Talent Hoarding in Organizations

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Abstract

Most organizations rely on managers to identify talented workers. However, because managers are evaluated on team performance, they have an incentive to hoard talented workers, thus jeopardizing the efficient allocation of talent within firms. This study provides the first empirical evidence of talent hoarding using a unique combination of personnel records and application data from a large manufacturing firm. When managers rotate to a new position and temporarily stop hoarding talent, workers' applications for promotions increase by 123%. Marginal applicants, who would not have applied in the absence of manager rotations, are three times as likely as average applicants to land a promotion, and perform well in higher-level positions. By reducing the quality and performance of promoted workers, talent hoarding causes misallocation of talent. Because female workers react more to talent hoarding than males, talent hoarding perpetuates gender inequality in representation and pay at the firm.

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1 Introduction

Firms must continually decide how to allocate workers to jobs, a process which has significant implications for firm productivity (Rosen, 1982, Holmstrom and Tirole, 1989). Because firms cannot perfectly observe worker ability, most firms rely on managers to identify talented workers who can be promoted to higher-level positions. However, a team's performance suffers when a talented worker leaves the team for a promotion. Since managers are rewarded based on team performance and firms cannot perfectly monitor manager actions, the conflicting interests of manager and firm create the potential for a classic organizational moral hazard problem (Holmstrom, 1979). In light of a growing body of evidence documenting the influence of high-level workers on firm performance (Bloom and Van Reenen, 2007 Lazear et al., 2015), managers may create significant efficiency costs if they hoard talented workers rather than promote them.

Despite ample anecdotal and survey evidence pointing to widespread managerial talent hoarding,[1] very little empirical evidence on talent hoarding exists in economics. Studying talent hoarding empirically is challenging. Talent hoarding behavior may take a number of forms and is difficult to observe, even in rich datasets. Furthermore, identifying the causal impacts of talent hoarding requires plausibly exogenous variation in hoarding.

This study provides the first empirical evidence on talent hoarding and its negative impacts on the efficient allocation of talent in organizations. I combine a rich dataset from a large manufacturing firm with a new identification strategy that leverages quasi-random variation in worker exposure to talent hoarding. When managers rotate to a new position within the firm, talent hoarding incentives abate, and worker applications double. I show that this increase in applications is consistent with a series of predictions on talent hoarding and that my results are not accounted for by alternative mechanisms, such as loyalty or manager-worker specific match effects. Talent hoarding deters high-quality applicants who would have performed well in higher-level positions, leading to misallocation of talent within the firm. Because women react more to talent hoarding than men, they experience greater misallocation effects, exacerbating gender disparities in pay and representation at the firm.

I develop a simple conceptual framework that captures managerial moral hazard and provides a formal definition of talent hoarding. Since managers are both tasked with identifying productive workers and are rewarded solely based on team productivity, managers have an incentive to hoard talent by preventing workers from seeking promotions. This framework predicts that managers engage in more hoarding when their workers are more productive and when worker departure is costlier. In addition, by shrinking the pool of workers identified for potential promotion, talent hoarding creates misallocation of talent in the firm. These predictions guide my empirical analysis.

To empirically test for talent hoarding, I use a unique combination of personnel records and internal job application data from a large manufacturing firm. In order to examine internal career progression to higher-level positions, I focus my analysis on the firm's largest internal labor market, consisting of over 30,000 white-collar and management employees in Germany. Even though my

[1] Half of US firms report that managers hoard subordinates (i4cp, 2016) and workers in a third of US firms feel the need to keep internal applications secret from their managers out of fear of retaliation (KornFerry, 2015).

analysis captures a single firm, I demonstrate that the firm is similar to other large firms in terms of its workforce and organizational design. Employees who want to switch to a new position or to be promoted are required to apply for the position. Since most workers in the same team are at very similar hierarchy levels, promotions typically require out-of-team transitions.

My research design leverages quasi-random variation in workers' exposure to manager rotation. When a manager learns that they will move to a new position on a different team, they no longer have an incentive to hoard talented workers on their current team. For workers whose manager will soon rotate, this creates a temporary window of time during which they will not be subject to talent hoarding. Therefore, analyzing manager rotations allows me to study the impacts of talent hoarding without requiring direct measurement of talent hoarding behavior. Empirically, rotation effects are large, effectively doubling worker applications in the same quarter. I demonstrate that these effects can be interpreted as reflecting the causal effect of a manager leaving her team. A placebo test shows that manager applications for job rotations only increase worker applications if managers are successful and actually leave the team.

Following the predictions from the conceptual framework, I provide evidence indicating that talent hoarding is the key mechanism underlying the observed impacts of manager rotations. I first show that rotations have larger effects on workers who were subject to greater levels of talent hoarding using three dimensions of heterogeneity: worker quality, costliness of worker departure, and managers' propensity to hoard talent. I then leverage the rich job application data and show that manager rotations disproportionally increase applications that under talent hoarding carry a greater risk of retaliation, either because managers are likely to find out about the application or because applications are unlikely to be successful. Moreover, I document that manager rotations only affect internal job transitions within the firm that are subject to talent hoarding, but not external job transitions out of the firm, which managers are not able to influence. I show that alternative mechanisms, such as loyalty or manager-worker specific match effects, are unlikely to drive the impacts of rotations.

My findings indicate that talent hoarding causes misallocation of talent by reducing the quality and performance of promoted workers. To analyze misallocation, I focus on major promotions, such as transitions from specialist to team leader positions, that reflect meaningful changes in job responsibility. Manager rotations increase worker applications for major promotions by 123%, indicating that talent hoarding deters a large group of workers from applying for promotions. To quantify how successful deterred applications would have been, I instrument for workers' applications with manager rotations. Marginal applicants are three times more likely to land a major promotion than average applicants and subsequently perform well in higher-level positions. A complier analysis finds that marginal applicants are positively selected in terms of their educational qualification and past performance. These findings suggest that in addition to reducing the number and the quality of applicants for higher-level positions, talent hoarding lowers team performance at these levels.

I find that talent hoarding has disparate impacts by gender. Talent hoarding deters a larger share of female applicants from applying for major promotions compared to men. Female marginal

applicants are twice as likely to land a major promotion than males, implying that talent hoarding is more consequential for women's career progression. Conditional on landing a promotion, women are almost three times as likely as their male counterparts to perform well in their new positions, suggesting that the firm may be failing to realize potential productivity gains by not enabling talented women to progress to higher-level positions. Female marginal applicants are much more qualified than males in terms of their educational qualification and past performance, indicating that talent hoarding affects women at a higher part of the quality distribution compared to men.

Talent hoarding exacerbates gender inequality in representation and pay. When comparing potential outcomes for marginal applicants, I find that increasing applications through manager rotations is much more beneficial for women than for men, reducing the gender representation gap by 91% and the gender pay gap by 77% within one year. The disparate impacts of talent hoarding by gender are not driven by differential treatment by managers. Rather, a survey of the firm's employees suggests that male and female workers react differently to talent hoarding. In line with the literature on gender differences in preferences, (Bertrand, 2011), the survey finds that women in the firm place more value on preserving a good relationship with their manager and rely more on managers' career guidance when making application decisions.

This study contributes to two broad strands of research on organizations. Prior theoretical research has hypothesized that managers engage in self-interested behavior (Holmstrom and Tirole, 1989), largely focusing on managers' misaligned incentives in the context of biased performance evaluations (Milgrom and Roberts, 1988, Prendergast and Topel, 1996, Fairburn and Malcomson, 2001). While research studying internal labor markets has documented the importance of incentive provision in organizations (Gibbons and Waldman, 1999, Prendergast, 1999), little attention has been paid to how managers' incentive problem may affect the efficiency of job assignments. One notable exception is theoretical work by Friebel and Raith (2013) who show that different organizational designs may change managers' incentives to train subordinates and accurately represent their abilities. My study provides the first empirical demonstration of a costly moral hazard problem among managers that affects the efficient allocation of talent within organizations.

