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 as the top 30% 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. Seven years after the manager transition, workers earn 10% more and perform better on objective performance measures. 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, career trajectories, internal labor markets, productivity

JEL: J24, M5

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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."

— 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.[1] 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, 1971). 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 Henderson, 2012).

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, 1776). 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 a job ladder. 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

[1] The share of workers employed by firms is 54% globally (World Bank, 2019).

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, Gibbs and Holmstrom, 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 29% of managers being singled out as high-flyers.[2]

To tackle the second identification step, I leverage managers' lateral rotations across teams that are outside of the control of the worker. 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.[3] This type of rotation policy is also not peculiar to this firm but rather a common managerial practice among large firms.

I conduct an event-study analysis exploiting the workers' first manager rotation and comparing different types of transitions. For example, 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

[2]I show that the high-flyer status is significantly positively correlated with other measures of ex-post performance such as managers' own performance ratings as well as workers' upward feedback on the managers' leadership.

[3]I carry out a series of empirical tests to confirm that the team assignment of a manager's internal rotation is orthogonal to workers' characteristics. I show that the type of transition faced by a team (e.g., from a low- to a high-flyer manager) is uncorrelated with the observable characteristics of the team, as well as with the characteristics of the incoming and outgoing managers. Most importantly, the career progression of workers undergoing different manager transitions follows parallel trends leading up to each type of manager transition.

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 manager but without changing manager type. I can compare the outcomes of the employees each month leading up to the manager transition date and each month after the transition.[4]

I show that good managers 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 worker.[5] My findings suggest that considerable gains in worker performance stem from efficiently allocating *existing* workers to jobs and that managers' role is crucial in creating more productive worker-job matches, all potentially at little additional cost for the organization.[6] As the managers' influences propagate inside the organization through their subordinates' careers, I demonstrate that they significantly impact firm-level productivity, thus linking individual-level effects to the productivity of an entire establishment.

First, gaining a good manager causes significant worker reallocation to different jobs inside the firm through lateral transfers (57% higher). Examples of lateral moves are transfers from customer service to logistics; from merchandising to sales; or from product development to quality. Moreover, I isolate task-distant transfers as those that represent a major horizontal change in tasks to be fulfilled and find that the number of cross-functional transfers with a simultaneous task-distant move is 0.06 higher for those who gain a high-flyer manager (139% higher) (for example, moving from human resources to marketing, or from R&D to supply chain management). I find no systematic pattern among the moves, they are scattered throughout the organization. In terms of dynamics, the transfers gradually increase until five years after the manager transition when they level off at a sustained higher level at least until seven

[4]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.

[5]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.

[6]Matching can be considered a resource-neutral policy when contrasted to the more resource-intense alternatives such as hiring, firing, and training.

years after.[7] The results of the lateral transfers cannot be reconciled 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.[8]

Second, gaining a good manager also results in an improvement in worker performance and long-run career progression. Seven years after the manager transition, when comparing the low-to-high transition group with low-to-high group, the number of salary grade increases is 0.2 higher, translating to a 10% higher salary. Combining the results on lateral reallocation with those on pay progression suggests that high-flyer managers facilitate the discovery of workers' aptitudes and spur workers to a higher rate of job changes, which results in workers finding positions that are better matched to their skills. A mediation analysis reveals that 59% of the higher salary grade increases are explained by lateral job changes. This is likely an underestimate of the managers' allocation channel. It excludes vertical transfers as by definition they involve a salary raise. Additionally, it does not account for the benefits gained when a worker remains in their current job (rather than changing jobs) due to it being a good match for them.

Third, using productivity data from sales bonuses on a sub-sample, I show that good managers boost worker performance, rather than inflating pay for the same performance. *I find that workers' sales performance increases by 27% up to 4 years after gaining a high-flyer manager.* Notes: The sales dataset and results should be rewritten since we are using a different sample, and get different results.[9] Additional empirical checks that compare the productivity gains among job moves initiated by a high-flyer with those from job moves initiated by a low-flyer indicate that the performance gains cannot be explained by a treatment effect of transfers by themselves, but rather by good managers causing more productive transfers (i.e. choosing the right transfer for the right worker in terms of the worker's skill set).

These effects are *asymmetric*. Gaining a good manager has positive effects while

[7] The time window is determined by the length of the panel data.

[8] 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.

[9] *I have sales bonus data for the entire field sales population in India over 2018-2021. The corresponding increase in salary is 8% in the same sales sub-sample and salary increases by 18% in the full sample 4 years after the manager transition.*

losing one 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 downgrade in manager quality. The asymmetric effects together with the persistence of the results help rule out alternative contemporaneous channels of managers such as monitoring or motivation and support the interpretation of the allocation channel as the gains of a good worker-job match do not rely on the co-presence of a good manager. In terms of organizational design, the asymmetries in the results also 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.

Additional tests allow me to rule out other alternative channels. First, the findings on worker performance 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. *Second, I do not find that the workers' lateral and vertical moves occur within the managers' networks of previous colleagues* Notes: This sentence should be rewritten as this is not implied by current results.[10] or that workers follow their managers as they move within the firm, thus excluding explanations related to social connections within the MNE. These findings as well as the evidence on higher worker sales productivity assuage concerns of manager bias.

I conclude by showing that the good managers' effects are associated with higher overall profits at the establishment level. I integrate the worker-level records with establishment-level productivity data (output per worker) and cost data (cost per ton of output) to connect the paths of individual workers to the overall productivity of the establishment. Although this piece of evidence is correlational in nature, it provides further evidence of a positive link between the career trajectories of individual workers and productivity at the site level. I estimate that the semi-elasticity of output per worker to workers' past exposure to high-flyer managers is 1.79, that is increasing

[10] *I define a socially connected move based on whether the manager has ever worked (i) with the new manager the worker moves to and/or (ii) in the same sub-function and/or office as the job the worker moves to. I find no differential impact of gaining a high-flyer manager on connected moves, whether these are lateral or vertical moves.* Notes:

the exposure to high-flyers by 10 percentage points is associated with an increase in output per worker by 18%. The same semi-elasticity is -1.1 for costs per ton. Taking the price level as given and combining together these two results, the analysis suggests that high-flyers are increasing profits. I also perform a cost-benefit analysis based on operating profits data from the company's income statements and estimate that the returns of high-flyer managers are well worth their costs.

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, Heining and Kline, 2013; Chade, Eeckhout and Smith, 2017; Card, Cardoso, Heining and Kline, 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; Baker, Gibbs and Holmstrom, 1994b; Baker and Holmstrom, 1995; Gibbons and Waldman, 1999; Kahn and Lange, 2014; Pastorino, Forthcoming; Huitfeldt, Kostøl, Nimczik and Weber, 2023). This is the first paper to study the role of managers in the allocation of workers to jobs within internal labor markets and to show that manager quality is the crucial ingredient needed to create more productive matches between workers and jobs.

My findings also advance our understanding of the impact of individual managers on firm and worker outcomes (e.g., Bertrand and Schoar, 2003; Bandiera, Barankay and Rasul, 2007; Lazear, Shaw and Stanton, 2015; Bandiera, Prat, Hansen and Sadun, 2020; Frederiksen, Kahn and Lange, 2020; Hoffman and Tadelis, 2021; Metcalfe, Sollaci and Syverson, 2023; Adhvaryu, Nyshadham and Tamayo, 2023; Adhvaryu, Kala and Nyshadham, 2022). 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 and overall firm productivity. In so doing, I also bring forth new evidence on the micro-level processes that link individual managers at lower levels of the firm hierarchy to firm-level outcomes. In terms of management practices, this study puts the emphasis on managerial policies governing the allocation of workers to jobs within firms, which have been overlooked by previous research.[11]

[11] The managerial practices analyzed by previous literature focus on workers' incentives via pay for performance, promotions, and monitoring (Bloom and Van Reenen, 2011). The tools of monetary

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, Hurst, Jones and Klenow, 2019).

The remainder of the paper is organized as follows. Section 2 describes the institutional 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 provides a conceptual framework to interpret the empirical results and discusses 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. This firm is one of the largest in the world and is headquartered in Europe. *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 (there are 12 salary grades in total). *Salary approximately increases by 20%-30% at each salary grade increase.* A salary grade increase entails a permanent change in salary but not a major change in job responsibilities

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; Bandiera, Barankay and Rasul, 2013; Bertrand, Burgess, Chawla and Xu, 2020).

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 the time of the sample. 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 my 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[12] in 118 countries (10,083,638 worker-month observations). Supervisors (i.e. those that supervise at least one worker) comprise 21% of the sample, although only 15% of the sample is in managerial roles (i.e. has a work-level above one).[13]

Panel (a) and (b) of Table II presents summary statistics for the main variables. Women represent 44% of employees in the sample, 39% of workers are aged between 30-39 and the large majority of workers are in work-level 1, WL1 (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 (31%). 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 very 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. 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,

[12]97% of employees work full time.

[13]This 15% share of managers is exactly the same as the global average share of managers among the white-collar workforce reported by ILO in 2019.

the typical large firm would have at least 4 hierarchical levels.[14] 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.[15]

2.2 The role of line managers

Line managers are responsible for setting team priorities, coaching, and giving feedback to workers. They can significantly influence job design through the assignment to projects inside and outside the team. Crucially, managers' input is key for promotion and transfer decisions (in line with other organizations, see for e.g. Frederiksen et al., 2020; Haegele, 2022). Managers have an explicit incentive to "develop and magnify the power of people" (excerpt from firm manual). 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" (excerpt from firm manual).

The firm uses 360-degree evaluations for the performance appraisal process: a line manager receives written evaluations from both superiors and subordinates on each of the indicators and his own manager reviews these to decide on a single (numerical) performance rating each year, which is then used to determine the annual bonus.[16] Line 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 (see Appendix Figure A.4 for an excerpt of the firm HR guidelines to managers).[17] In 2020, employees reported in the annual global pulse survey at the MNE that their line manager was among the top three areas of importance to them, further underscoring the relevance of this

[14] European-wide statistics are taken from the European Company Surveys (van Houten, Russo et al., 2020).

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

[16] The written text of these evaluations did not pass the confidentiality criteria for the data to be shared for this research as it was deemed that they could not be cleaned so as to preserve employee anonymity. Only the numerical performance ratings were shared.

[17] Qualitative evidence from focus groups of workers at the firm indicates that frequent 1-1 meetings with the line manager tend to go hand-in-hand with good managers.

relationship in the workplace.

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, Li and Shue, 2022).[18]

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 if she has decided to quit the job for alternative employment or other activities (voluntary exit).

In terms of the types of jobs, there are 16 Notes: The original number here is 14. However, when you check the value label for the `Func` variable, there are 18 different values. I assme that the "Data and Analytics" function is the same as the "Data & Analytics" function, and "UNKNW" represents unknown. To sum up, there are 16 different functions. 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

[18]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.

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.[19] I also observe the job titles detailing a worker's exact job within the sub-function. There are almost 1,000 (Notes: More specifically, 992. But the number is calculated only within WL1 workers, so I add more description in the sentence.) horizontally differentiated job titles within the firm for work level 1 employees, and, on average, there are two Notes: More specifically, the mean is 1.98, while median is 2. distinct job titles in a team.[20] Appendix Figure A.6 shows that lateral moves are common in every sub-function and that this is also true for salary grade increases.

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 data

I supplement these data with payroll data, which include employees' earnings, and bonus payments.[21] 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 a different salary: the salary grade[22], the salary band[23] and the annual bonus (variable

[19]The median size of a sub-function is 240 workers, the 10th percentile is 16 workers and the 90th percentile is 2103 workers.

[20]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.

[21]Salary is measured in euros in all countries.

[22]Panel (c) in Appendix Figure A.5 shows the positive relationship between the number of salary grade increases and pay in logs.

[23]*Within each salary grade, there is a salary band that goes from 80% to 120% of target pay determined via market benchmark data.*

pay, which is on average 10% of fixed pay for entry-level 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 her 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 full Indian sales population from January 2018 until December 2021 (around 2,500 employees).* Notes: All sentences about India sales sample will be marked, as the sales performance dataset is now different, and should be re-introduced.[24] 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.[25] 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).[26] Both of these measures are at the establishment-year level and the company shared all data available for every factory globally (around 150 sites) over 2019-2021. Because of changing reporting requirements, the costs per ton data could only be shared for the

[24] *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. India is the country where outsourcing had still not taken place at the time of data collection and it is also the country with the largest number of workers in the MNE.* Notes: This paragraph about the sales productivity data should be re-written.

[25] Panel (b) of Appendix Figure A.5 shows that there is a positive relationship between current productivity and future salary grade increase.

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

main product category (there are three product categories in total).

3.4 Digital platforms: skill development and flexible projects

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, Davis, Montagnes and Perkowski, 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.

3.5 Global employee surveys

I conduct additional 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%.*[27] 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, higher up in the hierarchy, and are marginally more likely to have a high-flyer manager (I provide details in the Supplementary Materials.

[27] In 2017 and 2018, the survey was only sent to a random sample of employees.

Notes: It is better if a new subsection is included to introduce the external data used in the paper, e.g., the ONET data, the world bank data to classify countries into low/medium/high-income countries (in the manager comparison table), the female labor force participation rate data, and the labor regulation index data, which are used in the heterogeneity table. I described the ONET data in the Data Appendix, but it is better to mention it in the main text.

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 fare better (e.g. have higher wage growth) 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 a new proxy 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; Gibbons and Waldman, 1999; Prendergast, 1998). The key metric I consider is age at promotion to manager, which is a measure of the managers' personal success in the organization and is not directly based on the outcomes of their workers. *In particular, I define high-flyer managers as those who achieve work-level 2 at a relatively younger age (time-invariant).* Notes: Maybe it is better to explain the construction in a more concrete way. The description here is misleadingly simple, compared with our genuinely complicated construction method. I consider worker age instead of tenure as the former is a better proxy of labor market experience. 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).

Because of data confidentiality, I only observe 10-year age groups. This restriction from the data ties my hands into how I can define fast promotions: *Figure I Panel (b) plots the distribution of age at promotion to work-level 2 and shows that the majority of workers achieve it after turning 30 years old.* Notes: More precisely, the panel plots the distribution of the minimum age observed in the dataset when a worker is at work-level 2 among a sample of workers whose tenure at that age is less than 10. As a result, there is only one way in which the high-flyer measure can be defined: workers who attain work-level 2 *before* the age of 30 (29% of managers). The share of high-flyers is broadly constant across functions, countries, and years.

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. Notes: Originally, here is some description about the manager FE and the high-flyer measure, but the figure is deleted, so the original paragraph is commented out. Panel (c) of Table III shows that the high-flyer manager status is positively correlated with a number of ex-post performance measures: managers' future salary growth, probability of promotion to work-level 3, performance ratings, and workers' anonymous upward feedback on the managers' leadership.

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. However, Panel (b) shows that they are not differentially likely to be in the sales function (biggest function) compared to other functions. Moreover, high-flyers are more likely to have been developed internally as they are 14p.p. less likely to be mid-career recruits and are slightly more likely to be in emerging economies compared to high-income countries.

4.1.1 Interpretation and 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 workers' 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, Li and Shue, 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 identify such exogenous transition events in the data by observing that the new manager assumes responsibility for all employees in the team.* Notes: There is no such restriction when constructing event indicators in practice. *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.* Notes: The only restriction we impose when constructing manager transition events is that the worker cannot have a simultaneous internal or lateral transfer.

