (i.e., workers have multidimensional skills).

Managers also differ in their task-specific human capital but, for simplicity and given the focus of this paper, I hone in on one overall human capital dimension for them, namely, managerial skill. In particular, let managerial skill take one of two types: high (H) and low (L) quality managers. The manager type categorization can be conceptualized in two complementary ways: good managers have a higher level of each skill and/or good managers have a higher level of all the skills related to managing subordinates, such as mentoring, teaching, and motivating workers.

The basic intuition can be developed with a one-period setup: managers are assigned to workers in a random fashion[28], observe worker productivity, and decide the job allocation of the worker. Throughout, the emphasis is on managers, and the workers are non-strategic players who follow the manager's decisions.

C.2. Workers

Occupations (o) are bundles of tasks and differ in the importance of each task for production. For simplicity, let there be two tasks (j): A and S (e.g. analytical and social). Let β_o^A be the weight on the analytical task and β_o^S be the weight on the social task. The weights, β_o^j, indicate how important a particular task j is for a given occupation o. The weights allow for both horizontal (the ratio of the weights indicates the relative importance of each task) as well as vertical job differentiation (the level of the weights indicates the task intensity).[29] As an example, occupations in managerial positions would exhibit higher returns to the same

[28] In the empirical strategy, I isolate exogenous assignments as part of the firm's policy of re-shuffling managers to teams to train and screen work-level 2 managers.

[29] For this reason, the weights are not constrained to be between 0 and 1 (and hence cannot be interpreted as the share of time a worker spends on average in a given task in occupation o).

tasks than the entry-level analogs, hence they would have higher weights for every task even though the ratios of the weights may be identical.

Workers have observed productivity in each task j, which is determined by a person's initial endowment m_i^j in each task ("talent"), the experience accumulated in task j until time t, E_{it}^j, and a noise term (ϵ_{iot}):

$$\begin{aligned} p_{iot}^j &= \underbrace{E_{it}^j}_{\text{experience}} + \eta_{iot}^j \\ \text{where} \quad \eta_{iot}^j &= \underbrace{m_i^j}_{\text{innate task talent}} + \underbrace{\epsilon_{iot}^j}_{\text{noise}} \end{aligned} \tag{C.1}$$

where t is time in the labor market, $m_i^j \sim N(\mu^j, \sigma^j)$ and $\epsilon_{iot}^j \sim N(0, \sigma_\epsilon^j)$. The noise or luck shocks, ϵ_{iot}^j, are uncorrelated across people, occupations, and tasks, and $\epsilon_{iot}^j \perp\!\!\!\perp m_i^j$.

There is learning-by-doing in each task, which depends on the task intensity on the job:

$$E_{it}^j = \sum_{o'} (\beta_{o'}^j) O_{io't} \tag{C.2}$$

where $O_{io't}$ is tenure in each prior occupation o'. For example, a worker accumulates more analytical skills if she works in an occupation in which analytical skills are very important (i.e., with a large β_o). In contrast, she will not learn anything in tasks that she does not use in her occupation.

Hence, worker i's overall productivity (P) in log units (assuming a Cobb-Douglas production function) is given by:

$$\begin{aligned} \ln(P_{iot}) &= \beta_o^A p_{iot}^A + \beta_o^S p_{iot}^S \\ \Longrightarrow \ln(P_{iot}) &= \underbrace{(\beta_o^A E_{it}^A + \beta_o^S E_{it}^S)}_{\overline{E}_{iot}=\text{task-specific experience}} + \underbrace{(\beta_o^A m_i^A + \beta_o^S m_i^S)}_{\overline{m}_{io}=\text{task match}} + \underbrace{(\beta_o^A \epsilon_{iot}^A + \beta_o^S \epsilon_{iot}^S)}_{\overline{\epsilon}_{iot}=noise} \end{aligned} \tag{C.3}$$

Note that learning by doing creates occupational persistence. As workers accumulate more and more task-specific experience as they age, a distant occupational switch tends to become increasingly costly.