Second, a large empirical literature in economics studies the impacts of managers on firm outcomes. The majority of this literature has focused on upper management, and in particular on documenting the impacts of CEOs on firm performance (Bertrand and Schoar, 2003, Bennedsen et al., 2007, Malmendier and Tate, 2009, Bennedsen et al., 2020). An emerging body of work uses detailed data on managers and workers to show that even managers at lower levels of the firm hierarchy have large impacts on worker outcomes, including worker productivity (Lazear et al., 2015, Frederiksen et al., 2020, Fenizia, Forthcoming), turnover (Hoffman and Tadelis, 2021), and career progression (Kunze and Miller, 2017, Cullen and Perez-Truglia, 2019, Benson et al., 2021). This study adds to these findings by uncovering talent hoarding as an important mechanism that influences managers' impacts on firms and workers. By demonstrating that talent hoarding has meaningful impacts on career progression, this study also contributes to an empirical literature seeking to understand the dynamics of internal promotions (Baker et al., 1994, Benson et al., 2019.

The rest of the paper proceeds as follows. Section 2 introduces a simple framework that offers a formal definition of talent hoarding. Section 3 describes the institutional background and novel data. Section 4 presents the empirical strategy centered around manager rotations. Section 5 demonstrates the impacts of talent hoarding on worker applications. Section 6 presents results on the efficiency costs of talent hoarding with respect to talent allocation. Section 7 provides suggestive evidence unpacking how talent hoarding effects arise. Section 8 concludes.

2 A Simple Framework of Talent Hoarding

In this section, I present a conceptual framework that offers a formal definition of talent hoarding, illustrates how managers' misaligned incentives deter worker promotions, and yields a set of predictions about manager and worker behavior that guides my empirical analysis.

Consider a firm that employs two types of agents, managers m and workers i, that work together in teams. For simplicity, teams are composed of one manager and one worker. Workers are characterized by a marginal productivity α_i drawn from some known distribution G. The firm seeks to efficiently allocate talent to maximize total firm productivity by choosing which workers to promote to managerial positions. Consistent with Rosen (1982), productivity is maximized when high-ability workers are assigned to high-level positions. Thus, in the absence of any constraints, the firm would fill a new managerial vacancy with the most productive worker and would fill the worker's vacated position by hiring a worker from outside of the firm (i.e. a random draw from G).

In practice, firms neither perfectly observe worker productivity, nor do they know which workers would accept a promotion. Accordingly, managers are tasked with identifying high-productivity workers and encouraging them to seek promotions. However, if a high-productivity worker is promoted and leaves their team, that team incurs a productivity loss. Managers, who observe the productivity of their workers, are compensated according to team productivity, creating a conflict of interest between the firm and managers. Talent hoarding is defined as the actions taken by managers that lower the likelihood that a worker applies for and receives a promotions.[2]

The one-period framework proceeds as follows. A managerial vacancy in the firm opens exogenously. M managers observe the productivity of the worker on their teams and decide to what extent to engage in talent hoarding. Based on managers' choices, workers decide whether to apply for a promotion. The firm then observes noisy signals of worker productivity and chooses the worker with the highest signal to fill the vacancy. The promoted worker's previous position is replaced with an outside hire. Finally, team productivity is realized and managers are compensated.

Let $\beta \in [0, \infty]$ index the degree of talent hoarding chosen by a manager, with 0 representing no talent hoarding. Let $q(\alpha_i, \beta)$ denote the equilibrium probability that a worker with productivity α_i

[2]Respondents to the survey discussed in Section 5.4 report that managers can deter workers from applying by explicitly discouraging or threatening them, underrating worker ability, and restricting access to high-visibility projects or trainings. In theory, the firm could offer managers a promotion-contingent contract to resolve the misaligned incentives. In practice, firms generally do not compensate managers for promoting their workers, plausibly because of the practical challenges associated with these contracts (discussed in detail in Friebel and Raith (2013)).

gets promoted, conditional on applying for a promotion. This promotion probability increases with worker productivity ($\frac{\partial q}{\partial \alpha_i} > 0$), but decreases in the level of talent hoarding ($\frac{\partial q}{\partial \beta} < 0$), and reflects the noisy signal received by the firm. Thus, one can interpret talent hoarding as impacting workers through the likelihood that they get promoted.[3] Furthermore, I assume that the effect of talent hoarding on the conditional promotion probability is larger for more productive workers ($\frac{\partial^2 q}{\partial \beta \partial \alpha_i} < 0$). Intuitively, given multiple applicants in an applicant pool, there is less scope to lower the odds that a low-productivity worker gets promoted given their already-low likelihood of promotion.

Workers decide whether to apply by weighing expected costs and benefits. Let b denote the benefits of a successful application and c denote the costs of applying. Workers apply if

$$q(\alpha_i, \beta)b \geq c + \varepsilon_i \tag{1}$$

where $\varepsilon_i \sim \Psi$ captures worker-specific heterogeneity, with Ψ known to the manager. Therefore, from the manager's perspective, the probability that the worker leaves the team is given by

$$p(\alpha_i, \beta) = q(\alpha_i, \beta)\Psi\big(q(\alpha_i, \beta)b - c\big)$$

It follows that talent hoarding reduces the probability that workers leave the team (i.e. $\frac{\partial p}{\partial \beta} < 0$).[4]

Managers optimize by choosing their level of talent hoarding β. If a worker leaves the team for a promotion, the firm hires a worker of unknown ability ($\alpha_j \sim G(.)$ with $E[\alpha_j] = \bar{\alpha}$) from outside the firm. Consequently, a high-productivity worker getting promoted out of the team is likely to decrease team productivity. Without compensation for promoting workers, managers have an incentive to engage in talent hoarding by reducing workers' likelihood of promotion. However, managers incur increasing and convex costs from talent hoarding, which vary in their magnitude by manager according to the parameter $\phi_m > 0$.[5] Thus, managers solve the following problem:

$$\max_{\beta} \left(1 - p(\alpha_i, \beta)\right)\alpha_i + p(\alpha_i, \beta)\bar{\alpha} - \frac{\phi_m}{2}\big(p(\alpha_i, 0) - p(\alpha_i, \beta)\big)^2$$

This optimization problem yields the following first-order condition, which provides a formal definition of talent hoarding as well as predictions with respect to the realized level of talent hoarding:

$$p(\alpha_i, 0) - p(\alpha_i, \beta^*) = \frac{1}{\phi_m}(\alpha_i - \bar{\alpha})$$

Definition. (Talent hoarding) When worker i's productivity exceeds the expected productivity of

[3] In practice, workers report that managers diminish their visibility within the firm, thus lowering their prospects of getting promoted (see section 5.4 for further discussion). In theory, talent hoarding could also affect worker applications through the cost of applying, which would lead to similar predictions

[4] For simplicity, this framework does not distinguish between different worker types. If workers differ in the extent to which talent hoarding affects their promotion probability, talent hoarding may exacerbate between-group differences in promotions through a differential effect on workers' decisions of whether to apply.