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.[28] Notes: Originally, there is a sentence describing managers' rotation and work duration distribution, but the figure is deleted, so as the sentence. Overall, *74% of managers make at least one of these transitions in my panel data.*

4.2.1 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 three years before the manager transition - includ-

[28]In the Supplementary Materials I provide additional details on the manager rotations.

ing team performance, inequality, transfer rates, and team diversity - cannot predict the quality 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:

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

where *High-flyer manager*$_{team}$ denotes the quality of the future manager and controls ($\boldsymbol{X_{team,t}}$) include function, country and year FE. 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: there is no evidence of high-flyer managers being assigned to teams with worsening or improving performance prior to their arrival.* Notes: To be honest, this interpretation is a little weird. In most DID checks, this evidence will be presented as "past team-level performance and other metrics measures cannot predict the incoming managers' quality." Here, it is paraphrased in a reversed way.

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:

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

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.[29]

The research design, by combining the measure of manager quality that is defined ex-ante, before a manager meets a given worker (sub-section 4.1), with the manager transitions, tackles a potential identification concern of common shocks to manager promotions and worker careers, whereby an exogenous shock to a given unit causes both the X and Y variables to change. The reason is that the manager's promotion is

[29] The statistically significant coefficient in Panel (c) of Table B.2 (Column 2, at 5% significance level) can be due to chance as I am testing 24 hypotheses, and hence there is a 71% chance of observing at least one significant result at the 5% level.

assessed at a different time (ex-ante), and, more importantly, in a different unit than the one where the manager's effects on workers are then evaluated. In Appendix Table B.3, I also assess directly whether there is a correlation between establishment growth and the share of high flyers, to assuage concerns of high flyers being a lagging indicator for positive persistent shocks at the establishment level, hence reflecting establishments' past positive performance shocks. I do not find evidence of a correlation between the share of high flyers and establishment growth.

4.3 Event study design

An example can illustrate the empirical strategy. Consider two workers, each supervised by a low-flyer manager. As a result of the managerial rotation scheme, one of these workers transitions from the low-flyer manager to a high-flyer manager, while the other worker transitions from the low-flyer manager to a different low-flyer manager. I compare the outcomes of the workers each month leading up to the manager transition date and each month after the transition. As both workers are affected by a manager transition, this design nets out the effect of the transition on outcomes. Similarly, I compare two workers, each supervised by a high-flyer manager, where one worker transitions to a low-flyer manager, and the other worker transitions to a different high-flyer manager.

I only consider *the first manager transition that a worker experiences* Notes: More precisely, we can only consider the first manager transition that can be observed in the data, which may not be the first manager change that a worker experiences. and keep following the evolution of worker outcomes up to ten years after the transition; a key objective of the paper is to examine the impact of managers on workers' careers.[30] The event-study data comprises 29,610 transition events, involving 29,610 unique workers and 14,664 unique managers.[31] Events occur every year but 50% 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

[30] In sub-section 5.5, I show that my results are robust to only considering new hires, for whom I can tell for certain that this is their first manager change at the firm.

[31] 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.

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[32], $\boldsymbol{\xi}_t$ 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 36 months before the event to 84 months after the event. The time window is determined by the length of the panel data. In particular, because I only look at the first manager transition, most events occur in the first three years of the panel (2011-2013) and hence this constrains the length of the pre-event time window. For example, the -12th quarter estimate is the average of the estimates in months -36, -35, and -34 before the event and hence, only workers who experience the event after December 2013 can identify these coefficients. 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. Notes: There are two issues not presented in text but are relevant in practice: (1) there are no never-treated workers in the regression sample, while all four event groups are included in one regression, and (2) there are eight binned endpoints included in the regression (4 event groups $\times$ 2 endpoints for each group).

In this setting, contamination from effects from other periods (cohort-specific effects) is not an issue as the firm's policies and organizational structure remained un-

[32]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.

changed for the 10-year period, as described in Section 2. To empirically validate this, I can also run the event study using the interaction-weighted estimator developed by Sun and Abraham (2021), which yields nearly identical estimates as the two-way fixed-effect estimates, as shown in Appendix Figure A.9 and Section 5.5.1. Notes: There was originally a paragraph about the negative weights test, which was deleted.

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. In other words, there are no never-treated workers in the event studies. Hence, the estimates of interest are the differences between types of transitions: $\hat{\beta}_{LtoH,s} - \hat{\beta}_{LtoL,s}$ (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.

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

$$y_i = \sum_{j \in J} \beta_j D_i^j + \boldsymbol{X_i \alpha_i} + \varepsilon_i, \tag{3}$$

where y_i is a set of outcome variables indicating whether the employee left the firm voluntarily or involuntarily within given 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[33]:

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

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 discuss that the job-allocation margin is a quantitatively important factor underlying the observed impacts of high-flyer managers.

5.1 Workers' transfers and exit from the firm

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 manager to another low-flyer manager ($LtoL$). Panel (a) shows the evolution of the number of lateral moves in each of the 12 quarters (3 years) leading up to a manager transition and the 28 quarters (7 years) after the manager transition. The quarter before the event (-1) corresponds to the omitted category, and thus the corresponding coefficient is always zero by construction.

Figure II shows that, prior to the event date, the differences in the coefficients are statistically indistinguishable from zero for all outcomes. 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. Notes: We should also mention the effects start to be significant from 8 quarters, or 2 years onwards. 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 0.12 higher in the $LtoH$ group than the $LtoL$ group (or a 57% increase, p-value <0.05). Notes:

[33] 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, Guimarães and Zylkin, 2020).

$\hat{\beta}_{LtoH,28} = 0.332, \hat{\beta}_{LtoL,28} = 0.212$. The first statistic is calculated as $\hat{\beta}_{LtoH,28} - \hat{\beta}_{LtoL,28}$, while the second is $(\hat{\beta}_{LtoH,28} - \hat{\beta}_{LtoL,28})/\hat{\beta}_{LtoL,28}$. The effects of gaining a high-flyer on 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 (a) of Appendix Figure A.7, which plots the probability of making at least one lateral move since the manager transition. This probability increases by 5.8p.p. or 24% for the workers in the $LtoH$ transition with respect to the workers in the $LtoL$ transition. Notes: $\hat{\beta}_{LtoH,28} = .299275, \hat{\beta}_{LtoL,28} = .2411141$. The first statistic is calculated as $\hat{\beta}_{LtoH,28} - \hat{\beta}_{LtoL,28}$, while the second is $(\hat{\beta}_{LtoH,28} - \hat{\beta}_{LtoL,28})/\hat{\beta}_{LtoL,28}$.

Notes: It may be better to also include baseline transfer rates in the text.

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 reveal that from the moment an employee begins to explore job opportunities within the multinational, it usually takes at least two years for a potential job change to materialize. Therefore, the patterns observed align with the constraints and rules governing the firm's internal labor market.

Next, I isolate task-distant lateral transfers. *I match the MNE job titles to the Occupational Information Network (O*NET) job classification data, which provides different scales on skills and activities required for each job, and construct angular separation measures of task distance across jobs. Then I count the number of cross-functional moves, with simultaneous task-distance moves that a worker experiences, and present the results in panel (b) of Appendix Figure A.7.* Notes: This whole paragraph is entirely re-written, as we have done something completely different from the original version. I will provide some practical details in the next paragraph for the O*NET regression.

Notes: The following paragraph is about how to construct the cumulative task distance measures used in panel (b) of Appendix Figure A.7.

Following Deming (2017) and Cortes, Jaimovich and Siu (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. By matching job titles inside the MNE to the O*NET occupation titles, I am able to transform a raw measure for each occupation into a percentile rank based on the empirical distribution of all MNE employees. For each job change, I calculate a composite measure of task distance between these three tasks using the angular separation as in Gathmann and Schönberg (2010). The task distance measure is in the range of 0 to 1, where zero means that the two jobs use identical skill sets and unity means that two jobs use completely different skills sets. Finally, I use the cumulative version of this variable as the outcome variable, and the event study results are in panel (b) of Appendix Figure A.7. More details on the construction of the outcome variable is in Appendix D.1.

To identify transition patterns across the three task groups. I classify a job to a cognitive, routine, or social job based on the highest intensity measure. Next, I focus on $LtoL$ and $LtoH$ workers in the event studies, and track their occupations after their first manager transition event. For example, among $LtoL$ workers, I collect their job information at the time of event and 2/7 years after the manager transition event, and construct a transition matrix with each entry representing the fraction of workers doing that transition (diagonal entries represent the fraction of occupation stayers. I do the same thing for $LtoH$ workers, and present heatmaps for the difference between $LtoH$ and $LtoL$ transition matrices. The results are shown in Appendix Figure A.8. It is obvious that for $LtoH$, there are more off-diagonal transitions, which means they have more meaningful lateral transfers.

In 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. In panel (a), I take the event study coefficient at the 8th quarter (approximately at the end of a manager rotation, as they last on average two years)[34] and shows that around 48% of the job moves are within the team, 37% are outside the team but within the same function, and 14% are across functions. In panel (b), 28th quarter estimate is decomposed in the same fashion, when the post-event manager is very likely not in charge. In the medium run, around 32% of job moves are within team, 53% are outside the team but within the same function, and 14% are across functions. Notes: I only modify the share numbers, more interpretation is better if we illustrate the change of effects from 2 years to 7 years after the event.

[34] I need to define a reasonably short time window to consider the within team job moves so to evaluate them while the original transitioning manager is still in charge. It is however important to note that the cross-functional transfers take longer to occur and they keep increasing until the 22nd quarter.

I also assess 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 lower-performing workers from the firm but rather they are finding alternative suitable deployments inside the organization.

5.2 Workers' career progression

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

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 manager 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. It keeps diverging up to the 20th quarter after which it levels off at the new higher level. At 28 quarters after transitioning to a high-flyer manager (relative to transitioning to another low-flyer manager), the salary grade promotion rates are 0.20 higher (p-value<0.05).

This corresponds to a salary that is 10% higher: Panels (a)-(c) of Figure IV show the salary estimates (pay plus bonus), and then the pay and bonus estimates separately. The bonus increases by 93%, but it should be considered that the bonus is around 10% of fixed pay for work-level 1 workers, and the effect on total pay is mainly driven by the increase in fixed pay as shown in Panel (b).[35] Notes: The number in the next sentence is calculated as follows. First, I calculate the mean average among WL1 US workers in 2019, and convert the euros into dollars (with exchange rate 1 euro = 1.1194

[35]The compensation data is only available from 2016 onwards, hence I can estimate the post-transitions coefficients only.

dollars). Next, I calculate the multiplication between 7th year coefficient difference, $\beta_{LtoH,7} - \beta_{LtoL,7}$, and the first-step average pay for US WL1 workers.The gap in overall pay is economically large: in the U.S. it represents \$8,651 in annual salary, on average.[36] An alternative way of illustrating the magnitude of this effect is to consider that a 10% higher salary corresponds, on average, to the salary increment an entry-level new hire would accumulate over four years of employment.

In Panel (d) of Figure IV, I look at work-level promotions, which in this case entail transitioning from a work-level 1 front-line worker position to a work-level 2 managerial position. At 28 quarters after transitioning to a high-flyer manager (relative to transitioning to another low-flyer manager), the number of work-level promotions is 0.03 higher (an increase of 41%, p-value<0.05). The work-level promotions manifest after the manager transition and start to show significant effects from 12 quarters onwards.

Notes: Originally, here is a paragraph talking about team-level event study results, but the figure is deleted, so as the paragraph.

5.3 Workers and factories' productivity

Do the effects of the high-flyer managers result in higher worker productivity or are they leading to the worker earning higher pay for the same performance? So far, I have interpreted higher worker pay growth as evidence of higher productivity. *By leveraging sales performance data from the subset of Indian sales workers (circa 2,500 workers), I can provide further evidence in favor of this interpretation.* Notes: The old data description applies to only Indian workers. This sentence should be rewritten.

The productivity data is obtained from the sale incentives records and it represents the monthly sales bonus in Indian rupees. Notes: The whole paragraph should be rewritten, since the productivity dataset is not restricting to India sample only. Field sales workers in India are paid a variable sales bonus according to what they achieve relative to

[36] 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 133% of average annual pay. Notes: The calculation is as follows: $\sum_{t=1}^{29} eff_t/(1+5\%)^t$, where for $1 \leq t \leq 7$, eff is the corresponding LtoH coefficient minus LtoL coefficient, and for $t > 7$, eff is the 7th year LtoH coefficient minus LtoL coefficient.

their targets each month.[37] The data is high-frequency as sales performance is tracked monthly but it is only available for 2018-2021, and it is relatively noisy.

Therefore, I can only run the following regression given the limited time window available:

$$y_{it} = \sum_j \beta_j Post^j_{it} + \boldsymbol{\xi_t} + \boldsymbol{\alpha_i} + \epsilon_{it} \tag{5}$$

where $Post^j$ denote the indicators for the onset of a transition event $j \in \{LtoH, LtoL\}$, $\boldsymbol{\xi}_t$ comprises of year-month FE, and $\boldsymbol{\alpha}_i$ is worker FE to control for permanent differences in worker productivity. Standard errors are clustered at the manager level. I cannot look at the reverse transition, losing a high-flyer manager, as the observations for the $HtoH$ manager transition are too few in this sales sub-sample. Notes: (1) In the table, we are effectively reporting $\beta_{LtoH} - \beta_{LtoL}$. In practice, we are running a different regression,

$$y_{it} = \alpha Post_{it} + \beta E^{LtoH}_i \cdot Post_{it} + \boldsymbol{\xi_t} + \boldsymbol{\alpha_i} + \epsilon_{it}$$

such that $\beta = \beta_{LtoH} - \beta_{LtoL}$. This is why the coefficient is called "LtoH × Post". We should better align the expression in the equation and the presentation in the table. (2) Besides, we should mention explicitly in the text that the regression sample consists of only LtoH and LtoH workers. (3) It is also better to mention the interpretation of the coefficients. The interpretation is different from the 28th quarter estimates that we commonly reported before. Current estimate also involves average across different treatment periods.

Table IV shows that sales performance increases by 0.18S.D. upon switching from a low to a high-flyer manager. In columns 2-3, separate the sample of workers who make at least one lateral move within 2 years of the manager transition from the workers who do not. For the workers who make at least one move, I compare the within-worker change in sales performance between those who make the lateral move under a high-flyer and those who make it under a low-flyer manager. For workers that move, those who do so following a high-flyer manager experience a 0.24S.D. improvement in sales performance compared to the workers who move after being exposed to a low-flyer. A similar result can be found for salary on the full sample of workers (column

[37] 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.

3). The results should be interpreted with caution as I am selecting observations based on an outcome, but they suggest that transfers *per se* do not necessarily have a positive impact on productivity and high-flyer managers are generating the right transfer for the right worker, or the right *worker-job matches*.[38]

Moreover, I can conduct a similar exercise for vertical moves. Columns 4-6 of Table IV show that, conditionally on being promoted to work-level 2, the workers promoted under a high-flyer manager perform better in terms of pay growth and of the anonymous leadership score given by subordinates in the annual survey.

Altogether, an efficient allocation of workers to jobs within sites should result in higher productivity for the entire site, creating a link between individual-level effects and firm-level outcomes. I turn to measures of productivity at the establishment level to assess whether high-flyers have aggregate effects. I provide suggestive correlational evidence that factories with white-collar workers who had more past exposure to high-flyer managers are more productive on the whole. For context, factories tend to have a non-trivial share of white-collar workers who manage operations and supervise blue-collar workers; *the average share across factories is 24%*. I obtain a measure of productivity at the factory-year level, *output per worker*, and a measure of costs per unit of output, *costs per ton*, for all factories globally over 2019-2021.[39] *For each worker, I construct a measure of past exposure to high-flyers as the share of months supervised by a high-flyer up to the year before productivity is measured (one-year lag).* Notes: This is not what we do in practice. When constructing individual-month level exposure to high-flyer managers, we count the number of months before current month when he was supervised by a high-flyer. However, when transforming this dataset into office-year level, we use the average expore across all worker-month pairs in the same office-year. This evidence is only correlational in nature as the variation at the factory level in the workers' past exposure to high-flyers is not necessarily exogenous.