C.3. Managers

Managers observe worker productivity and decide the next job allocation for the worker to maximize expected worker productivity.[30] Hence, the manager solves the following problem:

$$\max_{\beta_o} \sum_j \beta_o^j \mathbb{E}\left(p_{i,t+1}^j\right) \tag{C.4}$$

If full information on each worker were available, managers would assign workers to jobs based on comparative advantage. Without full information, managers choose the allocation that maximizes productivity in expectation. Expected productivity depends on expected task match ($\hat{m}_{iot}^j$), which is inferred from the productivity realization (p_{iot}^j) in each task j:

$$\hat{m}_{iot}^j = p_{iot}^j - E_{it}^j = m_i^j + \epsilon_{iot}^j \tag{C.5}$$

I allow good and bad managers to differ in two fundamental ways: in terms of solving the job assignment problem based on the expected task talents (*allocation channel*); and in terms of influencing the speed of workers' learning-by-doing (*teaching channel*).

First, the *allocation channel*: while bad managers infer workers' innate talents based on the productivity realization (as in equation C.5), good managers receive a private signal that enables them to fully discover the workers' talents, m_i^j (one-shot learning process). Managers use this information to potentially re-optimize the job allocation decision. Given that the good manager has fully revealed the worker's innate talents, future worker productivity is higher on average as the workers locate better matches.

Second, the *teaching channel*: good managers increase the speed of workers' learning-by-doing. Experience on the job depends on the manager's quality as follows:

$$E_{it}^j = \begin{cases} \sum_{o'} \beta_{o'}^j O_{io't} & \text{if } b = L \\ \sum_{o'} \beta_{o'}^j \tau O_{io't} & \text{if } b = H \end{cases} \tag{C.6}$$

[30] In this framework, I am not considering the manager's incentives. This is supported by the empirical strategy that compares outcomes between different types of managers, netting out common managerial behaviors due to the firm's policies.

where $\tau > 1$. After one period of working under a good manager, a worker has accumulated more on-the-job experience compared to working under a bad manager. There can be different reasons why good managers may increase workers' on-the-job experience such as teaching and training activities or motivating workers to exert higher effort.

C.4. Predictions

I now illustrate how the productivity and transfer dynamics depend on the manager of the worker. Let there be two jobs: one mostly analytical ($\beta^A = 1 - \delta; \beta^S = \delta$) and one mostly social ($\beta^A = \delta; \beta^S = 1 - \delta$), with $\delta \to 0$ (δ is infinitesimally small). Hence, while the manager observes the task-specific productivity for each task (as $\delta > 0$), only one task basically matters for each job (given that $\delta \to 0$). The worker starts with no experience in either the analytical or social job. For simplicity and without loss of generality, the initial job allocation is assumed to be orthogonal to the worker's innate talents. Let the worker have higher analytical skills $m^A > m^S$, thus output would be maximized by allocating the worker to the analytical job.

The dynamics will depend on the initial job allocation. Table C.1 shows how the expected worker productivity computed by the manager changes depending on the manager type and the job allocation. As a reminder, a good manager perfectly observes a worker's innate talents.

Table C.1: Expected productivity matrix by initial job allocation

Current $\text{job}_1 \longrightarrow^?$ Next job_2		Manager type: *Good*	Manager type: *Bad*
	Social $\longrightarrow^?$ *Analytical*	m^A	$m^A + \epsilon_1^A$
	Social $\longrightarrow^?$ *Social*	$\tau + m^S$	$1 + m^S + \epsilon_1^S$
	Analytical $\longrightarrow^?$ *Analytical*	$\tau + m^A$	$1 + m^A + \epsilon_1^A$
	Analytical $\longrightarrow^?$ *Social*	m^S	$m^S + \epsilon_1^S$

Notes. This table shows the expected worker productivity computed by the manager. It depends on the worker's job move and the manager type. The worker starts with no experience in either the analytical or the social job. The worker can move to either the analytical or the social job.