[5] The utility costs that managers experience when hoarding talent can be interpreted as consequence of manager altruism, in line with Hoffman et al. (2018) who motivate why managers might value making hiring decisions in the interest of the firm and not in their best self-interest. Alternatively, such costs could arise from the probability of detection, for instance in the form of reputation costs.

an outside hire, the manager optimally hoards talent by choosing $\beta^* > 0$. As a result, the likelihood that a worker leaves the team is lower relative to $\beta = 0$.

Prediction 1. (Worker heterogeneity)
High-productivity workers (i.e. high α_i) experience more talent hoarding.

Prediction 2. (Team heterogeneity)
Workers that are more difficult to replace (i.e. if $\bar{\alpha}$ is lower) experience more talent hoarding.

Prediction 3. (Manager heterogeneity)
Talent hoarding is greater among managers with low utility costs of hoarding (i.e. low ϕ_m).

In addition, workers' decision rule implies that talent hoarding reduces the number of applicants and the quality of the applicant pool, limiting the firm's ability to promote a high-productivity worker and generating misallocation of talent.

Prediction 4. (Number of applicants)
If workers face less talent hoarding, they are more likely to apply for a promotion
$\Pr[i \text{ applies}|\beta = \beta_1] > \Pr[i \text{ applies}|\beta = \beta_2]$ for $\beta_1 < \beta_2$

Prediction 5. (Composition of applicants)
Talent hoarding has larger impacts for high-productivity workers. Therefore, higher levels of talent hoarding lead to a lower-quality applicant pool:
If $\alpha_1 < \alpha_2$ and $\beta_1 < \beta_2 \implies \frac{\Pr[i \text{ applies}|\alpha_2,\beta_1]}{\Pr[i \text{ applies}|\alpha_1,\beta_1]} > \frac{\Pr[i \text{ applies}|\alpha_2,\beta_2]}{\Pr[i \text{ applies}|\alpha_1,\beta_2]}$

Appendix Section C contains formal derivations of these predictions.

3 Setting and Data

My analysis relies on a unique combination of personnel records and internal job application data from a German manufacturing firm. I show that the firm, one of the largest in Europe, is comparable to other firms in its sector. I then use the firm's data to construct a panel dataset that links workers to their managers and includes workers' application and hiring histories at the firm.

3.1 Firm Overview

I use data on over 30,000 white-collar and management employees from a large German manufacturing firm. This anonymous firm is one of the largest manufacturers in Europe, and employs over 200,000 workers around the world, the plurality of which work in Germany. Because I am interested in career progression to higher-level positions, my analysis focuses on employees in white-collar and management positions (i.e. employees that are either already in or could ultimately be promoted

to managerial positions). There are over 200 occupations represented in this sample, ranging from technical positions in engineering to support functions in HR and finance.

Table 1 describes my analysis sample, which consists of over 300,000 employee-by-quarter observations from 2015 to 2018.[6] Women represent only 21% of employees in the sample, stemming from the underrepresentation of women in technical occupations. Employees' educational qualifications are high on average, a result of restricting the sample to white-collar and management employees. The average employee holds a Bachelor's degree and 92% of employees work full-time. Employee tenures at the firm tend to be long, with an average tenure of 13 years, highlighting the importance of internal career progression for employees' long-term income. Managers (i.e. those that lead a team) comprise 19% of the sample.

The demographics of the employees at the firm are comparable to other large manufacturing firms in Germany. In Appendix Table A5, I compare employees in my sample to those employees in large manufacturing firms in the BiBB, a representative survey of the German workforce conducted in 2018. I find very similar patterns with respect to most employee characteristics (e.g. gender, age, German citizenship, marital and family status).

The firm resembles other large firms in Germany with respect to the design of its internal labor market (hkp///, 2021). As in most large German firms, employees who want to switch to a new position or to be promoted are required to apply for the position using a centralized online job portal. All job openings are posted to the job portal, where openings are visible to all employees. Applications through the portal typically take less than five minutes to complete. While employees can choose to apply to multiple positions at the same time, the median applicant applies to only one position in a given quarter. Callback and hiring decisions are also recorded in the job portal. Appendix Figure B1 depicts the appearance of the online job portal.

The internal labor market is comprised of competitive openings for new positions, much like the external labor market. Only 25% of applications are successful and the internal labor market is both spatially and interpersonally diffuse. The firm operates in over 50 cities in 250 establishments throughout Germany and one-third of internal applications are for positions in a different city. In 93% (99%) of cases, applicants (applicants' current supervisors) have not previously worked with the hiring manager of the position they are applying for, indicating that application and hiring decisions are distinct in the internal labor market.

Because most teams are small, consisting of one manager and six workers on average, and because most workers within a team are at similar hierarchy levels, workers must leave their team in order to move up the job ladder. In the data, 97% of applications are to positions outside of a worker's current team. Thus, managers who encourage their workers to pursue promotions lose team members.

[6] To maintain confidentiality, I do not disclose the exact number of employees in my sample.

3.2 Personnel Records

I merge the firm's internal personnel records from 1998 to 2020 with the universe of application and hiring decisions from 2015 to 2020. The personnel records capture over 30,000 employees. The application data cover over 16,000 job openings and over 200,000 external and internal applicants. My main analysis sample consists of over 300,000 employee-by-quarter observations from 2015 to 2018. Appendix Section D.1 contains details on data linkages.

The personnel records contain a large set of employee characteristics, such as family status, working hours, and earnings. The records also capture workers' assignment to teams and managers. I use this information to characterize manager behavior and to study the impact of talent hoarding on worker outcomes. In addition, the personnel records contain detailed position characteristics, such as position titles, leadership responsibility, and the reporting distance to the CEO.

I use the richness of the personnel records to account for factors unrelated to talent hoarding that may influence workers' career progression. Unless otherwise noted, all analyses include the following set of controls: worker demographics (age, German citizenship, educational qualification, marital status, family status, parental leave, firm tenure), position characteristics (position type, division, functional area, location, full-time, hours, number of direct reports), performance and potential ratings, and past mobility at the firm. These characteristics allow me to incorporate key determinants of career progression that are not available in settings studied in prior research.

I use application and hiring decisions to identify the impacts of talent hoarding on applications and promotions. Because all job openings are posted on the centralized portal and all applications and hiring decisions are required to be submitted through the portal, I observe the outcome of each applicant in terms of rejections, interview callbacks, and subsequent hiring outcomes. These features allow me to construct a panel dataset of employees' application and hiring histories at the firm from 2015 to 2020. Separately measuring applications and hiring outcomes is important given that one would expect workers with a higher application threshold (e.g. because they fear manager retaliation) to have higher hiring likelihoods if they apply. If that is the case, analyzing impacts on promotions alone would underestimate the effects of talent hoarding.

4 Empirical Strategy

My research design leverages quasi-random variation in workers' exposure to manager rotations. When a manager learns that they will move to a new position on a different team, they no longer have an incentive to hoard talented workers on their current team. For workers whose manager will soon rotate, this creates a temporary window of time during which they will not be subject to talent hoarding. Therefore, analyzing manager rotations allows me to study the impacts of talent hoarding without requiring direct measurement of talent hoarding behavior. In Section 5.3, I provide empirical evidence that supports the interpretation of rotations as capturing the impacts of talent hoarding.

I analyze 1,359 manager rotations by 1,276 unique managers. I define a manager rotation

as an instance in which a worker's direct supervisor leaves their team to make an internal job transition within the firm. Restricting attention to internal transitions serves to isolate manager-induced variation that is plausibly orthogonal to worker characteristics and team outcomes. Internal rotations are routine and encouraged by the firm as part of managers' career progression. In contrast, instances in which managers leave the firm through voluntary exit, layoff, or retirement are likely correlated with other factors that may affect worker outcomes.