I regress output per worker in logs against workers' past exposure to high-flyer

[38] Moving workers around could in fact be detrimental for productivity if there is no meaningful improvement in job match as previously accumulated job-specific human capital remains unused. The framework in sub-section 7.1 clarifies this trade-off.

[39] Tons of products produced per FTE is a common KPI for manufacturing firms (FTE stands for Full-Time Equivalent). The cost per ton measure considers the operational costs per ton which are predominantly made up of labor and energy costs (it does not include the cost of raw materials). Because of changing reporting requirements at the firm, the costs per ton data could only be shared for the main product category (there are three product categories in total).

managers in the factory, clustering the standard errors by factory. The regression controls for country, product category and year fixed effects, the share of managers, and the number of blue-collar and white-collar workers at the factory. Panel (a) of Figure V shows that increasing workers' past exposure to high-flyers by 10p.p. is associated with an increase in output per worker by 18%, that is the semi-elasticity between the two variables is equal to 1.79. Notes: I am not so sure about the semi-elasticity interpretation. The 1.79 value comes from the linear regression coefficient reported in the figure. Similarly, Panel (b) of Figure V shows that the semi-elasticity between costs per ton and workers' past exposure to high-flyers is -1.1. Altogether, these two results indicate that the high-flyers' effects are increasing profits, taking prices as given.[40]

5.4 Asymmetric effects for losing a high-flyer manager

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 VI shows that there is no differential impact in losing a high-flyer manager, the estimates are close to zero and statistically insignificant. Since only 6% of the events are $HtoH$, by virtue of the definition of a high-flyer manager that categorizes 30% of managers as high-flyers, it should be kept in mind that these results are less conclusive than those for gaining a high-flyer manager. Due to the smaller sample size, the confidence intervals are wider, and especially the coefficients leading up to the transition are more imprecisely estimated.[41] Yet, the point estimates are clearly smaller compared to Figure II and Figure IV and also do not exhibit a detectable downward trend, which would be expected if losing a high-flyer manager has the opposite effect of gaining a high-flyer manager.[42] Hence, the high-flyer manager results are asymmetric: compared to gaining a high-flyer, losing a high-flyer does not lead to similar findings in the opposite

[40] The assumption on constant prices is plausible for two reasons: first, I am controlling for country, product category, and time fixed effects in the regression, and second, it is the marketing teams that set prices, not the production managers in factories.

[41] As a reminder, most of the transition events occur in the first three years of the panel (2011-2013) since I only consider the first manager transition. For example, the -12th quarter estimate is the average of the estimates in months -36,-35, and -34 before the event; only workers who experience the event after December 2013 can identify these coefficients.

[42] Because of the reduced number of $HtoH$ transitions, 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.

direction such as lower salary growth and transfers (see Figure VII 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.[43] 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).

There is one caveat to bear in mind when comparing the impact of gaining versus losing a high-flyer manager. Unlike the manager transition used in the identification strategy, the *first* manager-worker assignment is not necessarily random. In fact, the identification strategy relies on the *second* manager-worker assignment being orthogonal to worker characteristics, but not necessarily the first assignment, which may be a result of sorting. In practice, it is impossible to check for this given the data is only available for 2011-2021 (i.e. I cannot observe the workers' histories before 2011). Hence, any differences in the outcomes of workers that start with a low-flyer manager against those of workers that start with a high-flyer manager could be either due to the treatment effect of high-flyers while managing the workers or due to differential selection of workers by manager type ex-ante. One could for instance imagine that the ability of high-flyers to spot unique talents occurs even before interacting directly with the worker in the day-to-day job, at the interview/selection stage. Overall, one might view this caveat as less critical for the validity of my results relative to other settings given that managers being able to select the right workers for their team is highlighted

[43] 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.

as the key channel that differentiates high-flyer managers from the rest.

5.5 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.

5.5.1 Cohort Dynamics

This section needs to be written. I have described the procedures for producing the plots. Appendix Figure A.9 presents the results.

Some clarification:

- For each regression, there are only two event groups in the sample (LtoL and LtoH when investigating the effect of gaining a H-manager, HtoH and HtoL when investigating the effect of losing a H-manager).
- The relative months included in the regressions are $[-36, +84]$ ($[-36, +60]$) when investigating the effect of gaining (losing) a H-manager. Also, two binned endpoints are included: relative months < -36 and $> +84$ (or $> +60$).
- The omitted relative months are -1, -2, -3 for each event group.

The procedures for obtaining the Sun and Abraham estimator:

1. For each "event $\times$ relative month indicator" dummy appeared in the normal TWFE regression, I interact it with 10 other dummies (from 2011 to 2020) indicating the year in which the manager change event happens.
2. The coefficients of these dummies are estimated using `reghdfe`, controlling for time and individual fixed effects.
3. For each event group, and for each relative month, I calculate the share of regression sample that belongs to each cohort (so there are 10 numbers that sum to one indicating the weights associated with each cohort).

4. The coefficients on "event $\times$ relative month indicator $\times$ cohort indicator" are first aggregated to coefficients on "event $\times$ relative month indicator" using the weights calculated in step 3.

5. Furthermore, coefficients are aggregated to "event $\times$ relative quarter" level based on the same quarter aggregation procedure in the TWFE regression.

5.5.2 Restricting the event-study to a single cohort

Since my panel covers 132 months, there is a mechanical restriction on the workers that identify the medium-run effects in the event study. That is, since the 28-quarter estimate is the average of the estimates in months 82, 83, and 84, only workers that experience the event before January 2015 can identify these coefficients. Even for workers who are in the panel in all periods, these coefficients are identified only from events that occur before January 2015. I show that these composition effects do not drive my results by replicating the analysis on a single cohort of workers. I restrict the workers who experience an event to those who have it during 2014, which constitute 9% of all events. Panels (a) and (b) of Appendix Figure A.10 show that the event studies limited to this cohort of workers retain the timing and magnitude of the baseline results.

5.5.3 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. However, I might be underestimating the effect of the first manager transition from low to high-flyer as some of these workers may have had additional high-flyer managers in the past. I show that my results are robust to only considering new hires, for whom I can tell for certain that this is their first manager change at the firm (I retain 73% of events). Notes: In practice, we keep only those workers whose minimum tenure observed in the dataset is strictly less than 2 years. It may be better to mention and justify the usage of this threshold. Given this tenure criterion, it is better to not say that "for whom I can tell for certain that this is their first manager change at the firm." Panels (c) and (d) of Appendix Figure A.10 show that the event studies limited to new hires retain the timing of the baseline results and, as expected, the estimates are larger.

5.5.4 Poisson model for count data

Panels (e) and (f) of Appendix Figure A.10 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 (b) of Appendix Figure A.10 indicates that workers gaining a high-flyer manager have a rate of salary increases 1.3 times greater, five years post-transition.* Notes: I am not so sure about the interpretation. The quarter aggregation programs are the same as the ordinary TWFE regressions, given that we are using a different model specification. I am not so sure how to interpret the coefficient differences reported in the figure.

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. 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 lateral moves and worker performance

6.1.1 Mediation analysis

A story related to me by a worker participating in an in-depth interview illustrates the proactive "match-making" role that managers can play: "My manager saw my passion for environmental sustainability and recommended me for a lead role in our new green initiative. This move not only aligned with my personal values but also marked a pivotal step in my career toward strategic leadership". On the other hand, another worker reported: "I expressed my desire to learn more about our analytics tools, hoping to shift towards data analysis. But without my manager's support for the necessary training, I've had to watch these opportunities pass by".[44]

To formally analyze the role of lateral moves behind the increase in salary, I perform a mediation analysis following the method by Imai, Keele and Tingley (2010a) and Imai, Keele and Yamamoto (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):

$$\frac{dY}{d\text{High-Flyer}} = \frac{\partial Y}{\partial M}\frac{\partial M}{\partial \text{High-Flyer}} + R \tag{6}$$

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 20th quarter as the mediator, M. I find that lateral transfers contribute to 59% of the total effect of high-flyers on the number of salary increases.[45] It is plausible to assume that 59% 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.[46]

As is typical in the literature, the results of the mediation analysis should be inter-

[44] I conducted 31 in-depth interviews with work-level 1 workers to discuss their experience with their managers. I opted for individual interviews rather than focus groups to ensure workers would feel safe expressing themselves authentically. All interviews were conducted under strict confidentiality, and I obtained explicit permission to use quotes anonymously.

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

[46] An anecdote from an in-depth interview participant illustrates how a manager can help improve on-the-job performance via task matching as in (iii): "My manager noticed my enthusiasm for graphic design during a routine project presentation. He arranged for me to lead the design aspect of our next campaign, aligning perfectly with my career interests and skills".

preted 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

Workers that participated in individual in-depth interviews run in London in March 2024 (31 workers), revealed that better managers engaged in proactive career pathing (e.g. by initiating conversations about career growth), constructive feedback (e.g. via dedicated structured meetings), encouraged employee autonomy (e.g. leaving room for involvement and initiative) and overall acted as a mentor more than a supervisor (e.g., instead of just assigning and overseeing tasks, probing workers on what they want to learn or improve on). As a concrete example, one employee said: "My manager noticed my enthusiasm for graphic design during a routine project presentation. He arranged for me to lead the design aspect of our next campaign, aligning perfectly with my career interests and skills".

Beyond the qualitative evidence, I find further support in time use and skills data. First, Appendix Table B.4 uses time-use data from Microsoft on a random sample of 2000 workers from multiple work levels, functions, and countries, and reveals that high-flyer managers dedicate 0.63 more weekly hours in 1-1 meetings with subordinates (a 19% increase relative to low-flyer managers). They also send more emails, have fewer open 1-hour blocks, and spend more time multi-tasking (sending emails or messages while in meetings), all in all suggesting that these managers might act more as coordinators.

Second, I use data on skills from a new platform introduced in 2019-2020 that is aimed at fostering learning and skills development. In particular, employees can post skills acquired, and these are in turn certified by their supervisor. Since the data is multidimensional as employees can post many skills, I first reduce the dimensionality by implementing a 3-topic Latent Dirichlet Allocation algorithm. The resulting 3 topics are a probability distribution over all words in the skills description, and are shown in the word clouds in panels b-c of Appendix Figure A.11. Broadly, by inspecting the word clouds, the 3 topics can be summarized as project management skills, strategy and talent management skills. The algorithm also results in a manager-level skill distribution over these three topics, which sums to one. Next, I run seemingly unrelated regressions with the managers' distribution over the three topics as the outcome (using the first topic, project management skills as reference group) and report the coefficients and 95% confidence interval in panel a of Appendix Figure A.11. I find that high-flyer managers have more strategy and talent management skills compared to low-flyer managers.

Third, I can look at workers' engagement with the platform. Appendix Table B.5 shows that workers gaining a high-flyer manager are more likely to engage in the career mobility platform and become "active learners", defined as having posted at least three focus skills, completed at least five courses/items, and shared at least one item with a colleague. This is an increase of 13% relative to a low-flyer manager. As this platform is used as an internal labor market tool to combine skill acquisition and career mobility, these results complement the findings on the higher lateral transfer rates.

Moreover, workers exposed to high-flyer managers are also more likely to participate in flexible projects, which are short-term projects inside the company but outside the worker's current team (Table B.6). Flexible projects were conceived to allow greater career and organizational agility by empowering workers to design their own career paths. Workers gaining a high-flyer manager are 17% more likely to register on the platform of the flexible projects (6ppt), 5% more likely to complete their profile in full (2ppt), 12% more likely to state that they are available for flexible opportunities (3ppt), 89% more likely to report being available to be a mentor (11pt) and 27% more likely to apply for jobs (1ppt).

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.

6.3 Heterogeneous effects

I look at some heterogeneous treatment effects to provide further evidence on the allocation mechanism. I extend the model in equation 2 to test for heterogeneous treatment effects, allowing for heterogeneity in H_i:

$$y_{it} = \sum_{j \in J} \sum_{s \neq -1} \beta_{j,s} D^j_{i,t+s} + \sum_{j \in J} \sum_{s \neq -1} \beta^H_{j,s} D^j_{i,t+s} \times H_i + \boldsymbol{\xi_t} + \boldsymbol{\alpha_i} + \epsilon_{it} \tag{7}$$

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. First, I look at workers and managers' characteristics: manager tenure, manager having the same gender as worker, manager and worker being in the same office, worker age, and worker tenure. Second, I consider characteristics concerning the environment in which they operate: office size, number of different jobs in the office, country female labor participation ratio (only for female workers), and country labor laws.[47] 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%. Notes: Originally, there was a sentence describing heterogeneity by whether the post-event manager stays with the worker for 2 years. The row is deleted, so as the sentence here.

Notes: There are several issues not mentioned in the text: (1) It is better to mention the outcomes of interest and corresponding econometric models, since the four columns in the heterogeneity table have three different regression equations. (2) It is also better to mention that we are using a simplified regression equation – including only the reference months, and the quarter of interest in the regression – instead of a full set of event dummies presented in equation (7). To some extent, this could be better since the coefficients are not contaminated by treatment effects of other periods.

[47] I use the Restrictive Labor Regulations Index from the World Bank. It is available for the period 2008-2017 and it is based on an annual survey of the most problematic factors for doing business (e.g. corruption, taxes, inflation, etc.). The survey is administered to a representative sample of around 15,000 business executives in 150 countries. The Restrictive Labor Regulations Index includes measures related to labor-employer relations, wage flexibility, hiring and firing practices, performance pay, labor taxes, attraction, and retention of talent.

6.3.1 Worker and manager characteristics

Panel (a) of Table V shows that the effects are strongest for (a) managers with higher tenure, (b) workers that are in the same office as their manager, (c) workers that share the same gender with the manager, and (d) younger workers.

These heterogeneous effects corroborate 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, in addition, they have not accumulated yet a lot of job-specific experience.[48] *The gender result indicates that there are no heterogeneous effects along this dimension.* Notes: The sentence should be rewritten since the effect is now stronger among those workers who have the same gender as their managers'. I expand on this finding in subsection 6.4.

6.3.2 Environment characteristics

Panel (b) of Table V shows that the gains are larger for bigger offices, offices with a larger number of different jobs, and countries with stricter labor laws. Notes: The Female labor participation row should be also described here. The heterogeneous effects along these dimensions also provide further support for 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.[49]

[48]The framework in sub-section 7.1 clarifies this trade-off between finding a better job match and losing previously accumulated job-specific human capital.

[49]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.

6.3.3 Worker and team performance

Panel (c) of Table V displays no evidence of heterogeneity in different dimensions of worker and team performance. I construct the average pay growth for each worker in the two years before the transition and I define whether a worker was above or below the median. I also compare the top 10 percent of workers against the bottom 10 percent of workers. In both of these cases, I do not find clear evidence of heterogeneous effects.

This indicates that high-flyers are not disproportionately benefiting higher or lower-performing workers. For instance, the 10th percentile split shows that the weakest workers' career progressions (the careers of the bottom 10 percent) also improve when transitioning from a low- to a high-flyer manager. 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. Relatedly, Panel (c) of Table V also shows no heterogeneous effects for baseline team performance.