Using Table C.1, I can derive the following predictions.

Prediction 1, good manager. *A good manager moves a worker from job $o^{'}$ to job o if:*

$$\underbrace{(\overline{m}_{iot} - \overline{m}_{io^{'}t})}_{\Delta\overline{m}_{iot}=\text{ gain in task match}} > \underbrace{\overline{E}_{io^{'}t} - \overline{E}_{iot}}_{-\Delta\overline{E}_{iot}=\text{ potential loss in task-specific experience}} \tag{C.7}$$

that is, a worker is assigned to a different job if the improvement in the expected task match exceeds the potential loss in task-specific experience.

Hence, given the example above, a bad manager moves the worker from the social to the analytical job if:

$$\underbrace{m^A - m^S}_{\text{gain in task match}} > \underbrace{\tau}_{\text{loss in task-specific experience}}$$

On the other hand, a good manager never moves the worker from the analytical to the social job. If the worker starts in the analytical job, she is well-matched according to her talents. Moreover, the teaching channel via learning-by-doing reinforces the gains of the initial allocation.

Prediction 2, bad manager. *A bad manager moves a worker from job $o^{'}$ to job o if:*

$$\underbrace{(\hat{\overline{m}}_{iot} - \hat{\overline{m}}_{io^{'}t})}_{\Delta\hat{\overline{m}}_{iot}=\text{gain in expected task match}} > \underbrace{\overline{E}_{io^{'}t} - \overline{E}_{iot}}_{-\Delta\overline{E}_{iot}=\text{potential loss in task-specific experience}} \tag{C.8}$$

that is, a worker is assigned to a different job if the improvement in the expected task match exceeds the potential loss in task-specific experience.

Hence, given the example above, a bad manager moves the worker from the social to the analytical job if:

$$(m^A + \epsilon_1^A) - (m^S + \epsilon_1^S) > 1 \Rightarrow (\epsilon_1^A - \epsilon_1^S) > 1 - (m^A - m^S)$$

that is, the probability of a bad manager moving the worker is given by:

$$1 - \Phi\left(\frac{1 - (m^A - m^S)}{\sigma_\epsilon^{2A} + \sigma_\epsilon^{2S}}\right) = \Phi\left(\frac{(m^A - m^S) - 1}{\sigma_\epsilon^{2A} + \sigma_\epsilon^{2S}}\right)$$

by symmetry of the standard normal distribution and if Prediction 1 holds $\left(m^A - m^S > \tau\right)$.

Similarly, a bad manager moves the worker from the analytical to the social job if:

$$(m^S + \epsilon_1^S) - (m^A + \epsilon_1^A) > 1$$

that is, the probability of a bad manager moving the worker is $1 - \Phi\left(\frac{(m^A - m^S)+1}{\sigma_\epsilon^{2A} + \sigma_\epsilon^{2S}}\right)$. The two moving probabilities do not sum to one given the experience term that accumulates via learning by doing.

C.5. Manager transitions

I discuss the conditions under which: (i) moving from a bad to a good manager compared to moving from a bad to another bad manager (*gaining a good manager*) leads to higher job transfer rates and future productivity, and (ii) moving from a good to a bad manager compared to moving from a good to another good manager (*losing a good manager*) has no differential impact on job transfer rates and future productivity. This requires me to step outside the one-period setup and evaluate the equilibrium path for two periods. I use the worker expected productivities illustrated in Table C.2 and Table C.3.