During the four-year study period, 20% of managers rotate at least once. Rotations do not occur on a regular schedule, and workers cannot easily predict when managers will leave the team. Appendix Figure B2 documents large variation in the time that managers spend in a position before rotating. In order to rotate, managers must apply through the firm's internal application system. In order to encourage smooth transitions, the firm has a strict policy that requires managers to inform their teams as soon as possible when they accept a new position. On average, managers learn about their new position two to three quarters before they rotate, at which time managers inform their teams about their rotation.

4.1 A Measure of Talent Hoarding

In a complementary empirical exercise, I infer managers' propensity to hoard talent using a novel measure of worker visibility. While my main empirical tests for talent hoarding do not rely on this measure, it offers the advantage of directly capturing manager behavior, which provides a useful test of the predictions that emerge from my conceptual framework in Section 2.

Talent hoarding is difficult to measure because it typically occurs through interpersonal interactions. To capture talent hoarding in the data, I identify systematic differences between performance and potential ratings. While performance ratings provide task-specific feedback to workers about their past performance and potential ratings inform the firm about a worker's future potential for higher-level positions, they are both conducted simultaneously by a worker's direct supervisor.

One way in which managers can limit workers' opportunities to leave the team is by suppressing potential ratings relative to performance ratings. Performance ratings are private signals to the worker and are not shared with other units across the firm I study. If a worker applies for a job in a different unit, that unit will not be able to access the worker's past performance ratings. In contrast, potential ratings are public signals of worker talent and are widely circulated within the firm. The firm's HR department regularly compiles and circulates lists of high-potential workers to be considered for promotion, making these workers highly visible. Intuitively, a manager that wants to hoard talent should give workers lower (public) potential ratings relative to their (private) performance ratings. A survey of the firm's employees indicates that this suppression of worker visibility is a key dimension of talent hoarding.[7] For each worker, the difference between performance and potential ratings is likely influenced by factors other than talent hoarding; however, because managers typically have substantial discretion in conducting these evaluations, comparing systematic

[7]For instance, one worker states, "Supervisors suppress potential ratings because of fear that employees will leave their current position for a promotion." (Appendix Table A1).

differences between these ratings across workers can capture differences in manager behavior.[8]

I construct a measure of a manager's propensity to hoard talent by limiting worker visibility based on the difference between actual and predicted potential ratings they assign to their workers. Specifically, I take the predicted values from the following regression of the potential rating given to worker i in quarter t by manager m on their performance rating and other worker characteristics:

$$\text{potential}_{imt} = \beta_1 \text{performance}_{imt} + \beta_X X_{it} + \beta_t + \varepsilon_{itm} \tag{2}$$

In Equation 2, X_{it} denotes the vector of controls described in Section 3.2. I compute the average difference (over workers and quarters) between predicted and actual potential ratings for each manager. I classify a manager as having a high propensity to hoard talent if this difference is in the bottom tercile of the manager distribution (Appendix Figure D1).

A number of empirical exercises, which are described in detail in Appendix Section D.2, support the validity of this measure of talent hoarding. The underrating in potential captured by this measure does not represent managers' correct assessment of workers' future performance. When managers who have a high propensity to hoard talent rotate, underrated workers not only experience increases in applications and promotions, they also are likely to perform well at higher levels, demonstrating that their initial low potential rating was inaccurate. This measure is not strongly correlated with managers' ability to assess talent, suggesting that differences between performance and potential ratings are unlikely to be a result of managers' involuntary mistakes.

The measure of talent hoarding is highly correlated with workers' realized visibility at the firm, confirming that managers' suppression of public signals has a meaningful impact. I measure worker visibility by collecting data on workers' nominations to succession lists. As in many large organizations, the firm compiles lists of three to five candidates as potential successors for about one-fifth of positions in my sample. The lists are assembled by HR employees who search for suitable candidates across the firm. Workers' appearance on such a list represents a measure of their visibility outside of the team. If a manager is successful at hoarding talent, worker visibility should be low, and thus their likelihood of appearing as a nominee on a succession list should also be low. I estimate a version of Equation 2 to compute the difference between actual nominations and predicted nominations, then classify managers as high- and low-propensity talent hoarders, defined as those in the bottom and top terciles of this difference.

4.2 A Granular Measure of Job Hierarchy

In order to assess whether talent hoarding leads to misallocation, I implement a test of whether high-ability workers are underpromoted to high-level positions due to talent hoarding. This test requires a measure of internal job hierarchy. While previous research studying internal hierarchies has typically used position titles, this approach is not well-suited to testing for misallocation. Since

[8] In contemporaneous work, Benson et al. (2021) find that managers in a large retailer overrate men's potential compared to women's, possibly as a reaction to men's higher turnover risk.

26% of workers in my sample share the same position title with their supervisor or their supervisor's supervisor, the standard approach would miss granular differences in the job hierarchy and thus likely underestimate the efficiency losses of talent hoarding.

To overcome these challenges, I apply the methods developed in Haegele (2021) to define a granular measure of job hierarchy. This measure combines three dimensions of leadership responsibility: the number of cumulative reports, the reporting distance to the CEO, and the managerial autonomy of a position. The hierarchy ranking is the first principal component of these three dimensions, which provides a consistent ordering of all positions at the firm. Following Haegele (2021), I define major promotions as increases in the hierarchy index of 20 or more. These transitions typically reflect a meaningful increase in leadership responsibility, such as from working as an engineer on a team to managing other engineers. See Appendix Section D.3 for further details on the construction of the hierarchy measure.

5 Results

This section documents that manager rotations have large effects on worker applications. Several robustness tests support the causal interpretation of these rotation effects. I provide evidence that talent hoarding is the key mechanism underlying the observed impacts of manager rotations. Responses to a survey of employees add to this evidence and document that managers purposefully hoard talent to deter workers from applying to new positions. Finally, I demonstrate that manager rotations are a valid instrument for worker applications, allowing me to measure forgone promotions.

5.1 Effect of Manager Rotations on Worker Applications

Manager rotations lead to large short-term increases in worker applications. Panel A of Figure 1 presents coefficients from a quarterly event study around manager rotations.[9] In the quarter in which a manager rotation occurs, worker applications increase by 2.3 percentage points, almost doubling workers' baseline application rate of 2.7% per quarter. Application rates start to increase up to three quarters before the manager rotation takes place, which is when managers start to inform their teams about their upcoming departure. However, before $t = -3$, when managers do not know yet about their job rotation, trends in applications are flat. As the manager's replacement settles in, application rates return to baseline levels within one to two quarters.

The effect of manager rotations on worker applications is not a result of managers taking their subordinates with them to the new team or of workers replacing managers in their old position. Rather, 97% of applications in my sample are for positions outside of the worker's current team, but not to the managers' new team. Even though manager rotations have large impacts on workers' job transitions within the firm, they have no impact on external transitions out of the firm. Panel

[9] I estimate a specification with worker and quarter fixed effects, binning event time dummy variables at $t = -8$ and $t = 4$, and clustering standard errors at the worker level. The sample of 3,xxx workers includes those who have not experienced a manager rotation (i.e. never-treated).