Notes: Originally, there was a paragraph describing the heterogeneity based on whether the manager is different two years after the event. That raw is deleted from the table, so the paragraph is commented out.

6.4 Alternative channels

6.4.1 Manager bias and social connections

I interpret the results on the workers' lateral moves and career progression as reflecting the causal impact of high-flyer managers improving the worker-job match, thereby increasing worker performance. The primary threat to this interpretation is that high-flyer managers might be boosting workers' salaries through means other than enhancing worker productivity. An extreme view could argue that the results found are due to high-flyer managers inflating their workers' pay and promotion prospects, because of having leniency bias with respect to their workers for instance (Frederiksen et al., 2020). It is important to note that, for this interpretation to hold, the leniency bias must be correlated with the high-flyer manager status. Otherwise, in the case that leniency bias is present but is uncorrelated with being a high-flyer manager, it would be shut down by design as my methodology compares worker outcomes across different types of manager transitions. Moreover, I present three pieces of evidence indicating that manager bias is unlikely to drive the estimated effects of high-flyer managers on workers' careers.

First, having a high-flyer manager causes higher worker sales productivity as shown in Table IV: being exposed to a high-flyer manager increases monthly sales productivity by 0.18S.D.

Second, I investigate whether workers that are exposed to high-flyer managers are more likely to move within managers' network. For each incoming manager in the event groups, I first obtain a comprehensive list of his or her experienced subfunctions, officies, managers, subordinates, and same-level colleagues working together before the manager's earliest involved event month. Then I investigate whether those event workers' subfunction, office, and supervising managers 3 or 7 years after the event are within this list, separately for each event group. Appendix Table B.7 presents the results. It presents a different story from the network explanation: if anything, workers exposed to high-flyers are more likely to move outside managers' pre-existing connections. Notes: The description is not complete regarding the network table.

Notes: Originally, there was a paragraph describing the old network table, which was commented out!

Third, I find that the high-flyer manager effects are unrelated to the workers' degree of homophily with the manager, such as sharing the same gender. Panel (a) in Table V shows that high-flyer managers have a positive effect on workers' careers regardless of whether workers share the same gender with their managers. As noted before, my estimates do not identify any differential effect *between high and low-flyers; it could still be that both manager types exhibit biases favoring workers of their own gender. In other words, even though these alternative explanations do not account for my findings, such dynamics may very well be present within the organization.* Notes: This paragraph should be rewritten, since there is now heterogeneity effects based on gender homophily.

6.4.2 Manager teaching, motivating, or monitoring workers

High-flyer managers might be increasing worker productivity through alternative ways such as teaching, transmitting higher motivation to work, or monitoring, rather than primarily through the job allocation channel.

As a first point, the evidence on lateral moves, including on task distant moves and on the decomposition of moves within and outside of the team, cannot be easily reconciled with these other channels (see Panels (a) and (b) in Figure II, Figure III, and Panel (b) in Appendix Figure A.7). This is also discussed more formally in sub-section 7.1 with a framework, which shows how these other channels would have opposite predictions on lateral moves.

Second, the asymmetric results are also hard to reconcile with these alternative channels. If high-flyers were mainly teaching, 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).

Third, I complement the worker-level regressions with team-level analysis to look at pay inequality.[50] I find that teams transitioning from a low- to a high-flyer manager experience a higher coefficient variation in pay relative to teams transitioning to another low-flyer manager (an *18%* increase at 28 quarters, Appendix Figure A.12). Notes: I am not so sure which estimate you want here. $\beta_{LtoH,28} = -.0195507$ (p=0.460), $\beta_{LtoL,28} = -.0513649$ (p=0.013), $\beta_{LtoH,28} - \beta_{LtoL,28} = .0318142$ (p=0.133). The increase in dispersion suggests that high-flyers are exacerbating natural differences in ability by directing workers to the jobs most suited to their skills. This is another result that would be challenging to resolve with high-flyer managers only engaging in teaching/motivating/monitoring, which would predict a *lower* variance in performance among team members.

6.4.3 Managers engaging in talent hoarding

Does talent hoarding explain my findings? I consider how my results relate to potential talent hoarding behavior on behalf of managers, which depends on the correlation between being a high-flyer manager and talent hoarding behavior.

If there is no correlation between high-flyer status and talent hoarding, then hoarding behavior would be orthogonal to being a high-flyer and could not explain my re-

[50] 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 be working under the manager of the transition or changes manager after some time.

sults. This would indicate that talent hoarding may well exist in the organization, but cannot be the reason for my findings. This is in line with Haegele (2022) that shows that managers' talent hoarding behavior is not correlated with manager characteristics.

If there is a positive correlation - high-flyer managers are more likely to engage in talent hoarding - then the results found are a lower bound for the impacts of high-flyer managers on workers' careers as talent hoarding behavior would predict less lateral and vertical moves.

If there is a negative correlation my results could be explained by the fact that high-flyer managers are less prone to engage in talent hoarding in comparison to low-flyer managers. However, if talent hoarding behavior of the low-flyers were to largely explain the results, I should find heterogeneous treatment effects by baseline worker performance as low-flyers would deny movements out of the team only for the high performers and instead kick out of the team low performers. This is inconsistent with the results in Panel (c) of Table V. Moreover, in the Supplementary Materials, I show that the workers that transfer do not report different answers on the engagement annual survey. This rules out that workers are changing jobs because of escaping a manager who is hoarding them, rather than the proposed interpretation of workers finding a better match in terms of their skills in the organization. Finally, the asymmetries in the career trajectories when losing a high-flyer manager provide a further test against talent hoarding as the main channel.

6.4.4 Congestion effects

Given that the high-flyer managers have a higher chance to be promoted to work-level 3 (Panel (a) of Table III), a concern could be that the impacts on the workers exposed to high-flyers are in part explained by a career spillover effect (Bianchi, Bovini, Li, Paradisi and Powell, 2023): high-flyers, by being promoted faster, leave room for a promotion for one of their subordinates. Three facts alleviate this concern.

First, the asymmetric effects of the impact of losing a high-flyer manager represent evidence against this possibility. One would expect a negative impact on the probability of a vertical transfer for the workers experiencing the *HtoL* transition when compared to those with the *HtoH* transition.

Second, I can check directly whether the workers moving from a low- to a high-flyer have a higher chance of taking the exact position of their manager when compared to the workers moving to another low-flyer. *The share of workers taking the place of their managers is actually 1p.p. higher for the workers in the* LtoL *transition (8.9%) as opposed to the* LtoH *(7.9%).*[51]

Third, institutionally, the relevant unit for managerial promotion decisions is the sub-function rather than the team. This is the same unit within which work-level 2 managers typically rotate as part of the rotation policy. Hence, a faster promotion of a high-flyer manager from work-level 2 to work-level 3 would open up a managerial position for all workers within a sub-function, irrespective if they are in a team supervised by a low-flyer or a high-flyer.

6.4.5 Managers changing the jobs available for the workers

The analysis conducted takes as fixed the nature of the jobs that workers can get allocated into. However, rather than shaping the matching of workers to jobs, high-flyer managers might change the jobs available to match them better to the skills of the existing workers.

To check for this, I test if high-flyer managers are more likely to change the type of jobs by replacing "old" jobs with "new" ones. I define a job to be new if it does not appear in the previous months within a given team. Correspondingly, I define a job to be old if it no longer appears in subsequent months within a given team. I also compute the share of managerial jobs (work-level 2+) within the same sub-function. Appendix Table B.8 shows that there are no differential effects of high-flyer managers on new job titles created, old job titles destroyed within a team, and the share of managerial jobs within a sub-function. Hence, I do not find evidence of high-flyer managers changing the type of jobs by replacing old jobs with new ones: they are re-shuffling workers to existing jobs instead of changing the jobs around the workers.

[51] *In unreported results, I can replicate the event-study plots of the effects of gaining a high-flyer manager when leaving out the workers who at one point are promoted to exactly the respective managerial positions. The results remain unchanged.* Notes: This set of results are never replicated. For now, I am not sure about the definition of "taking the exact position of their managers".

7 Discussion

7.1 Conceptual framework

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. I develop the framework in Appendix C but I summarize here the basic intuition. 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.

In addition, I can use the framework to illustrate how workers' lateral moves and productivity depend on their history in relation to different manager types, thus mapping the empirical research design. In particular, I am interested in the predictions around gaining a good manager (moving from a low- to a high-flyer compared to moving from a low- to another low-flyer manager) and losing a good manager (moving from a high- to a low-flyer compared to moving from a high- to another high-flyer manager). The framework makes clear that, if the allocation channel is more important than the teaching channel, the effects of a good manager depend on a worker's history in the following way. If the previous manager was bad, there is a non-zero probability of job misallocation, and hence a good manager can increase worker productivity by changing her job allocation: this is the impact of gaining a good manager. On the other hand, if the previous manager was good, the probability of job misallocation is zero, as workers have already been assigned to jobs according to their talents.

Therefore, another good manager does not have an additional impact. The framework thus predicts that losing a good manager would have no effect on worker outcomes, which is also found empirically (see sub-section 5.4 for the specific discussion of this asymmetry in the empirical results).[52]

Since the framework illustrates how, through matching, there are dynamic benefits of having had a good manager *once* during a worker's career, it also follows that the predictions should be stronger when a worker's initial labor market experience is low (for e.g. younger workers), as found in the heterogeneity analysis discussed in sub-section 6.3. This is because, when experience is low, there is more scope for gains out of a job re-allocation since the potential loss in task-specific experience would be small (as captured by equation C.8 in Appendix C).

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. Overall, high-flyer managers receive significant benefits in some important dimensions. On average, a high-flyer manager has a 14.4 percentage point larger increase in salary over a 12-month period compared to a low-flyer manager (from Panel (c) of Table III, which shows that the monthly salary growth is 1.2 percentage point higher). As the average annual increase in salary for low-flyer managers is 9.6%, the estimate is economically meaningful: being a high-flyer manager more than doubles the salary growth rate. Panel (c) of Table III also shows that high-flyer managers have an 2.9 percentage point higher probability of being promoted to work-level 3.

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 retrieved 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

[52] For the predictions from this simple model to match exactly with the empirical results, either the teaching has to be the same between a good and a bad manager or there have to be some decreasing returns to experience, which are both plausible.

14.4 percentage point salary raise each year relative to low-flyers (Panel (c) in Table III), (2) workers are 0.18S.D. more productive when exposed to a high-flyer manager (Col. 1 in Table IV), and (3) median team size for work-level 2 managers is 3 workers. Hence, I compute the cost-benefit ratio as:

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

I find that the firm pays out roughly \$0.36 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-rating supervisor. My estimates are closely aligned: upon switching from a low to a high-flyer manager, sales performance increases by 0.18S.D. and pay is 10% higher from five years onwards. Notes: The results are not so comparable under current estimates.

I add to these findings by showing that matching workers to jobs is an important mechanism underpinning the performance results and by examining workers' careers, which reveals that the impact of good managers is long-lasting. 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, Kramarz and Margolis, 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.

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*.[53] 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).[54] 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).[55] 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, 2022).

While the results pertain to only one firm (which is standard in the literature, for e.g. Baker et al., 1994a; Lazear et al., 2015; Hoffman and Tadelis, 2021), 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.

My identification strategy can be applied to other contexts. First, 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; Haegele, 2022). In addition to firms in the private sector, rotation policies are also used in large public organizations such as the World

[53]Based on OECD Structural and Demographic Business Statistics. Moreover, Autor, Dorn, Katz, Patterson and Van Reenen (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.

[54]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".

[55]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. Increasingly, the responsibility for talent management is shifting from HR to frontline managers (Whittaker and Marchington, 2003; Perry and Kulik, 2008; Cappelli, 2013).

Bank and the United Nations. Second, managerial promotion speed can easily be adapted to other organizations as data on age and seniority in the hierarchy is tracked pervasively.

8 Conclusion

Managers are at the heart of organizations, within which they determine the allocation of resources, and thus fundamental in the theory of the firm (Coase, 1937; Chandler, 1977). 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 individual managers on workers' careers and its link to firm-level outcomes 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 the worker performance and career path, as well as on the productivity of an establishment as a whole.

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.

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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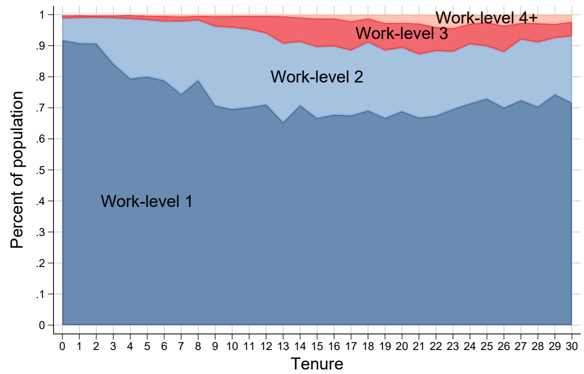
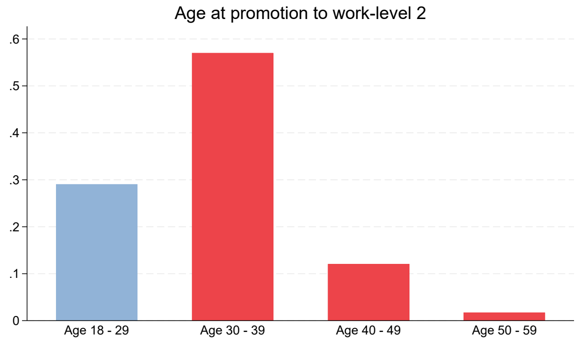
10 Figures

Figure I: Work-levels, tenure and promotion

(a) Distribution of work-levels by tenure



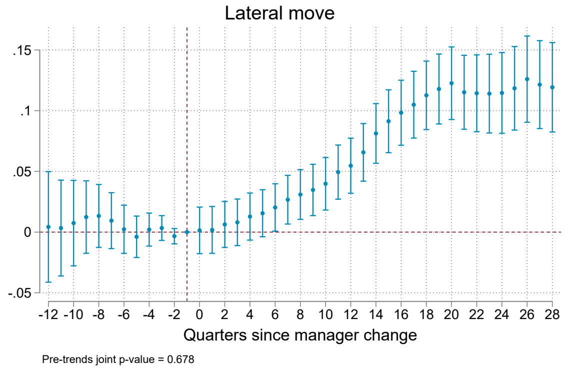
(b) Age at promotion: work-level 2



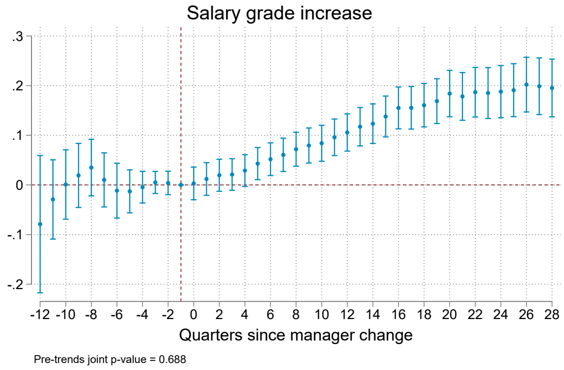
Notes. Panel (a) shows the cumulative distribution of work-levels at different tenure years. Panel (b) shows the distribution of the age at promotion to work-level 2.