Table C.2: Expected productivity by manager transition, first job is analytical

		Manager transition			
		$Bad_1, Good_2$	Bad_1, Bad_2	$Good_1, Bad_2$	$Good_1, Good_2$
Job_1	Anal.$_1 \to$ Anal.$_2 \to^?$ Anal.$_3$	$1+\tau+m^A$	$2+m^A+\epsilon_2^A$	$\tau+1+m^A+\epsilon_2^A$	$2\tau+m^A$
$=$ Anal.	Anal.$_1 \to$ Social$_2 \to^?$ Anal.$_3$	$1+m^A$	$1+m^A+\epsilon_2^A$	$\tau+m^A+\epsilon_2^A$	$\tau+m^A$
$\to Job_2$	Anal.$_1 \to$ Social$_2 \to^?$ Social$_3$	$\tau+m^S$	$1+m^S+\epsilon_2^S$	$1+m^S+\epsilon_2^S$	$\tau+m^S$
$\to^? Job_3$	Anal.$_1 \to$ Anal.$_2 \to^?$ Social$_3$	m^S	$m^S+\epsilon_2^S$	$m^S+\epsilon_2^S$	m^S

Notes. This table shows the expected worker productivity computed by the manager. It depends on the worker's history in terms of jobs and manager types. The worker starts with no experience in the analytical job. The worker can move to either the social or the analytical job in periods 2 and 3.

Table C.3: Expected productivity by manager transition, first job is social

		Manager transition			
		$Bad_1, Good_2$	Bad_1, Bad_2	$Good_1, Bad_2$	$Good_1, Good_2$
Job_1	$\text{Social}_1 \rightarrow \text{Anal.}_2 \rightarrow^? \text{Anal.}_3$	$\tau + m^A$	$1 + m^A + \epsilon_2^A$	$1 + m^A + \epsilon_2^A$	$\tau + m^A$
$= \text{Social}$	$\text{Social}_1 \rightarrow \text{Social}_2 \rightarrow^? \text{Anal.}_3$	m^A	$m^A + \epsilon_2^A$	$m^A + \epsilon_2^A$	m^A
$\rightarrow \text{Job}_2$	$\text{Social}_1 \rightarrow \text{Social}_2 \rightarrow^? \text{Social}_3$	$1 + \tau + m^S$	$2 + m^S + \epsilon_2^S$	$1 + \tau + m^S + \epsilon_2^S$	$2\tau + m^S$
$\rightarrow^? \text{Job}_3$	$\text{Social}_1 \rightarrow \text{Anal.}_2 \rightarrow^? \text{Social}_3$	$1 + m^S$	$1 + m^S + \epsilon_2^S$	$\tau + m^S + \epsilon_2^S$	$\tau + m^S$

Notes. This table shows the expected worker productivity computed by the manager. It depends on the worker's history in terms of jobs and manager types. The worker starts with no experience in the social job. The worker can move to either the social or the analytical job in periods 2 and 3.

First, consider the effects of losing a good manager. As the first manager is good, the probability that the worker is in the bad job match (which is the social job given the model set-up) is zero, given Prediction 1 (in sub-section C.4). A good manager never moves the worker. A bad manager never moves the worker if she knows that the previous manager of the worker was good. Hence, average future worker productivity will be the same among the two manager types if $\tau = 1$ (no difference in teaching between a good and bad manager) or if there are decreasing returns to learning-by-doing (the accumulation of experience must go to zero after one period on the job). Although this prediction implies a coarse restriction to the evolution of learning-by-doing (which is a consequence of the simple model set-up), it is plausible that learning exhibits decreasing returns.