B of Figure 1 illustrates this fact, indicating that the impacts of manager rotations are confined to worker interactions with the internal labor market. In addition, my findings do not suggest that that the impacts of manager rotations are driven by the incoming manager.[10]

Since manager rotation appears to have the largest impact on worker applications in the quarter of the rotation, the remainder of the analysis focuses on worker behavior in that quarter. I analyze the effect of manager rotations on worker applications by estimating a linear model for workers' internal application choices using an OLS regression of the following form:

$$\text{Applied}_{it} = \delta_1 \text{Rotation}_{it} + \delta_X X_{it} + \delta_t + u_{it} \tag{3}$$

Applied_{it} and Rotiation_{it} are indicators that worker i in quarter t applies for an internal job opening and experiences a manager rotation, respectively. X_{it} includes a broad set of worker and position controls.[11] Column 1 of Table 2 shows that applications increase by 2.2 percentage points in the quarter of a manager rotation, representing a 76% increase compared to the baseline application rate of 2.9% and echoing the results illustrated in Panel A of Figure 1.

5.2 Ruling Out Correlated Team-Level Shocks

I interpret manager rotations as reflecting the causal effect of a manager leaving her team. The primary threat to this interpretation is that there are team-level shocks that are correlated with manager rotations, such as unpleasant working conditions, bad news about the future outlook of the team, or the completion of a major milestone. These shocks may induce both managers and workers to apply away from the team. I present five pieces of evidence indicating that the estimated rotation effects are not driven by correlated team-level shocks.

First, if the observed patterns result from correlated shocks, it should not matter whether a manager who has applied for a rotation actually rotates. Instead, one would expect that worker applications increase even if a manager's application for rotation is unsuccessful. Accordingly, I conduct a placebo test where I examine the effect of managers' unsuccessful applications for a job rotation on worker applications. Panel A of Figure 2 shows that while managers' successful job rotations double worker applications, managers' unsuccessful applications have no effect.

Second, in the presence of correlated shocks, the effects of a teammate's rotation should be larger than those of a manager's rotation, because teammates are generally more similar to workers than managers. Panel B of Figure 2 estimates the impacts of rotations of the most senior teammate and shows that these events have much smaller, rather than larger, impacts on worker applications.[12] This pattern is only consistent with a correlated shock that increases in magnitude with teammates'

[10] Appendix Table A6 finds similar effects when distinguishing rotations by the incoming manager's characteristics. The fact that applications start to increase around $t = -3$, long before the firm typically begins to look for a replacement, further suggests that (expectations about) incoming managers do not play a key role.

[11] These controls, described in Section 3.2, include age, German citizenship, educational qualification, marital status, family status, parental leave, firm tenure, position type, division, functional area, location, full-time, hours, number of direct reports, performance and potential ratings, and past mobility at the firm.

[12] Similar patterns arise when other types of teammates rotate (e.g. most junior, randomly chosen).

seniority, which is difficult to reconcile with the expected impacts of most correlated shocks.

Third, in addition to applications, one would expect other team-level outcomes like absenteeism to react to many correlated team-level shocks, like a deterioration in working conditions. Appendix Figure B3 estimates an event study around manager rotations and rejects economically significant changes in team-level absenteeism rates in the lead-up to a manager rotation. Fourth, many correlated shocks like bad news about the team's long-term future would be expected to have long-lasting impacts on applications, which is not consistent with the short-lived nature of the observed increase in applications (Panel A of Figure 1).

Fifth, results presented in Section 5.3 show that the application effects of manager rotations are much larger for managers who have higher propensities to hoard talent. It is difficult to reconcile these patterns with the expected impacts of many correlated shocks, which would need to increase with managers' talent hoarding propensity to explain the observed patterns.

5.3 Interpretation of Manager Rotations As Evidence for Talent Hoarding

In this section, I provide evidence indicating that talent hoarding is the key mechanism underlying the observed impacts of manager rotations. Alternative mechanisms, such as loyalty or manager-worker specific match effects, are unlikely to drive the impacts of rotations.

Worker Quality.—The conceptual framework in Section 2 predicts that managers are more likely to hoard high-productivity workers. Therefore, when managers rotate and talent hoarding temporarily subsides, application effects should be larger for the high-productivity workers who experienced more talent hoarding than their low-productivity peers. To test this prediction, I compare the impacts of rotations on applications by worker quality. I construct a measure of worker quality as the predicted values from a regression of applicants' internal hiring probabilities on applicant characteristics. The predicted value of this regression provides an index of worker quality for all workers, weighting worker characteristics by their importance for hiring prospects within the firm.[13] I compare workers in the top and bottom quartile of the index. Panel A of Figure 3 shows that high-quality workers experience a 3.4 percentage point increase in applications when a manager rotates, while applications among low-quality workers increase by only 0.9 percentage points, in line with the predicted patterns. Note that baseline application rates (not reported) are very similar across the different worker groups I compare in this section.

Departure Costs.—A second prediction from the conceptual framework is that managers hoard talent more when the costs of worker departures are larger. I test this prediction using two measures of departure costs. The first measure is the number of other workers in the team, since a larger team allows for more workers to compensate for a teammate's departure. Panel B of Figure 3 presents estimated effects of manager rotations for workers in the bottom and top quartiles of team size. By including detailed worker and position characteristics, this analysis compares workers with

[13]This definition of worker quality has the advantage that it reflects the values that the firm places on worker qualifications. Robustness exercises in Appendix Section E find similar patterns when using alternative measures such as educational qualification or past performance.

similar qualifications in similar positions, but in teams of different sizes. Applications increase by 4.3 percentage points among workers in small teams (one to three teammates) but only by 1.4 percentage points in large teams (10 or more teammates). Measuring departure costs using the average number of days required to fill a worker's vacated position yields similar results. Panel C of Figure 3 compares effects for high-cost workers (more than 174 days to fill their position) to low-cost workers (less than 135 days). Applications among workers who are hard to replace increase by 3.3 percentage points, compared to 1.3 percentage points for workers who are easy to replace.

Talent Hoarding Propensity.—The impacts of manager rotations are strongly correlated with direct measures of manager propensity to hoard talent. Panel D of Figure 3 compares the impacts of rotations between managers with a high versus low propensity to hoard talent, using the measure of talent hoarding based on differences between potential and performance ratings (described in detail in Section 4.1). Applications increase by 3.7 percentage points when a manager with a high propensity to hoard talent rotates, but only by 1.6 percentage points under managers with low propensities to hoard talent. An alternative measure of talent hoarding based on nominations to succession lists yields similar results. Panel E of Figure 3 shows that rotations of managers with a high propensity to hoard talent according to the measure based on succession lists increase applications by 3.2 percentage points, compared to only 1.4 percentage points under low-propensity managers. In addition, the conceptual framework predicts that managers with high propensities to hoard talent have particularly large impacts on more productive workers. Figure 4 confirms this prediction, indicating that under both measures of talent hoarding, rotation effects are concentrated among high-quality workers.

Risk of Retaliation—In survey results (Section 5.4), workers report fear of managers' retaliation as a reason they refrain from applying for internal positions, which represents a form of talent hoarding. If workers are more likely to refrain from applying to positions that carry a greater risk of manager retaliation, applications to these positions should increase the most when managers rotate. I measure the risk of retaliation in two ways. First, applications that are less likely to be successful necessarily carry greater risk of manager retaliation. I test this predictions by analyzing whether manager rotations have larger effects for applications that typically yield lower success likelihoods. Table 2 confirms this prediction and documents that baseline applications for lateral transitions increase by 61%, while small and major promotions increase by 98% and 123%, respectively. Second, managers should be more likely to learn about worker applications to positions that are closer in proximity. I test this prediction by comparing workers' application to job openings within versus across their current division, functional area, and location. Appendix Table A8 shows that manager rotations have much larger effects on applications in close proximity to workers' current position with respect to all three dimensions, confirming the prediction.[14]

Short-Lived Impacts.—Since all managers face incentives to hoard talent, a new manager taking

[14]Talent hoarding could lead to an opposite prediction on proximity if it were to operate through the visibility channel instead of retaliation. However, while the suppression of visibility is a common form of talent hoarding, manager rotations do not immediately increase visibility since worker evaluations only occur one to two times a year.

over a team should also exhibit talent hoarding behavior. Therefore, manager rotations should induce transitory increases in applications. Panel A of Figure 1 confirms this prediction and shows that applications increase once managers begin to announce their departure from the team and return to baseline levels within one to two quarters after a new manager has taken over.