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

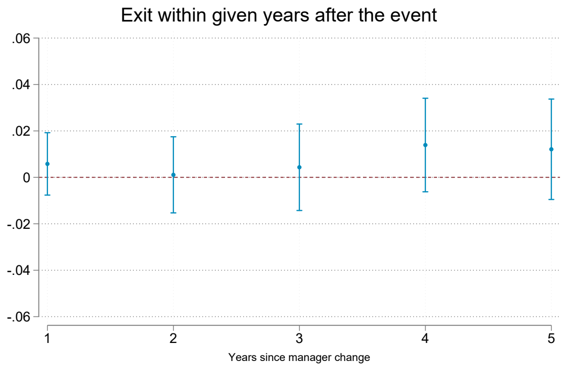
(a) Lateral transfers



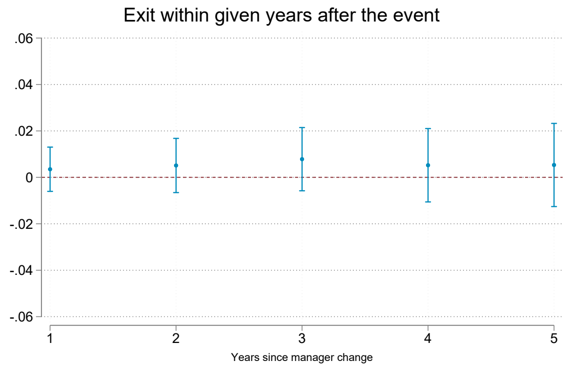
(b) Salary grade



(c) Quits



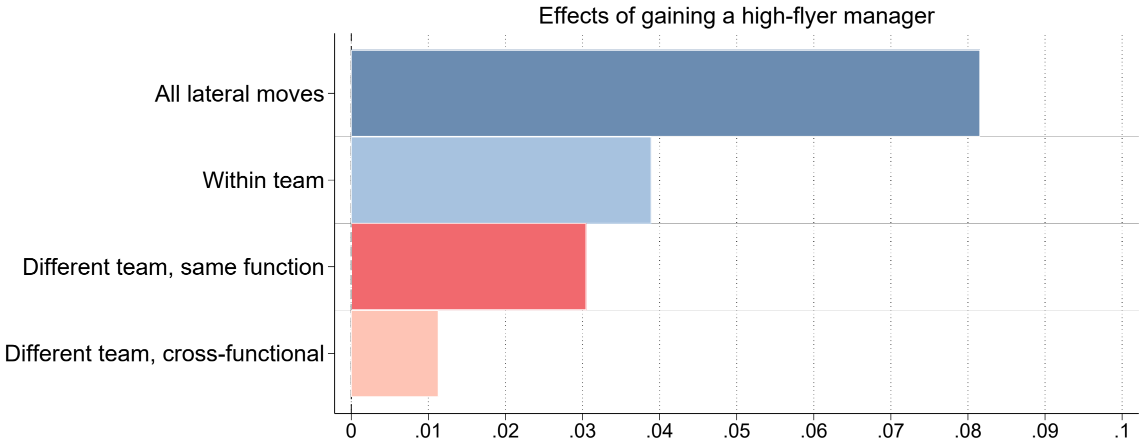
(d) Layoffs



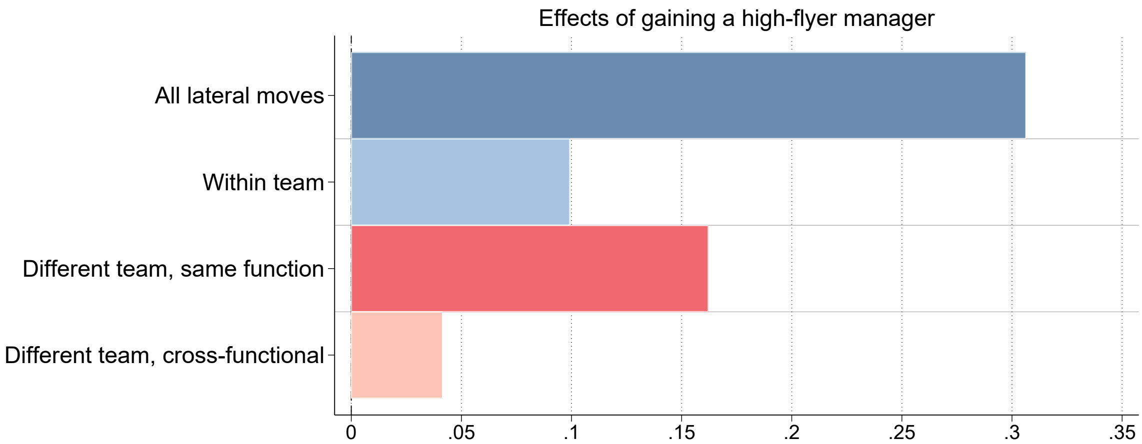
Notes. For (a) and (b), an observation is a worker-year-month, coefficients are estimated from equation 2, and are aggregated to the quarterly level for ease of presentation. The outcome variables are: number of *lateral transfers*, and number of *salary grade increases*. For (c) and (d), an observation is a worker, coefficients are estimated from equation 3. The outcome variables are: whether the worker *quits* or *gets laid off* within given years after the event. 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. For the four treatment groups, these controls are at the time of event. All standard errors are clustered by manager and 95% confidence intervals are presented.

Figure III: Gaining a high-flyer manager: decomposing lateral moves

(a) During rotation (8th quarter)



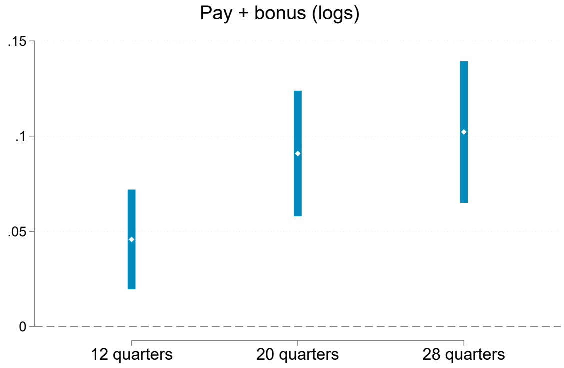
(b) After rotation (28th quarter)



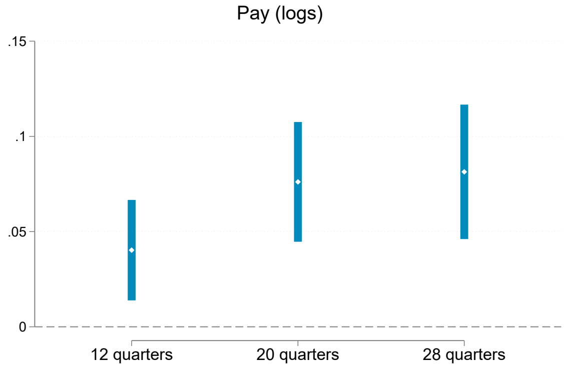
Notes. An observation is a worker-year-month. Panel (a) decomposes the lateral job moves in the 8th quarter since the manager transition (because the average duration of a manager's assignment is two years). Panel (b) decomposes the lateral job moves in the 28th quarter.

Figure IV: Effects of gaining a high-flyer manager on salary, $(\hat{\beta}_{LtoH,s} - \hat{\beta}_{LtoL,s})$

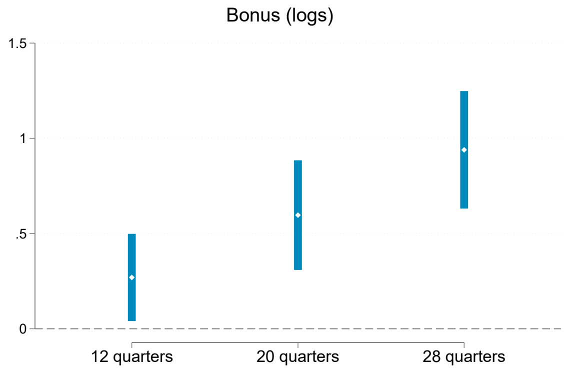
(a) Pay + bonus (logs)



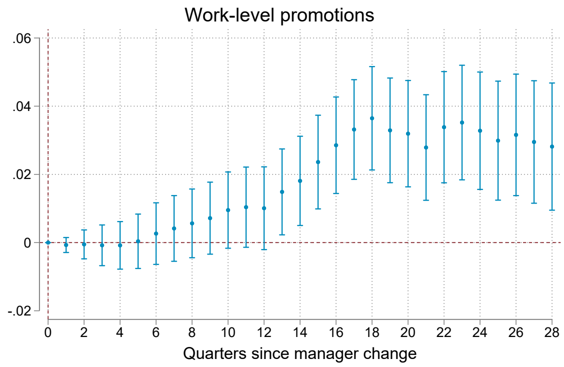
(b) Pay (logs)



(c) Bonus (logs)



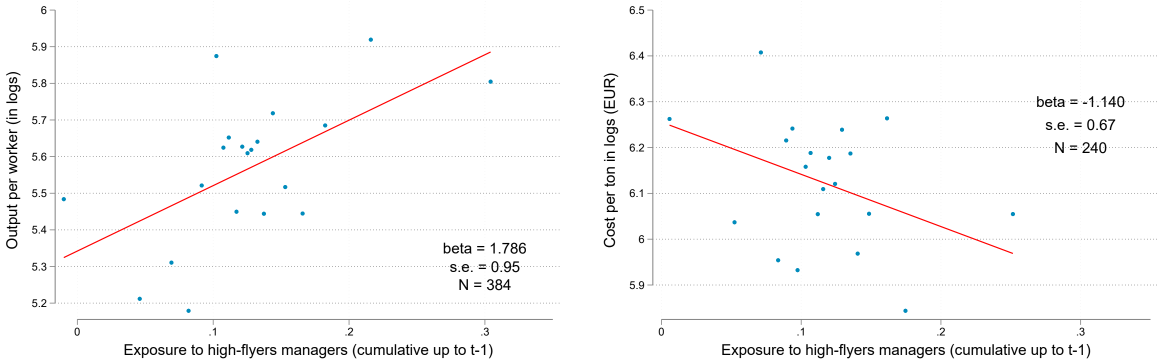
(d) Work-level promotions



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. 95% confidence intervals used and standard errors clustered by manager. The outcome variables in the first three panels are: *pay + bonus* in logs, *pay* in logs, *bonus* in logs, where the estimates at 12, 20 and 28 quarters after the manager transition and 95% confidence intervals are reported. The outcome variable in the last panel is the number of *work-level promotions*. Since the sample consists of workers who experience the manager transition in work-level 1, there are no pre-event promotions and only post-transition coefficients can be estimated.

Figure V: Factory productivity and past exposure to high-flyer managers

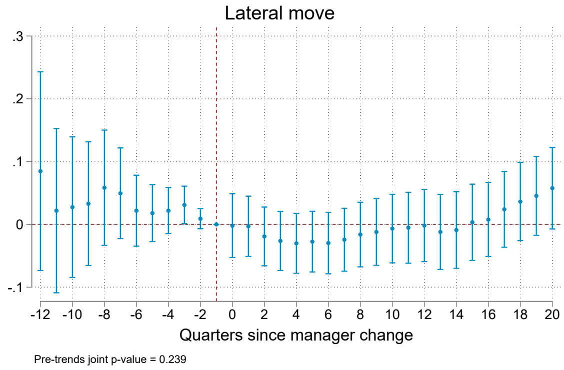
(a) Factory output per worker **(b)** Factory output per worker



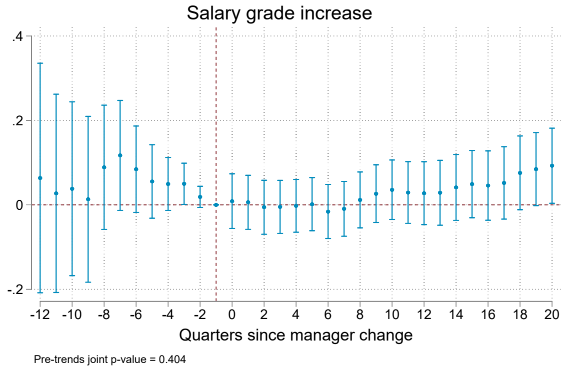
Notes. An observation is a factory-year. The figure is a binned scatterplot. The y-axis is *output per worker* in logs (tons per worker) in Panel (a) and *operational costs per ton* (EUR) in logs in Panel (b). The x-axis is the workers' cumulative exposure to high-flyers up to the year before. Because 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). Controls include: country, product category and year fixed effects, share of managers, number of blue-collar and white-collar workers. Standard errors clustered by factory.

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

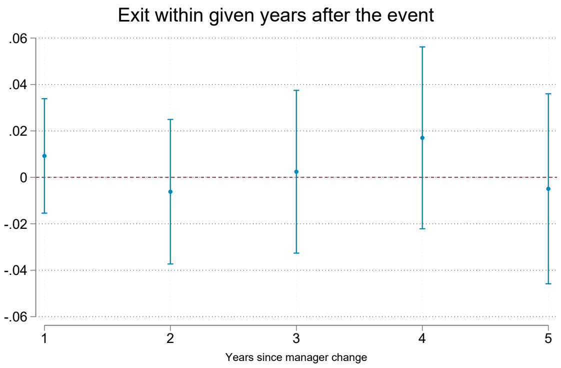
(a) Lateral transfers



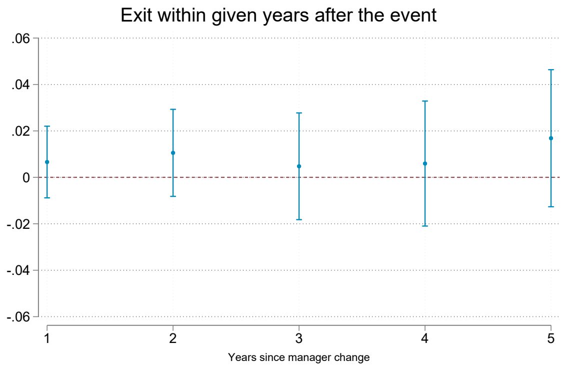
(b) Salary grade



(c) Quits



(d) Layoffs

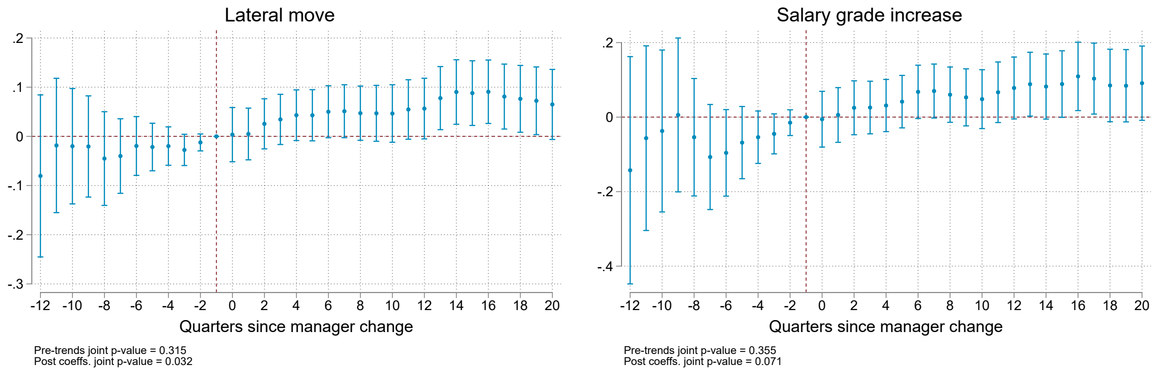


Notes. For (a) and (b), an observation is a worker-year-month, coefficients are estimated from equation 2, and are aggregated to the quarterly level for ease of presentation. The outcome variables are: number of *lateral transfers*, and number of *salary grade increases*. For (c) and (d), an observation is a worker, coefficients are estimated from equation 3. The outcome variables are: whether the worker *quits* or *gets laid off* within given years after the event. 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. For the four treatment groups, these controls are at the time of event. All standard errors are clustered by manager and 95% confidence intervals are presented.