Second, consider the effects of gaining a good manager. As the first manager is bad, there is a non-zero probability of the worker being in the bad job match (which is the social job given the model set-up). If the worker is in the social job, a good manager moves her with probability 1 to the analytical job if $m^a - m^s > 2$ (if job allocation is more important than learning by doing). On the other hand, a bad manager moves her with probability $\Phi\left(\frac{(m^A - m^S) - 2}{\sigma_\epsilon^{2A} + \sigma_\epsilon^{2S}}\right) < 1$ (if the first job was social) or with probability $\Phi\left(\frac{(m^A - m^S)}{\sigma_\epsilon^{2A} + \sigma_\epsilon^{2S}}\right) < 1$ (if the first job was analytical). If the worker is in the analytical job, a good manager never moves the worker to a social job, while a bad manager moves her to the social job with probability $1 - \Phi\left(\frac{m^A - m^S}{\sigma_\epsilon^{2A} + \sigma_\epsilon^{2S}}\right) > 0$ (if the first job was social) or probability $1-\Phi\left(\frac{m^A-m^S+2}{\sigma_\epsilon^{2A}+\sigma_\epsilon^{2S}}\right)>0$ (if first job was analytical).

Note that both $\left(\Phi\left(\frac{(m^A-m^S)-2}{\sigma_\epsilon^{2A}+\sigma_\epsilon^{2S}}\right)+1-\Phi\left(\frac{m^A-m^S}{\sigma_\epsilon^{2A}+\sigma_\epsilon^{2S}}\right)\right)$ (if the first job was social) and $\left(\Phi\left(\frac{(m^A-m^S)}{\sigma_\epsilon^{2A}+\sigma_\epsilon^{2S}}\right)+1-\Phi\left(\frac{m^A-m^S+2}{\sigma_\epsilon^{2A}+\sigma_\epsilon^{2S}}\right)\right)$ (if the first job was analytical) are less than one. Hence, there is a higher chance of the worker changing jobs when the second manager is good compared to when the second manager is bad. It follows that average future productivity is also higher as the worker is more likely to end up in the right job match with a good manager.

D. Data Appendix

D.1. O*NET task classification

Occupations, as discrete classification units, can be viewed as vectors of tasks to be carried out by workers. I manually match the occupation codes in the firm to the Occupational Information Network (O*NET) classification codes and obtain vectors for each occupation. The O*NET (National Center for O*NET Development, 2024) is a database containing measures of occupational characteristics. More specifically, the set of O*NET descriptors used to construct intensity for different tasks is the same as Cortes et al. (2023), which itself builds on Deming (2017) and Autor et al. (2003).[31]

First, I transform the raw scores on each O*NET descriptor into a score ranging from 0 to 10 following the instructions provided by O*NET (link here). For each task and each occupation, I calculate the average across all the corresponding descriptors to obtain a raw intensity measure. Second, I use all MNE employees' occupation distribution to transform the three raw task intensity measures into percentile ranks, which have a clearer interpretation.

As an example, for "Public Relations Specialists", the scores for cognitive, routine, and social tasks are 0.451, 0.085, and 0.907, respectively. This means that 45.1% (8.5%, 90.7%) of employee-month observations who have a cognitive (routine, social) task intensity score no greater than that of Public Relations Specialists. See Appendix Table D.1 for the full list of task intensity measures for each O*NET occupation title (sorted by cognitive task intensity).

[31] For cognitive task: (a) What level of mathematical reasoning is needed to perform your current job (question 12 in the Abilities Questionnaire)? (b) What level of mathematics is needed to perform your current job (question 5 in the Skills Questionnaire)? (c) What level of knowledge of mathematics is needed to perform your current job? (question 14 in the Knowledge Questionnaire; item 2.c.4.a) (d) What level of management of financial resources is needed to perform your current job (question 33 in the Skills Questionnaire)? (e) What level of management of material resources is needed to perform your current job (question 34 in the Skills Questionnaire)? (f) What level of management of personnel resources is needed to perform your current job (question 35 in the Skills Questionnaire)? For routine task: (g) How automated is your current job (question 49 in the Work Context Questionnaire)? (h) How important to your current job are continuous, repetitious physical activities (like key entry) or mental activities (like checking entries in a ledger) (question 51 in the Work Context Questionnaire)? For social task: (i) What level of social perceptiveness is needed to perform your current job (question 11 in the Skills Questionnaire)? (j) What level of coordination is needed to perform your current job (question 12 in the Skills Questionnaire)? (k) What level of persuasion is needed to perform your current job (question 13 in the Skills Questionnaire)? (l) What level of negotiation is needed to perform your current job (question 14 in the Skills Questionnaire)?