External Transitions.—While managers may frequently learn about workers' unsuccessful applications to internal positions and possibly retaliate or interfere with those applications, this is not the case for applications to positions outside of the firm. Therefore, manager rotations should only impact internal applications and not external applications outside of the firm. Because I do not observe external applications, I test this prediction by comparing the effect of manager rotations on internal job transitions within the firm and external job transitions out of the firm. Panel B of Figure 1 shows that manager rotations only increase worker transitions within the firm and not outside of the firm, even though both types of transitions trend identically in quarters prior to the rotation. Columns 1 and 2 of Appendix Table A7 confirm this finding quantitatively. Manager rotations increase internal transitions by 1.1 percentage points, but have negligible effects on external transitions (0.09 percentage points) compared to the identical baseline rate of 0.7%.

Alternative Explanation: Loyalty or Match Effects.—Manager rotations may affect worker applications through alternative channels. Workers may refrain from applying for a new position because of loyalty towards their manager or because manager-worker specific match effects make their current position particularly appealing. Under such mechanisms, manager rotations increase applications through a decrease in the value of workers' default option and should thus make any type of transition more appealing. If these mechanisms are quantitatively important, there should be at least some effect on external job transitions given that internal and external transitions trend identically prior to the rotation. However, this pattern is not borne out in the data (Panel B of Figure 1). These mechanisms can also not explain why rotations disproportionally deter applications for positions that are more selective (Table 2) or closer in proximity (Appendix Table A8).

Loyalty and match effects are typically assumed to compound over time, implying the importance of exposure time for the magnitude of rotation effects. Appendix Figure B4 finds no evidence for an increase in rotation effects by the length of worker exposure to the rotating manager. Rotation effects arise even for workers who have been exposed to their manager for one quarter or less. Similarly, the short-lived nature of the increase in applications implies that loyalty and match effects would immediately build up as soon as a new manager joins the team, which is difficult to reconcile with the expected patterns of these mechanisms. Under manager-worker specific match effects, rotations should affect workers more who were hired by that manager (providing scope for selective matching), relative to workers who started at the team before the manager did. Instead, Columns 3 and 4 of Appendix Table A7 document that manager rotations have very similar effects on both groups. In addition, neither mechanism can simultaneously produce the findings that rotations have larger effects among workers who (i) experience a suppression of worker visibility, (ii) are more qualified, (iii) work in small teams, or (iv) work in positions that are hard to replace.

Alternative Explanation: Role-model Effects.—Another explanation could be an information-based mechanism, such as a role model effect, that operates through making career planning (success) more salient. However, a mechanism that affects applications through information provision is difficult to reconcile with the short-lived nature of the observed application effects. Moreover, under information provision even managers' unsuccessful applications for rotations should have some effect, since these make topics such as career progression and application planning more salient. However, Panel A of Figure 2 finds no effect on worker applications if managers unsuccessfully apply for a job rotation. In addition, if observing others navigate their career is a key underlying factor of rotation effects, such a role model effect is not limited to managers. Instead, one would expect larger effects for observing coworkers rotate, since they are more similar to the worker than their manager. Instead, Panel B of Figure 2 illustrates that a manager rotation causes four times larger application rates in the same quarter than a coworker rotation. These findings suggest that a role model effect as key mechanism underlying manager rotations is not borne out in the data.

5.4 Survey Evidence on Talent Hoarding

Responses to a survey of employees provide further evidence in support of talent hoarding. All employees in my sample were invited via e-mail by the firm's human resources department and were asked to provide their perspectives on the internal job market at the firm. Employees described challenges regarding their internal career progression both in the form of free text responses and in multiple choice answers. The survey received over 15,000 responses, yielding a 50.0% response rate. Respondents are similar to non-respondents in terms of demographics (Appendix Table A3). I find no evidence for differential selection into response by gender (Appendix Table A4).

Respondents report a variety of different actions through which managers hoard talent, which include suppressing public signals of worker ability, restricting access to high-visibility projects or trainings, and explicitly discouraging workers from applying to internal positions. Appendix Table A1 provides selected quotations. In addition, then asked to state the biggest challenge to their internal career progression, the modal answer (provided by 22% of workers) is managers' limited support for career progression, such as refusal to assist in career planning and denial of requests to participate in development programs that would increase workers' visibility outside the team.

Not only do many employees report managers trying to prevent workers from pursuing promotions, managers' actions also appear to strongly influence workers' application decisions. 41% of respondents indicate that they are afraid to apply to internal positions, fearing negative repercussions if managers find out about the application. 25% of workers state that they feel the need to ask for their managers' permission before applying for an internal job opening, even though the firm's internal policies are meant to enable workers to initiate an application on their own. 16% of respondents indicate that applying away from the team is perceived as disloyal.

In the survey, managers themselves acknowledge the existence of talent hoarding. 32% of managers report that negative repercussions follow when managers find out about internal applications. 28% of managers state that workers should ask their managers for permission before applying for an

internal application. Appendix Table A2 provides anecdotal evidence of managers' descriptions of talent hoarding, offering direct evidence that misaligned incentives lead managers to hoard talent. One manager explains, "Managers pursue their own goals and often prevent further development of workers, because they are not rewarded for developing talent.", while another manager reports that "Selfish managers are not willing to promote or recommend subordinates to other areas of the firm, even if that would add value to the firm.".

While these results provide the first detailed empirical evidence on talent hoarding in organizations, additional evidence suggests that this talent hoarding behavior is endemic. In a survey of the heads of talent management at the top publicly listed companies in Germany, 83% cite talent hoarding as a crucial friction in their organization (hkp///, 2021). Firm surveys in the United States document that talent hoarding is also common in US companies (i4cp, 2016) and represents an impediment for worker's internal applications (KornFerry, 2015).

5.5 Instrumenting for Applications with Manager Rotations

To assess whether talent hoarding causes misallocation of talent, I instrument for worker applications with manager rotations and estimate the marginal probability of landing a promotion, which provides a direct measure of the firm's willingness to promote marginal applicants. Equation 4 represents the reduced-form model for the effect of manager rotation on workers' hiring outcomes:

$$\text{Hired}_{it} = \theta_1 \text{Rotation}_{it} + \theta_X X_{it} + \theta_t + \epsilon_{it} \tag{4}$$

Hired_{it} is a binary indicator, which is always zero if workers do not apply. The IV-estimator divides the reduced-form effect of manager rotation, θ_1, by the first-stage effect on application choice, δ_1:

$$\beta_{IV} = \frac{\theta_1}{\delta_1} \tag{5}$$

I estimate β_{IV} by two-stage least squares. The coefficient β_{IV} can be interpreted as the local average treatment effect (LATE), defined as the effect of application on hiring outcomes for workers induced to apply by manager rotation. The interpretation of β_{IV} as the LATE requires four assumptions to hold: relevance, independence, exclusion, and monotonicity (Angrist and Imbens, 1995, Angrist et al., 1996). Section 5.1 demonstrated relevance by documenting that manager rotations have large application effects. I now provide evidence in support of the other three assumptions.