Figure VII: Test for asymmetries, $(\hat{\beta}_{LtoH,s} - \hat{\beta}_{LtoL,s}) - (\hat{\beta}_{HtoL,s} - \hat{\beta}_{HtoH,s})$

(a) Lateral transfers

(b) Salary grade



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. 95% confidence intervals used and standard errors clustered by manager. The outcome variables are: number of *lateral transfers*, and number of *salary grade increases*.

11 Tables

Table I: Size of groups: workers, managers, jobs

Variable	No. unique values
Total white collar × months	10,083,638
Employee	224,117
Managers (work-level 2+)	32,483
Supervisors	47,816
Year-month	132
Standard job	2,118
Sub-function × work-level	473
Offices	2,645
Countries	118
Country × Year	1,187
Office × Year	14,769
Employee × 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	2.48	3.0	0.0	12.0	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 job transfers	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 January 2015 and the information on sales bonus is only available for a subset of countries.

Table III: High-flyer managers

Variable	(1) Not High Flyer	(2) High Flyer	(3) Difference
Panel (a): demographics			
Female	0.456	0.558	0.102***
	(0.498)	(0.497)	(0.000)
MBA	0.000	0.001	0.000
	(0.021)	(0.029)	(0.549)
Econ, Business, and Admin	0.452	0.567	0.115***
	(0.498)	(0.496)	(0.000)
Sci, Tech, Engin, and Math	0.343	0.210	-0.133***
	(0.475)	(0.407)	(0.000)
Social Sciences and Humanities	0.141	0.196	0.055***
	(0.348)	(0.397)	(0.000)
Other Educ	0.069	0.040	-0.029***
	(0.254)	(0.197)	(0.000)
Panel (b): work-related variables			
Customer development function	0.227	0.230	0.002
	(0.419)	(0.421)	(0.653)
Mid career hire	0.278	0.141	-0.137***
	(0.448)	(0.348)	(0.000)
Low income countries	0.191	0.210	0.019***
	(0.393)	(0.407)	(0.000)
Middle income countries	0.259	0.286	0.027***
	(0.438)	(0.452)	(0.000)
Panel (c): performance after high-flyer status is determined			
Monthly salary growth	0.008	0.021	0.012***
	(0.036)	(0.054)	(0.000)
Promotion work-level 3	0.031	0.060	0.029***
	(0.137)	(0.185)	(0.000)
Perf. rating (1-150)	96.949	101.487	4.538***
	(21.027)	(18.523)	(0.000)
Effective leader (survey)	4.050	4.140	0.090***
	(0.693)	(0.712)	(0.000)
Observations	23,656	9,542	33,198

Notes. Showing mean and standard deviations (in parentheses) and p-values for the difference in means. The difference in means is computed using standard errors clustered by manager. *Perf. rating* refers to the performance assessment given annually to each employee; *Effective leader (survey)* refers to the workers' anonymous upward feedback on the managers' leadership; and *Mid-career recruit* refers to managers who have been hired directly as managers by the firm (at work-level 2 instead of work-level 1). Working countries' income groups are classified by World Bank, and the omitted income group is high income country.

Table IV: Sales, lateral and vertical moves

	Full	Conditional on lateral move		Conditional on vertical move		
	Sales bonus (s.d.)	Sales bonus (s.d.)	Pay + bonus (in logs)	Pay + bonus (in logs)	Effective leader	High Effective leader
	(1)	(2)	(3)	(4)	(5)	(6)
LtoH × Post	0.175**	0.243*	0.143***			
	(0.09)	(0.15)	(0.02)			
LtoH				0.021**	0.195	0.273**
				(0.01)	(0.16)	(0.11)
Mean, LtoL group	0.009	-0.017	10.127	11.046	4.047	0.516
R-squared	0.225	0.205	0.879	0.734	0.262	0.313
N	63766	23185	1125284	110430	2918	2918

Notes. An observation is a employee-month. Standard errors clustered at the manager level. Column (1) is a DiD specification as equation 5 on the sample of LtoL and LtoH workers. Columns (2) and (3) are the same DiD specification conditional on the worker making at least one lateral moves within 2 years after the event. Columns (4), (5), and (6) are estimated using periods after the LtoL and LtoH workers are promoted as managers. Since they can only be promoted as managers after the manager transition events, this is not a DiD design, and the estimated coefficients on whether the worker is in the LtoH event group are reported. *Sales bonus (s.d.)* is normalized sales bonus as a measure of productivity. The variable is available in the following countries: BLR, COL, CRI, ECU, GRC, GTM, HND, IDN, IND, ITA, MEX, MYS, NIC, PAN, PHL, RUS, SGP, SLV, ZAF. *Pay + bonus (in logs)* is the sum of regular pay and additional bonuses. *Effective leader score* is the workers' anonymous rating of the manager via the survey question *My line manager is an effective leader* with scale 1-5, which is asked every year in the annual survey and the overall mean is 4.1. *High Effective leader score* is a binary variable indicating if the score is larger than 4.

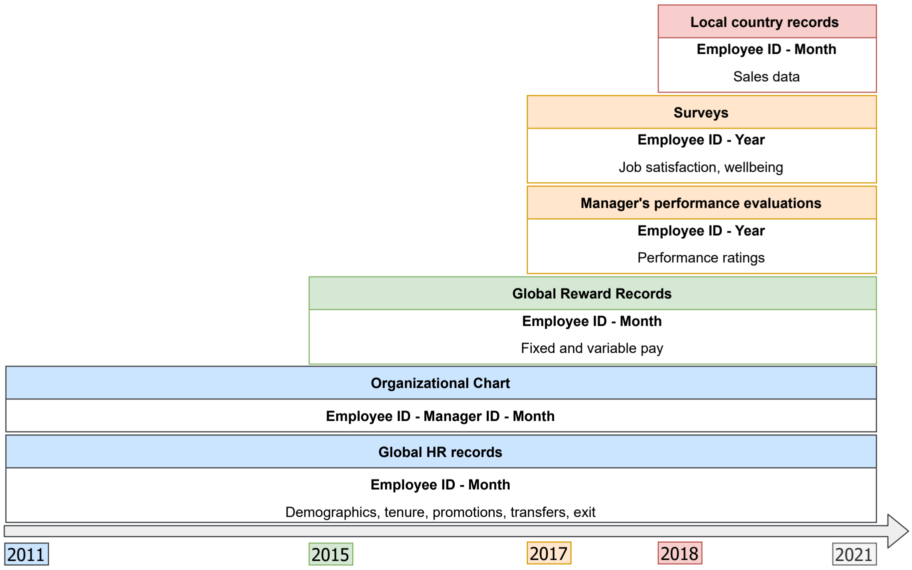
Table V: Heterogeneous effects of gaining a high-flyer manager

	Pay increase (1)	Lateral moves (2)	Vertical moves (3)	Exit from firm (4)
Panel (a): worker and manager characteristics				
Manager tenure, high	0.298**	0.135*	0.091**	0.039
	(0.13)	(0.07)	(0.04)	(0.03)
Same office as manager	0.261***	0.245***	0.061***	0.002
	(0.06)	(0.04)	(0.02)	(0.02)
Same gender as manager	0.170***	0.096**	0.035	0.016
	(0.06)	(0.04)	(0.02)	(0.02)
Worker age, young	0.068	0.150***	0.071***	0.006
	(0.06)	(0.04)	(0.02)	(0.03)
Panel (b): office and country-wide characteristics				
Office size, large	0.321***	0.310***	0.106***	0.006
	(0.06)	(0.04)	(0.02)	(0.03)
Office job diversity, high	0.247***	0.259***	0.081***	-0.008
	(0.06)	(0.04)	(0.02)	(0.03)
Labor laws, high	0.420***	0.267***	0.131***	0.005
	(0.06)	(0.04)	(0.02)	(0.02)
Female labor force participation, low [Female]	0.213**	0.075	0.020	-0.011
	(0.10)	(0.08)	(0.05)	(0.03)
Panel (c): worker performance and moves				
Worker performance, high (p50)	-0.292	-0.173	0.063	-0.034
	(0.19)	(0.13)	(0.07)	(0.04)
Worker performance, high (p90)	-0.163	-0.291	-0.029	0.054
	(0.30)	(0.20)	(0.08)	(0.10)
Team performance, high (p50)	-0.210	-0.106	0.088	-0.003
	(0.18)	(0.13)	(0.06)	(0.03)

Notes. An observation is a worker-year-month. 95% confidence intervals used and standard errors are clustered by manager. Coefficients in columns (1), (2), and (3) are estimated from a regression as in equation 7 and the table reports the coefficient at the 20th quarter since the manager transition. Controls include worker FE and year months FE. 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. 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-flyers 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 being under and over 30 years old; the fourth row looks at the differential impact between being under and over 2 years of tenure; the fifth row looks at the differential impact between sharing and not sharing the same gender with the manager. 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); the fourth row looks at the differential impact between the gender gap (women - men) in countries with the female over male labor force participation ratio 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; the fourth row looks at the differential impact between workers changing and not changing the manager 2 years after the transition.

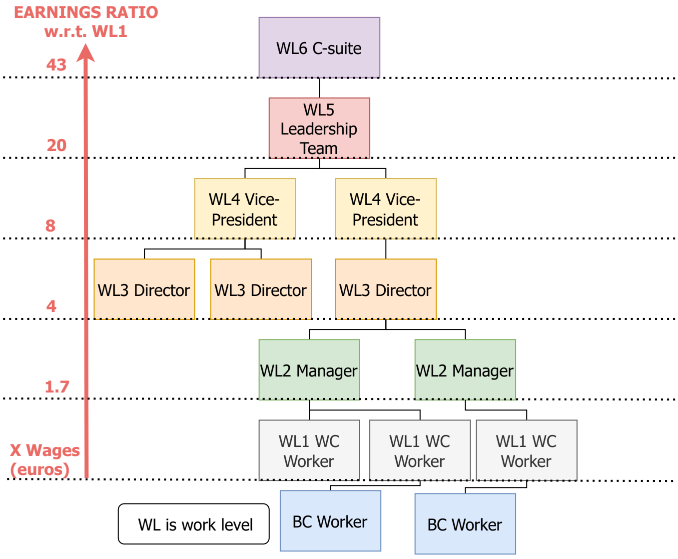
A Appendix Figures

Figure A.1: Data sources and time periods



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

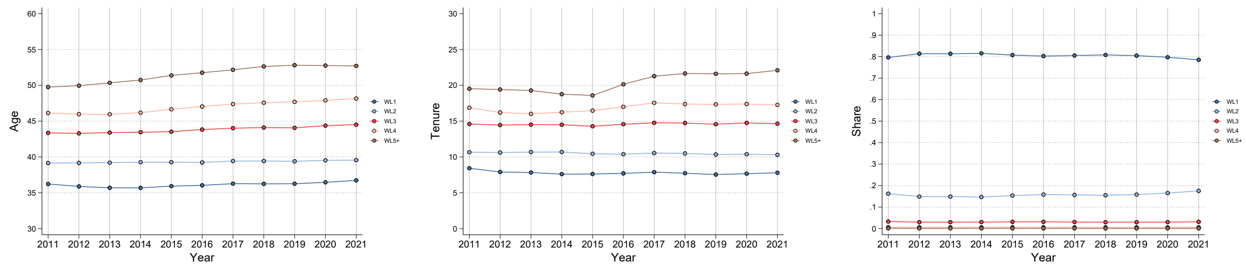
Figure A.2: Hierarchy



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



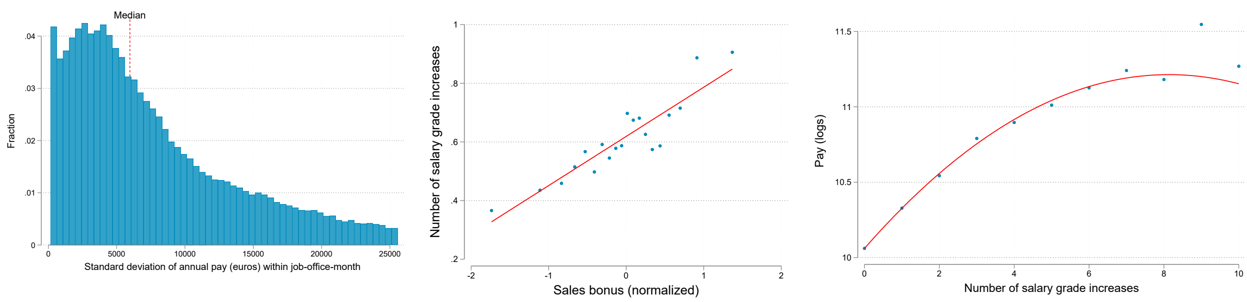
Notes. This figure shows the average age, tenure, and share of workers across work-levels over the years. Since the data comes aggregated into 10-year age groups, I take the following procedures to construct a continuous age measure. For those employees whose age band transition can be observed in the dataset, I can identify their exact age. Otherwise, the age is imputed based on the average of the maximum and minimum possible year of birth.

Figure A.4: Guidelines for line managers

Notes. This figure is an excerpt from the guidelines set by HR for managers regarding the contents of the check-ins managers should be doing with their teams on a weekly basis.

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

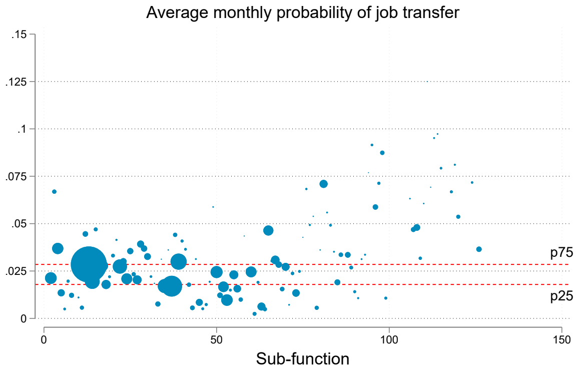
(a) S.D. of pay, job-office-month **(b)** Sales bonus and salary grade **(c)** Pay and salary grade



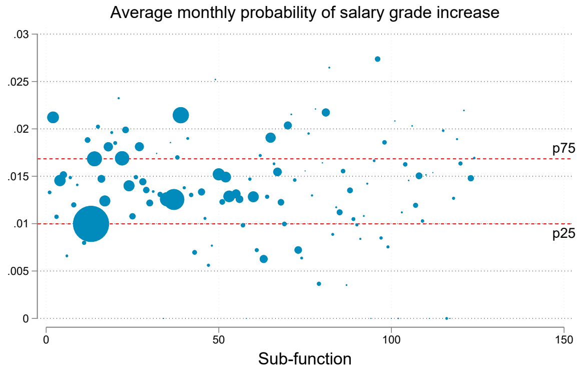
Notes. Panel (a) shows the distribution of the standard deviation in overall pay (fixed pay plus variable pay) within a given job title in an office and year-month. Panel (b) presents binned scatter plots of (normalized) sales bonus against the number of salary grade increases. Panel (c) presents a binned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

Figure A.6: Average job transfer and salary increase rates by sub-function

(a) Average job transfer rates



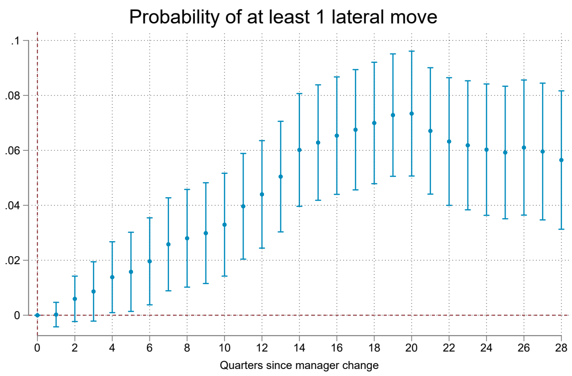
(b) Average salary increase rates



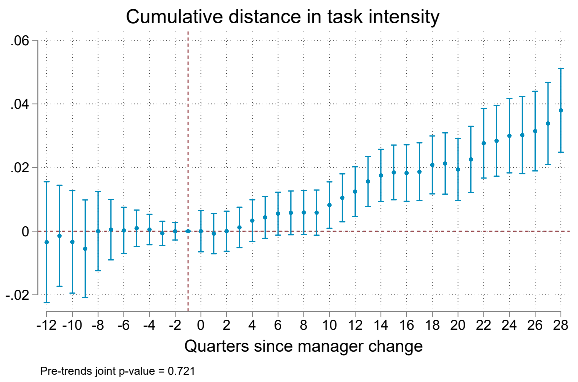
Notes. This figure shows the average monthly probability of a lateral move and of a salary grade increase by sub-function. The size of the circles is proportional to the size of the sub-function. The x-axis indexes the sub-function. To avoid the effect of small-scaled subfunctions, average monthly lateral transfer rates and salary grade increase rates are winsorized at 99%.