D.2. Angular task distance

Each occupation o is characterized by a three-dimensional task vector, $q^o = (q_c^o, q_r^o, q_s^o)$, where q_c^o is the cognitive task intensity, q_r^o is the routine task, while q_s^o is the social task intensity. I follow Gathmann and Schönberg (2010) and define the angular separation between occupation j and occupation k as a measure of similarity using their corresponding task vectors.

$$AngSim_{jk} = \frac{\sum_{l\in\{c,r,s\}} \left(q_l^j \times q_l^k\right)}{\left[\sum_{l\in\{c,r,s\}} (q_l^j)^2 + (q_l^k)^2\right]}$$

This angular separation measure defines the distance between two occupations as the cosine angle between their positions in vector space. I define $(1 - AngSim_{jk})$ as the distance between occupation j and occupation k: $Dist_{jk} = (1 - AngSim_{jk})$. The measure ranges between zero and one. It is zero for occupations that use identical skill sets and unity if two occupations use completely different skill sets. The measure will be closer to zero the more two occupations overlap in their skill requirements.[32] I use the cumulative sum of the task distance measure as the outcome variable in the event study.

As the focus here is job moves within the same firm as opposed to moves across firms, there are many moves where task distance is 0, for example between a recruitment specialist and a general talent advisor, both in human resources. An example of a distant move is between the O*NET occupation titles ”Secretaries and Administrative Assistants, Except Legal, Medical, and Executive”, which is in the workplace services function within the MNE, and ”Labor Relations Specialists”, which is in the general management function. The least distant move (yet with distance > 0) is between the O*NET occupation titled ”First-Line Supervisors of Non-Retail Sales Workers” and ”First-Line Supervisors of Office and Administrative Support Workers”.

[32]Measuring similarity between two vectors by the angular separation was first proposed by Jaffe (1986) in the innovation literature to characterize the proximity of firms’ technologies. Subsequently, a number of other studies have used the measure in various contexts, such as spillovers of university research to commercial innovation (Jaffe, 1989), and similarity of tasks performed across occupations (Gathmann and Schönberg, 2010; Cortes and Gallipoli, 2018).