Independence—A key threat to my research design is that workers who experience a manager rotation might differ in their hiring likelihood from workers who do not. This possibility could arise if manager rotation is not as good as randomly assigned. To evaluate the independence assumption, I test for balance across worker characteristics. Panel B of Appendix Table A9 shows that workers in teams that experience a manager rotation are observationally similar to those that do not. This similarity holds with respect to worker demographics, such as age, tenure, and marital status, as well as for workers' career trajectories leading up to the manager rotation, such as past earnings growth,

absenteeism, applications, and internal job transitions. In additional results, I find no substantial differences in manager attributes, further supporting the random assignment assumption.[15]

Exclusion—The exclusion restriction in my setting requires that manager rotation does not affect hiring outcomes other than through workers' decision to apply. This assumption would be violated if departing managers intercede in workers' subsequent hiring outcomes. Such a violation could occur if departing managers take their workers with them to their new position or replace themselves with workers in their team. However, this occurs in less than 3% of applications, suggesting that departing managers generally do not make subsequent hiring decisions for their subordinates. Alternatively, departing managers may try to influence hiring outcomes by reaching out to hiring managers. However, close formal ties between the departing manager and the hiring manager are very rare. For over 99% of applications, the current supervisor has not previously worked with the hiring manager. I test for the influence of more distant formal ties, such as the rotating managers ever having worked in the same location or functional area that the posted job is located in, which increases the probability that the departing manager has ever interacted with the hiring manager. However, I do not find any evidence that relative hiring rates are higher for job opening to which managers have closer ties to (Panel A of Appendix Table A10).

Another violation of the exclusion restriction could occur if manager rotation increases worker qualifications, making them more likely to get hired. If this channel is quantitatively important, one would expect to see larger hiring effects for workers under managers with high managerial quality or who have been exposed to the manager for longer. Panel B of Appendix Table A10 documents that the marginal hiring probability is similar across different types of rotating managers, where manager types are defined by using past leave-out means of three team outcomes: promotions, turnover, and absenteeism. Panel C of Appendix Table A10 shows that marginal hiring probabilities are comparable across exposure length, even for workers who have been with the manager for only one quarter, suggesting that such a channel is unlikely to violate the exclusion restriction.[16]

Monotonicity— I do not find any evidence suggesting that my results are biased by the existence of a large defier population. In my setting, defiers are individuals who would have applied in the absence of a manager rotation, but whose unobserved propensity to apply is reduced by the instrument. Following Arnold et al. (2018) and Bhuller et al. (2020), I show that the first-stage relationship between applications and manager rotation remains positive for all subgroups of workers defined by eight observable worker characteristics: age, tenure, educational qualification, marital status, family status, German citizenship, team leadership, and past performance rating (Panel A of Appendix Table A11). To further test for the presence of defiers, I use two measures. First, I split my sample into workers who have never applied before and those who have applied before. Columns 1 and 2 of Appendix Table A11, Panel B show that workers who applied in the past and who are

[15] An alternative approach to illustrate random assignment is presented by the event study in Panel A of Figure 1 that shows the absence of pre-trends in worker applications before managers announce their rotation.

[16] Moreover, any estimated gender differences in hiring outcomes in Section 6.1 will be unaffected by biases that affect men and women equally.

more likely to be defiers do not experience lower or negative application effects when managers rotate. Second, I use the leave-out team mean of past application rates as predictor for workers' unobserved application propensity. Columns 3 and 4 of Appendix Table A11, Panel B show that even workers in teams with high application rates experience positive rotation effects.

6 Talent Hoarding, Misallocation, and Gender Inequality

This section demonstrates that talent hoarding has important efficiency costs in the form of misallocation of talent. I find that talent hoarding reduces the quality and subsequent performance of promoted workers. Moreover, misallocation effects are larger for women, implying that talent hoarding exacerbates gender inequality with respect to representation and pay.

To test for misallocation, I evaluate whether qualified workers are deterred from moving to higher-level positions in which they could be more productive. This notion of misallocation is in line with the literature on optimal hierarchies (Rosen, 1982), which holds that firms must promote high-ability workers to high-level positions to efficiently allocate talent. I analyze transitions to higher-level positions by focusing on major promotions, described in Section 4.2. These promotions represent critical decisions for the firm's allocation of talent because they reflect meaningful changes in job responsibility, such as transitions from specialists to managers.

I begin by analyzing the extent to which talent hoarding deters applications for major promotions. Column 1 of Table 3 shows that rotations increase applications for major promotions by 0.65 percentage points, corresponding to a 123% increase. This finding suggests that talent hoarding deters a large group of workers from applying for major promotions, shrinking applicant pools and potentially limiting the ability of the firm to fill high-level positions with high-ability workers.

While these findings are suggestive of the negative impacts of talent hoarding on the efficient allocation of talent, impacts may be modest if marginal applicants are unlikely to be successful. To evaluate whether this is the case, I use manager rotation as an instrument for worker applications to estimate the success probability of deterred (marginal) applications. Column 2 of Table 3 reports 2SLS estimates of Equation 5. I find that marginal applications have a 15.11% hiring probability, substantially higher than the baseline success rate of 3.00%. This finding implies that a substantial share of marginal applicants forgoes high-stakes applications, indicating that talent hoarding creates misallocation. Effects are not limited to major promotions as documented by robustness exercises in Appendix Section E, which examine other transition types (e.g. small and very large promotions).

Going a step further, I leverage data on employees' performance ratings to show that deterred applicants would have been more productive at higher-level positions. Performance ratings are designed to provide task-specific feedback on whether a worker has accomplished her tasks in the past evaluation cycle. Since most workers in a team perform very similar tasks, performance ratings are particularly well-suited for drawing comparisons across workers within teams. I assess whether talent hoarding causes forgone performance at higher levels by estimating a 2SLS regression in which the outcome is defined as a worker landing a major promotion *and* performing better than the leave-

out average performance of the new team one year later. Column 3 of Table 3 presents the results of this analysis and shows that 8.40% of marginal applicants land a promotion and outperform their teammates, strongly suggesting that the firm would have foregone higher performance at higher-level jobs had the marginal workers not been promoted.

I provide more detail on the characteristics of deterred applicants using a complier analysis based on Abadie (2003).[17] Table 4 compares average characteristics across the entire employee population (Column 1), always takers who apply even in absence of manager rotations (Column 2), and marginal applicants who only apply if their manager rotates (Column 3), and shows that marginal applicants are positively selected. For instance, while 48.6% of always takers hold a graduate degree, this is true for 63.3% of marginal applicants. Similarly, 56.9% of always takers received high performance ratings prior to applying, compared to 65.2% of marginal applicants, and 5.7% of marginal applicants (but only 2.4% of always takers) have been nominated to a succession list at the firm.

Taken together, these results are consistent with the predictions of the conceptual framework in Section 2: talent hoarding reduces the share of high-quality workers in the applicant pool, limiting the firm's ability to efficiently fill high-level positions. Not only are marginal applicants well-qualified and likely to be successful in their applications, they would also perform well in high-level positions.

6.1 Gender Differences in Misallocation

Survey responses discussed in Section 5.4 indicate that managers hoard talent through direct interpersonal interactions. Such behavior raises the possibility that talent hoarding may be particularly impactful for workers who depend more heavily on managerial support or are more sensitive to confrontation with their manager. Motivated by previous work on gender differences in preferences (Bertrand, 2011), I test whether talent hoarding has differential effects by gender.