Figure A.7: Effects on transfers: probability of at least one transfer and task-distant moves, gaining a high-flyer manager, $(\hat{\beta}_{LtoH,s} - \hat{\beta}_{LtoL,s})$

(a) Probability of making at least one lateral transfer



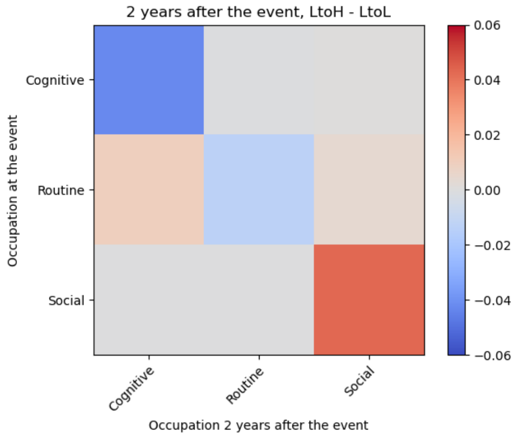
(b) Cumulative task distance



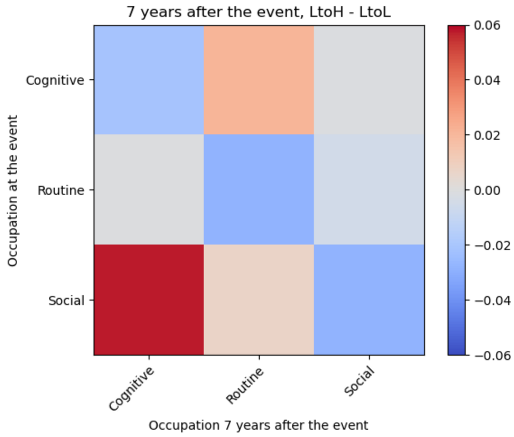
Notes. An observation is a worker-year-month. All coefficients are estimated from a single regression as in equation 2 and are aggregated to the quarterly level for ease of presentation. 95% confidence intervals used and standard errors clustered by manager. The outcome variables are: *probability of at least one lateral transfer* and *cumulative measure of task distance moves* using O*NET data. Task distance across jobs is constructed by matching the firm's job titles with O*NET data, and focusing on three tasks: cognitive, routine, and social.

Figure A.8: Differences in transition ratio matrices between LtoH and LtoL workers

(a) 2 years later



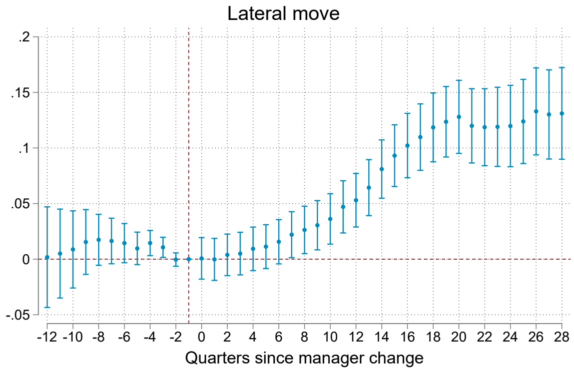
(b) 7 years later



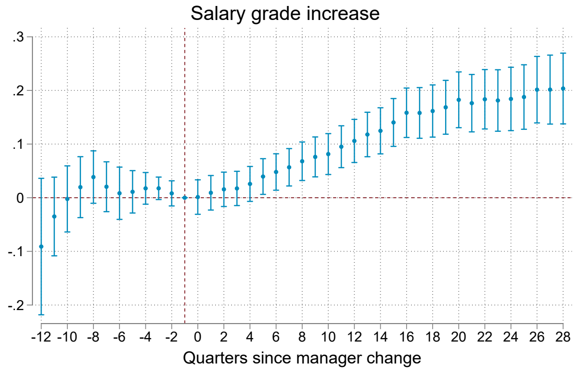
Notes. The heatmaps plot the differences in transition ratio matrices between $LtoH$ and $LtoL$ workers 2 and 7 years after the manager transition event. A job is classified into a cognitive, routine, or social job based on the highest intensity measure. Separately for $LtoL$ and $LtoH$ workers, I construct two transition ratio matrices, where the entries denote the fraction of workers doing that transition. The differences in the transition ratios are plotted.

Figure A.9: Robustness: incorporating cohort dynamics

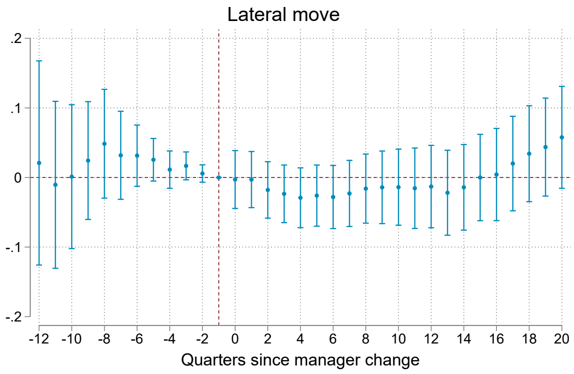
(a) Lateral transfers, gaining a high-flyer manager



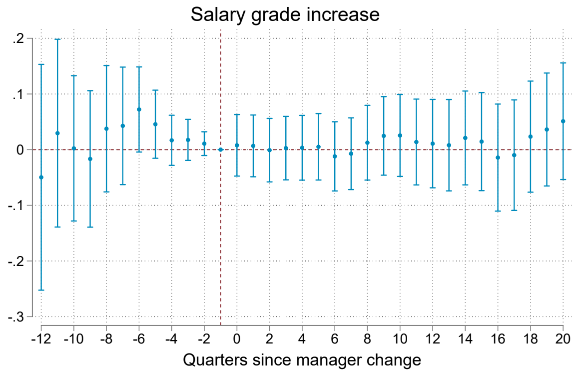
(b) Salary grade, gaining a high-flyer manager



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



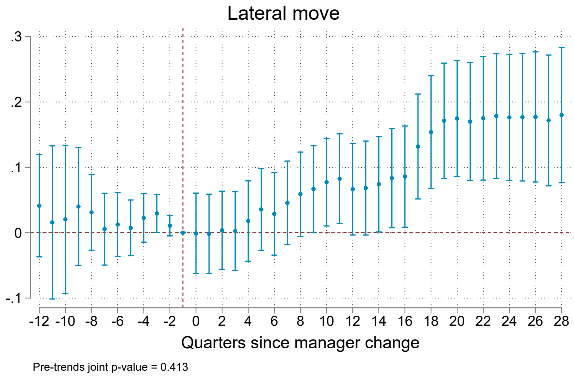
(d) Salary grade, losing a high-flyer manager



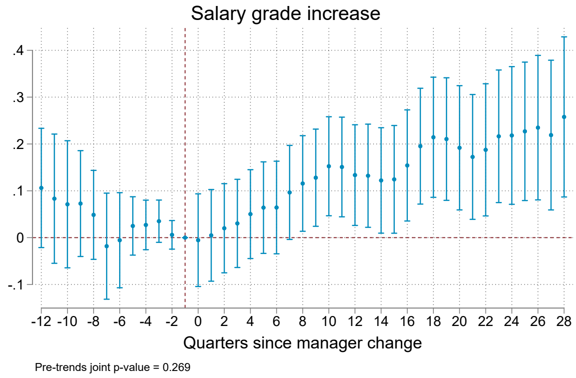
Notes. An observation is a worker-year-month. All coefficients are estimated from a modified version of equation 2. 95% confidence intervals used and standard errors clustered by manager. The outcome variables are: the number of *lateral transfers*, and the number of *salary grade increases*. The regression equation is different from equation 2 in two respects: (1) panels (a) and (b) only consist of workers in the $LtoL$ and $LtoH$ groups, while panels (c) and (d) consist of workers in the $HtoH$ and $HtoL$ groups. (2) Each event dummy is further interacted with 10 other dummies indicating the year in which the manager transition event happens. To get the a monthly coefficient, the cohort-month specific coefficients are first aggregated based on the share of each cohort in the regression. Next, the monthly coefficients are aggregated into a quarter level.

Figure A.10: Effects of gaining a high-flyer manager, robustness

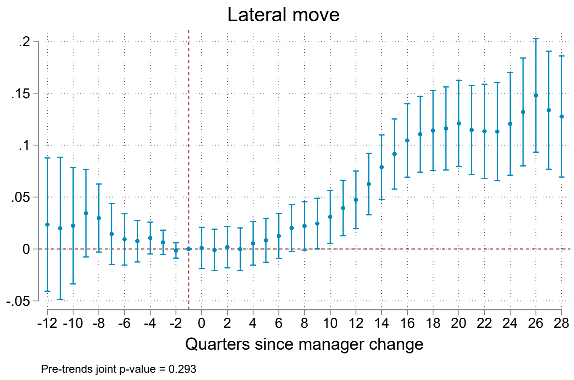
(a) Lateral transfers, single cohort



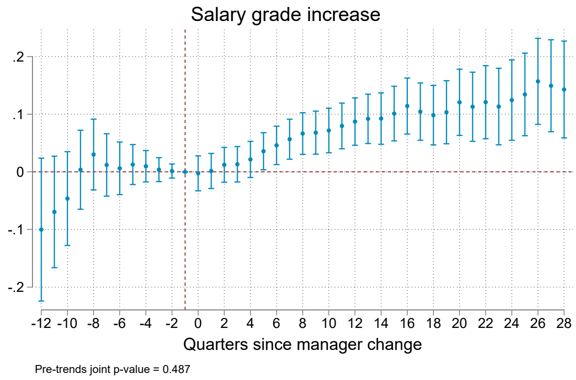
(b) Salary grade, single cohort



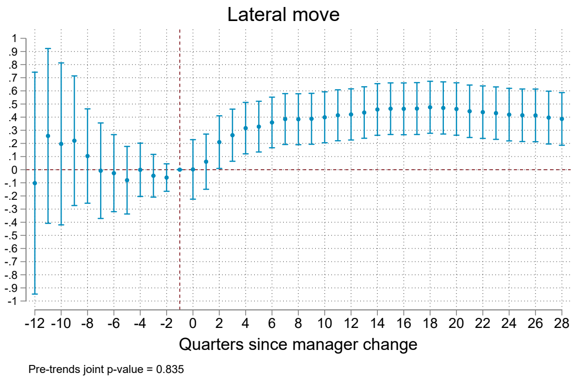
(c) Lateral transfers, new hires



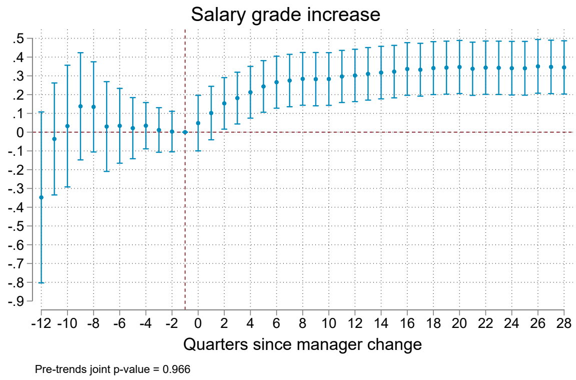
(d) Salary grade, new hires



(e) Lateral transfers, Poisson model



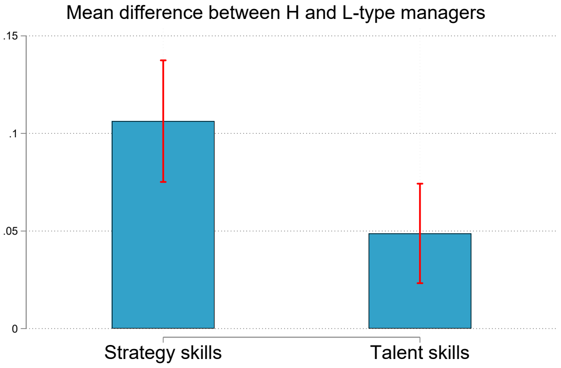
(f) Salary grade, Poisson model



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. 95% confidence intervals used and standard errors clustered by manager. The outcome variables are: the number of *lateral transfers*, and the number of *salary grade increases*. In the single cohort robustness exercise, the sample is restricted to those workers who experienced their first manager change event during 2014. In the new hires robustness exercise, the sample is restricted to new hires (with strictly less than two years of tenure). In the Poisson model robustness exercise, the model is estimated using equation 4 on the full event sample.

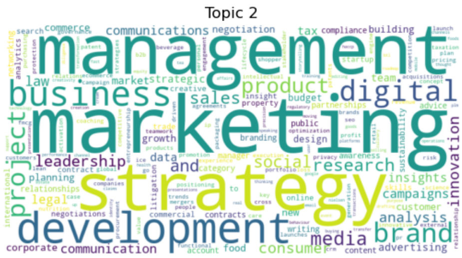
Figure A.11: Skill difference between H- and L-type managers

(a) Mean difference



(b) Topic 1 (Project management skills)

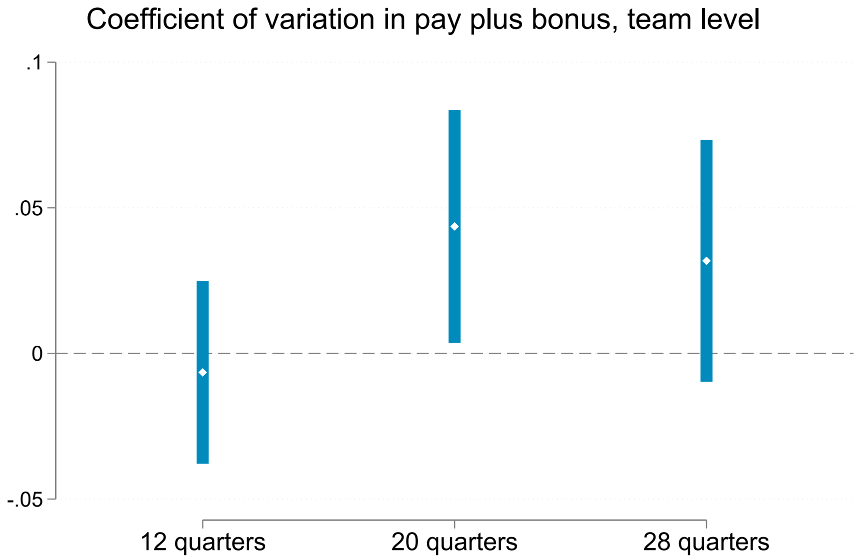
(c) Topic 2 (Strategy management skills)



(d) Topic 3 (Talent management skills)

Notes. For a set of managers, their specific skill sets are known in text. A 3-topic Latent Dirichlet Allocation algorithm is conducted, and the corresponding word clouds are presented in the last three subfigures. Subfigure (a) presents the mean difference and 95% confidence interval between H- and L-type managers' distribution over these topics.