Table D.1: Task intensity measures: sorted by cognitive task

Title	Cognitive	Routine	Social
Demonstrators and Product Promoters	0.003	0.005	0.394
Computer User Support Specialists	0.010	0.330	0.052
Customer Service Representatives	0.032	0.895	0.283
Human Resources Assistants, Except Payroll and Timekeeping	0.050	0.938	0.204
Compliance Officers	0.056	0.856	0.385
Secretaries and Administrative Assistants, Except Legal, Medical, and Executive	0.063	0.792	0.044
Equal Opportunity Representatives and Officers	0.063	0.247	0.818
Human Resources Specialists	0.069	0.911	0.407
Executive Secretaries and Executive Administrative Assistants	0.082	0.769	0.186
Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products	0.380	0.735	0.754
Public Relations Specialists	0.451	0.085	0.907
Order Clerks	0.451	0.769	0.260
Payroll and Timekeeping Clerks	0.452	0.999	0.001
Information Security Analysts	0.452	0.247	0.172
Compliance Managers	0.452	0.323	0.448
Food Science Technicians	0.452	0.904	0.001
Medical and Clinical Laboratory Technicians	0.453	0.999	0.045
Labor Relations Specialists	0.453	0.001	0.995
Quality Control Analysts	0.470	0.785	0.068
Production, Planning, and Expediting Clerks	0.530	0.308	0.172
Occupational Health and Safety Technicians	0.538	0.136	0.291
Bookkeeping, Accounting, and Auditing Clerks	0.566	0.993	0.030
Regulatory Affairs Specialists	0.570	0.116	0.448
Geographic Information Systems Technologists and Technicians	0.577	0.918	0.044
Medical and Clinical Laboratory Technologists	0.578	1.000	0.172
Training and Development Specialists	0.583	0.014	0.455
Regulatory Affairs Managers	0.583	0.125	0.388
Sustainability Specialists	0.583	0.000	0.388
Electrical and Electronic Engineering Technologists and Technicians	0.583	0.125	0.030
Dietetic Technicians	0.585	0.844	0.225
Procurement Clerks	0.602	0.873	0.224
Search Marketing Strategists	0.602	0.116	0.407
Financial Examiners	0.602	0.116	0.394
Food Scientists and Technologists	0.602	0.125	0.407
Database Administrators	0.602	0.769	0.068
Business Intelligence Analysts	0.606	0.321	0.224
Occupational Health and Safety Specialists	0.613	0.112	0.401
Computer Systems Analysts	0.621	0.904	0.234
Computer Systems Engineers/Architects	0.621	0.848	0.283
Clinical Research Coordinators	0.621	0.769	0.750
Industrial Engineering Technologists and Technicians	0.643	0.756	0.380
Administrative Services Managers	0.643	0.323	0.408
Management Analysts	0.646	0.128	0.826
Commercial and Industrial Designers	0.646	0.330	0.391
Compensation, Benefits, and Job Analysis Specialists	0.649	0.847	0.390
Customs Brokers	0.649	1.000	0.291
First-Line Supervisors of Office and Administrative Support Workers	0.659	0.318	0.767
Loss Prevention Managers	0.704	0.320	0.754
Market Research Analysts and Marketing Specialists	0.727	0.203	0.380
Business Continuity Planners	0.727	0.105	0.444
First-Line Supervisors of Production and Operating Workers	0.762	0.365	0.444
Training and Development Managers	0.762	0.085	0.448
Accountants and Auditors	0.765	0.920	0.387
First-Line Supervisors of Non-Retail Sales Workers	0.832	0.437	0.975
Industrial Engineers	0.875	0.246	0.111
Logisticians	0.926	0.843	0.818
Quality Control Systems Managers	0.926	0.436	0.448
Compensation and Benefits Managers	0.926	0.849	0.444
Dietitians and Nutritionists	0.927	0.002	0.976
Logistics Analysts	0.954	0.965	0.261
Purchasing Agents, Except Wholesale, Retail, and Farm Products	0.954	0.847	0.754
General and Operations Managers	0.956	0.323	0.837
Computer and Information Systems Managers	0.957	0.850	0.455
Human Resources Managers	0.960	0.119	0.978
Operations Research Analysts	0.961	0.006	0.173
Information Technology Project Managers	0.964	0.369	0.837
Supply Chain Managers	0.967	0.124	0.831
Marketing Managers	0.983	0.105	0.994
Financial Managers	0.987	0.998	0.826
Investment Fund Managers	0.987	0.119	0.407
Sales Managers	0.992	0.090	1.000
Purchasing Managers	0.993	0.848	0.979
Industrial Production Managers	0.995	0.121	0.831
Architectural and Engineering Managers	0.996	0.323	0.837
Natural Sciences Managers	0.999	0.009	0.767
Manufacturing Engineers	1.000	0.117	0.409
Treasurers and Controllers	1.000	0.847	0.444
Chief Executives	1.000	0.330	1.000

Notes. This table reports task intensity measures of cognitive, routine, and social tasks for O*NET occupation titles that are matched with the MNE standard job titles. Take "Public Relations Specialists" as an example, the resulting measures for cognitive, routine, and social tasks are 0.451, 0.085, and 0.907, respectively. This means that 45.1% (8.5%, 90.7%) of employee-month observations who have a cognitive (routine, social) task intensity score no greater than that of Public Relations Specialists.