Figure A.12: Effects of gaining a high-flyer manager on pay dispersion within the team, $(\hat{\beta}_{LtoH,s} - \hat{\beta}_{LtoL,s})$



Notes. An observation is a team-year-month. Aggregating the monthly coefficients to the quarterly level. Reporting the estimates at 12, 20 and 28 quarters after the manager transition. 95% confidence intervals used and standard errors clustered by manager. 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 be working under the manager of the transition or changes manager after some time.

B Appendix Tables

Table B.1: Endogenous mobility checks

Panel (a): team performance

	(1) Salary (logs)	(2) Salary grade increase	(3) Lateral move	(4) Cross-functional move
High-flyer manager	-0.0130	0.0002	-0.0020	0.0001
	(0.031)	(0.001)	(0.001)	(0.000)
Mean, low-flyer manager	10.158	0.010	0.013	0.001
R-squared	0.738	0.016	0.016	0.027
N	9175	45788	45788	45788

Panel (b): team diversity

	(1) Diversity, gender	(2) Diversity, age	(3) Diversity, office	(4) Diversity, nationality
High-flyer manager	-0.0044	-0.0004	0.0018	-0.0042
	(0.011)	(0.010)	(0.014)	(0.006)
Mean, low-flyer manager	0.243	0.442	0.141	0.034
R-squared	0.109	0.100	0.194	0.245
N	45788	45788	45788	45788

Panel (c): team homophily with manager

	(1) Same gender	(2) Same age	(3) Same office	(4) Same nationality
High-flyer manager	-0.0270	0.0001	0.0115	0.0057
	(0.020)	(0.016)	(0.019)	(0.011)
Mean, low-flyer manager	0.647	0.313	0.802	0.925
R-squared	0.094	0.060	0.193	0.188
N	45788	45788	45788	45788

Notes. An observation is a team-month. Sample restricted to observations between 6 and 36 months before the manager switch. Standard errors clustered at the manager level. Controls include: function, country and year FE. In Panel (a), *Salary (logs)* is the log of the average salary in the team; *Salary grade increase* is share of workers with a salary increase; *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. In Panel (b), 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. In Panel (c), each outcome variable is the share of workers that share the same characteristic with the manager (gender, age group, office, nationality).

Table B.2: Endogenous mobility checks (transitions)

Panel (a): team performance

	(1) Salary (logs)	(2) Salary grade increase	(3) Lateral move	(4) Cross-functional move
LtoH - LtoL	-0.0297	0.0001	-0.0023	0.0000
p-value:	0.420	0.942	0.149	0.916
HtoL - HtoH	-0.0745	-0.0006	-0.0002	-0.0003
p-value:	0.135	0.786	0.955	0.690
Mean, LtoL group	10.190	0.010	0.013	0.001
R-squared	0.741	0.016	0.016	0.027
N	9175	45788	45788	45788

Panel (b): team diversity

	(1) Diversity, gender	(2) Diversity, age	(3) Diversity, office	(4) Diversity, nationality
LtoH - LtoL	-0.0028	0.0044	-0.0049	-0.0073
p-value:	0.817	0.699	0.744	0.232
HtoL - HtoH	0.0074	0.0096	-0.0401	-0.0091
p-value:	0.752	0.716	0.255	0.518
Mean, LtoL group	0.245	0.444	0.140	0.034
R-squared	0.110	0.101	0.195	0.245
N	45788	45788	45788	45788

Panel (c): team homophily with manager

	(1) Same gender	(2) Same age	(3) Same office	(4) Same nationality
LtoH - LtoL	-0.0237	-0.0262	0.0271	0.0100
p-value:	0.271	0.130	0.190	0.418
HtoL - HtoH	0.0190	-0.0854	0.0550	0.0141
p-value:	0.686	0.029	0.297	0.617
Mean, LtoL group	0.648	0.310	0.807	0.925
R-squared	0.096	0.069	0.194	0.188
N	45788	45788	45788	45788

Notes. An observation is a team-month. Sample restricted to observations between 6 and 36 months before the manager switch. Standard errors clustered at the manager level. Controls include: function, country and year FE. In Panel (a), *Salary (logs)* is the log of the average salary in the team; *Salary grade increase* is share of workers with a salary increase; *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. In Panel (b), 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. In Panel (c), each outcome variable is the share of workers that share the same characteristic with the manager (gender, age group, office, nationality).

Table B.3: High-flyers are not lagging indicators for growth

	Output per worker in logs			Costs per output in logs		
	Current Year	Lagged -1 Year	Lagged -2 Year	Current Year	Lagged -1 Year	Lagged -2 Year
	(1)	(2)	(3)	(4)	(5)	(6)
Share of high-flyers among all managers	0.339	-0.0152	0.242	-0.168	0.00727	0.0743
	(1.20)	(-0.05)	(0.61)	(-0.67)	(0.02)	(0.17)
Mean	5.567	5.590	5.602	5.693	5.696	5.677
R-squared	0.381	0.444	0.469	0.515	0.545	0.499
N	372	229	81	316	207	72

Notes. An observation is an office-year. Standard errors clustered at the office level. Control variables include country FE, year FE, 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 year) costs per output in logs.

Table B.4: High-flyer managers and time use

Variable	Not High Flyer	High Flyer	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 dataset documents 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 a 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-valuses are calculated using robust standard errors.

Table B.5: Active learning behavior

	Number of skills ≥ 3 (1)	Completed items ≥ 5 (2)	Shared items with colleagues > 0 (3)	Meeting all conditions: active learner (4)
High-flyer manager	0.0579***	0.0175***	0.00611**	0.00467**
	(0.00599)	(0.00370)	(0.00200)	(0.00178)
Mean, low-flyer	0.494	0.296	0.043	0.035
N	1571321	1571321	1571321	1571321

Notes. An observation is a worker-year-month. Standard errors are clustered by manager. Controls include year FE and contry FE. Data from the internal talent matching platform. *Number of skills* $\geq$ *3* equals to 1 if the worker has more than 3 skills in the platform. *Completed items* $\geq$ *5* equals to 1 if the worker has completed more than 5 items in the platform. *Shared items with colleagues* $>$ *0* equals to 1 if the worker has done items with colleagues. *Active learner* equals to 1 if the worker meets all the above three conditions.

Table B.6: Engagement in flexible projects

	Registered on Platform (1)	Profile Completed (2)	Available for Jobs (3)	Available for Mentors (4)	Applied to Position (5)
High-flyer manager	0.0556***	0.0231*	0.0281**	0.108***	0.00620*
	(0.00836)	(0.00917)	(0.00885)	(0.0103)	(0.00311)
Mean, low-flyer	0.330	0.470	0.243	0.122	0.023
N	911703	321278	321278	321278	321278

Notes. An observation is a worker-year-month. Standard errors are clustered by manager. Data are taken from flexible project program at the firm since 2020 that allows workers to apply for short-term projects inside the company but outside their current team. *Registered on the platform* indicates whether the employee created an account on the flexible projects platform. The remaining outcomes are for those employees that registered on the platform: *Profile Completed* indicates whether the profile on the platform is fully completed; *Available for Jobs* indicates whether the employee is available for jobs; *Available for Mentors* indicates whether the employee is available for mentors; and *Applied to Position* indicates whether the employee has applied to a position on the platform. Controls include country and year FE.

Table B.7: 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 - LtoL	-0.0461	0.0026	-0.0073	-0.1305	-0.1190
p-value:	0.026	0.551	0.113	0.000	0.000
HtoL - HtoH	0.0045	-0.0001	0.0161	0.0150	0.0099
p-value:	0.919	0.983	0.004	0.521	0.694
Mean, LtoL group	0.566	0.022	0.023	0.292	0.214
R-squared	0.047	0.040	0.042	0.062	0.068
N	14412	14352	9219	12018	15326
Panel (b): 7 years after the event					
LtoH - LtoL	-0.1085	-0.0023	-0.0110	-0.0832	-0.0516
p-value:	0.000	0.563	0.170	0.000	0.000
HtoL - HtoH	0.0808	-0.0031	0.0025	-0.0198	0.0069
p-value:	0.177	0.554	0.850	0.433	0.432
Mean, LtoL group	0.498	0.012	0.021	0.123	0.067
R-squared	0.074	0.020	0.041	0.068	0.072
N	6286	6259	3912	5037	6722

Notes. An observation is a worker. The regression sample consists of those event workers 3 or 7 years after the event. Standard errors clustered at the manager level. Controls include: country and event time FE. 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.8: Changes in the organizational structure of teams, jobs created and destroyed

	Probability of job created	Probability of job destroyed	Share of managerial jobs
	(1)	(2)	(3)
High-flyer manager	-0.0003	0.0004	0.0020
	(0.000)	(0.000)	(0.003)
Mean, low-flyer	0.015	0.018	0.174
R-squared	0.102	0.401	0.212
N	1871500	1871500	1871500

Notes. An observation is a worker-year-month. 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. Controls include function and year-month FE. Standard errors are clustered by manager.

C Theoretical Appendix

Through the lenses of a framework, I discuss how the allocation channel of managers can be empirically distinguished from teaching, the most plausible alternative channel.[56] The objective is not to develop a realistic model of the role of managers in internal labor markets but rather to elucidate some of the essential lessons from the empirical results.

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.

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, pro-

[56] 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.

gramming, and managing personnel (Autor, Levy and Murnane, 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[57], 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).[58] As an example, occupations in managerial positions would exhibit higher returns to the same 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

[57]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.

[58]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).

j until time t, E^j_{it}, and a noise term (ϵ_{iot}):

$$\begin{aligned} p^j_{iot} &= \underbrace{E^j_{it}}_{\text{experience}} + \eta^j_{iot} \\ \text{where} \quad \eta^j_{iot} &= \underbrace{m^j_i}_{\text{innate task talent}} + \underbrace{\epsilon^j_{iot}}_{\text{noise}} \end{aligned} \tag{C.1}$$

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

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

$$E^j_{it} = \sum_{o'} (\beta^j_{o'}) O_{io't} \tag{C.2}$$

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:

$$lnP_{iot} = \beta^A_o p^A_{iot} + \beta^S_o p^S_{iot}$$

$$\longrightarrow lnP_{iot} = \underbrace{(\beta^A_o E^A_{it} + \beta^S_o E^S_{it})}_{\bar{E}_{iot} = \text{task-specific experience}} + \underbrace{(\beta^A_o m^A_i + \beta^S_o m^S_i)}_{\bar{m}_{io} = \text{task match}} + \underbrace{(\beta^A_o \epsilon^A_{iot} + \beta^S_o \epsilon^S_{iot})}_{\bar{\epsilon}_{iot} = noise} \tag{C.3}$$

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.[59] Hence, the manager solves the following

[59] 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.

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:

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

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

		Manager type	
		Good	*Bad*
Current job$_1$ $\longrightarrow^?$ Next job$_2$	*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:*

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

that is if the allocation gain outweighs the teaching loss or in other words if the allocation channel is more important than the teaching channel.

Hence, given the example above, a good 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:*

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

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	$Anal._1 \rightarrow Anal._2 \rightarrow^? Anal._3$	$1 + \tau + m^A$	$2 + m^A + \epsilon_2^A$	$\tau + 1 + m^A + \epsilon_2^A$	$2\tau + m^A$
$= Anal.$	$Anal._1 \rightarrow Social_2 \rightarrow^? Anal._3$	$1 + m^A$	$1 + m^A + \epsilon_2^A$	$\tau + m^A + \epsilon_2^A$	$\tau + m^A$
$\rightarrow \text{Job}_2$	$Anal._1 \rightarrow Social_2 \rightarrow^? Social_3$	$\tau + m^S$	$1 + m^S + \epsilon_2^S$	$1 + m^S + \epsilon_2^S$	$\tau + m^S$
$\rightarrow^? \text{Job}_3$	$Anal._1 \rightarrow Anal._2 \rightarrow^? Social_3$	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$_1$	$Social_1 \rightarrow Anal._2 \rightarrow^? Anal._3$	$\tau + m^A$	$1 + m^A + \epsilon_2^A$	$1 + m^A + \epsilon_2^A$	$\tau + m^A$
$= Social.$	$Social_1 \rightarrow Social_2 \rightarrow^? Anal._3$	m^A	$m^A + \epsilon_2^A$	$m^A + \epsilon_2^A$	m^A
$\rightarrow$ Job$_2$	$Social_1 \rightarrow Social_2 \rightarrow^? Social_3$	$1 + \tau + m^S$	$2 + m^S + \epsilon_2^S$	$1 + \tau + m^S + \epsilon_2^S$	$2\tau + m^S$
$\rightarrow^?$ Job$_3$	$Social_1 \rightarrow Anal._2 \rightarrow^? Social_3$	$1 + m^S$	$1 + m^S + \epsilon_2^S$	$\tau + m^S + \epsilon_2^S$	$\tau + m^S$

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 o, $q_o^c=(q_{o1},\ldots,q_{oN})$ where c is skills, activities, abilities, work contexts. These job content measures can be understood as describing a position in the task space. My baseline results make use of the skills vector but they are robust to taking the average of the different vectors. I consider the skills vector as my empirical analogue of the occupation-specific weights on tasks in the conceptual framework: occupations with a high weight in a particular task w, β_o^w, will have a high q_{ow}^{skills}. The Occupational Information Network (O*NET) offers multiple sources for job content descriptors, and has been used frequently in empirical work on job tasks (David, 2013).* Notes: The whole paragraph should be re-written, as we no longer follow the same procedures. The next paragraph is a more accurate description.

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 (version 29.2) is a database containing measures of occupational characteristics. More specifically, the set of O*NET descriptors[60] used to

[60]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)

construct intensity for different tasks is the same as Cortes et al. (2023), which itself builds on Deming (2017) and Autor et al. (2003). Then, I transform the raw scores on each O*NET descriptor into a score ranged from 0 to 10 following the suggestions (link) here. For each task and each occupation, I calculate the average across all the corresponding descriptors to obtain a raw intensity measure. Next, I use all MNE employees' occupation distribution to transform the three raw task intensity measures into percentile ranks, which have a clearer interpretation. 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. See Appendix Table D.1 for the full list of task intensity measures for each O*NET occupation title (sorted by cognitive task intensity).

Notes: I delete the original description on the construction of the outcome variable.

D.2 Angular task distance

Each occupation o is characterized by a three-dimensional task vector, $q^o = (q^o_c, q^o_r, q^o_s)$, where q^o_c is the cognitive task intensity, q^o_r is the routine task, while q^o_s 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.

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

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)?

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. I use the cumulative sum of the task distance measure as the outcome variable in the event study.

Measuring similarity between two vectors by the angular separation has first been 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).

The mean distance between occupations in my data is 0.06, with a standard deviation of 0.14. 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. The most distant possible move is between a tax administrator in finance and a production supervisor on the factory floor in supply chain.
Notes: I didn't check the details. I will do it later.

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