I first analyze the effects of manager rotations on worker applications separately for men and women. Column 1 of Table 5 shows that men's applications increase by 0.55 percentage points (a 98% increase), while manager rotations increase women's application rate by 1.05 percentage points, a 244% increase (Column 2). These findings reveal that talent hoarding deters a larger share of female applicants from applying for major promotions compared to males.

To evaluate whether talent hoarding is more detrimental for women than for men, I compare hiring probabilities for men and women at the margin, which can be interpreted as a Becker outcome test. Columns 3 and 4 of Table 5 report the 2SLS estimates of Equation 5, which are separately estimated by gender and capture the probability of landing a major promotion for marginal applicants. Both men and women experience positive and statistically significant marginal hiring probabilities

[17] Under standard IV assumptions discussed in Section 4, complier characteristics can be estimated as $E[X_{it}|\text{Compliers}]$ for some characteristic X_{it}. I calculate average complier characteristics and standard errors by performing 2SLS using the first-stage Equation 3 and a reduced-form equation replacing the outcome variable in Equation 4 with $X_{it}A_{it}$, where X_{it} corresponds to a characteristic of individual i and A_{it} is a binary indicator for i applying in quarter t. I compute characteristics for always takers, who apply even in the presence of talent hoarding, by estimating an OLS regression of $X_{it}A_{it}(1-Z_{it})$ on $A_{it}(1-Z_{it})$, which allows me to estimate $E[X_{it}|\text{Always takers}]$.

of 12.78% and 25.78%, respectively. However, the hiring probability for women is twice that for men, implying that talent hoarding is more consequential for women's career progression.

Differences in promotion likelihoods may also reflect differential labor demand, such as affirmative action policies. To verify that this is not the case, I test whether women would also be more likely to perform well in high-level positions. Columns 5 and 6 of Table 5 present the 2SLS estimate for landing a major promotion and performing better than the average in the new team one year later. Women exhibit a marginal probability of outperforming their teammates of 17.66%, which is almost three times higher than men's marginal probability of 6.38%. This finding suggest that marginal female applicants would not only be more likely to land promotions, they would also be more likely to perform well in these positions.

These findings suggest that talent hoarding may deter higher-quality women compared to men. I again conduct a complier analysis, now separately by gender. Since men and women work in very different positions at the firm, I adjust population characteristics using the same set of baseline controls used in computing complier and always taker characteristics. Table 6 documents that marginal female applicants who are deterred from applying by talent hoarding are strongly positively selected compared to always takers and average workers. While 74.7% of marginal female applicants hold a graduate degree, this is only true for 39.0% of always takers. Similarly, 73.6% (73.4%) of women at the margin received high performance (potential) ratings in the past relative to 53.8% (43.1%) of always takers. 8.7% of female marginal applicants have been nominated to succession lists (i.e. suitable successors for high-level positions), while the firm only nominated 2.9% of always takers. For men, the extent of this positive selection is substantially less pronounced, suggesting that talent hoarding affects women at a higher part of the quality distribution compared to men. Together, these results indicate that talent hoarding has more severe misallocation effects on women.

6.2 Impacts on Gender Inequality in Pay and Representation

The preceding results documenting disparate impacts of talent hoarding by gender suggest that talent hoarding may exacerbate gender inequality at the firm. To quantify the differential effect of talent hoarding by gender, I make use of the potential outcomes framework that follows from the interpretation of β_{IV} as the LATE for marginal applicants. In this framework, $Y(0)$ represents potential outcomes in the untreated state, had marginal applicants not applied for promotions because of talent hoarding. $Y(1)$ denotes the treated state, had marginal applicants applied for promotions because talent hoarding subsided. I compare the outcomes that would be observed for marginal applicants in presence versus in absence of talent hoarding by assessing the effect of applications on workers' real annual earnings and hierarchy levels one year later.

Within the potential outcomes framework, I compare the gender gap in the untreated state to the gender gap in the treated state, allowing me to evaluate the effect of applications on gender disparities. The advantage of using this potential outcomes framework is that it allows a comparison of the same set of individuals across two different potential outcomes, avoiding potential composition bias. Limiting attention to marginal applicants is not restrictive, since they represent the group of

workers whose outcomes differ because of talent hoarding. To test for gender differences in these worker outcomes, I follow the literature assessing gender pay gaps (Blau and Kahn, 2017) and estimate worker outcomes separately by gender for marginal applicants in each potential outcomes state. I include the same set of controls X_{it} as in previous models and focus on hierarchy levels and log annual earnings measured in quarter $t+4$ for my outcomes of interest.

Panel A of Figure 5 presents estimates of hierarchy levels in quarter $t+4$ for marginal applicants in both potential outcomes states by gender. Outcomes are reported in terms of percentiles at the firm. Both men and women experience higher hierarchy levels if they choose to apply; however, the larger gains realized by women lead to a reduction in the representation gap by 91%. This reduction in gender differences with respect to hierarchy levels translates into a substantial reduction in the earnings gap. Panel B presents log annual real earnings across treatment states in percentiles. Applying substantially increases worker earnings four quarters later and appears to reduce gender disparities in pay by 77%. This finding suggests that talent hoarding exacerbates gender inequality with respect to pay and representation in the firm, highlighting the negative consequences of talent hoarding with respect to both efficacy and equity in the internal labor market.

7 Unpacking Talent Hoarding: Suggestive Evidence

The documented costs of talent hoarding, particularly for women, raise the question of which factors underlie these impacts. Do talent hoarding effects depend on manager and worker characteristics? For instance, do managers treat women differently, or are there differences in how women and men react to talent hoarding? This section investigates the role of manager and worker characteristics and what this implies for how organizations may react to talent hoarding.

Previous research has highlighted the importance of manager gender as a key correlate of manager behavior, particularly when trying to explain gender differences in worker outcomes (e.g. Kunze and Miller, 2017, Cullen and Perez-Truglia, 2019). Accordingly, I begin by comparing the first-stage effects of manager rotations on worker applications by manager gender. Columns 1 and 2 of Table 7, Panel A show that there is no statistically detectable difference between the impacts of rotations by male and by female managers. Similarly, Columns 3 and 4 show that there are no substantial differences by whether managers and workers have opposite genders. In unreported results, I find that this pattern persists when conducting estimation separately for male versus female workers.

Talent hoarding behavior may also differ due to other manager characteristics. Table 7 examines heterogeneity in rotation effects by key manager characteristics, such as age (Columns 5 and 6 of Panel A), experience (Columns 1 and 2 of Panel B), and managerial quality (Columns 3 to 6 of Panel B). To assess managerial quality, I use managers' own performance ratings which they received from their direct supervisor and the leave-out mean absenteeism rate that the manager's team had in the past. Comparing bottom and top quartiles of these measures, I do not find differential effects by manager characteristics. In unreported results, I also find that leave-out mean team turnover rates in the past and other manager evaluations by their supervisor that complement performance

ratings (e.g. rating of problem solving ability) do not predict the magnitude of rotation effects.

I find similar patterns using managers' suppression of worker visibility as direct measure of their talent hoarding propensity. An F-test of all manager characteristics included in the logit regressions presented in Columns 1 and 2 of Table 8—which besides manager gender include their age, marital and family status, tenure at the firm, division, function, and location—rejects their joint significance in explaining the propensity to hoard talent. While the survey results support the interpretation of manager differences in talent hoarding as differences in self-interest or altruism, future research that elicits managers' personality traits that are not contained in personnel records may help to provide additional information on the reasons why some managers hoard more than others.

The finding that talent hoarding behavior is not correlated with manager or team-level characteristics that are easily observable has important implications for how to detect talent hoarding. My analysis suggests that it is not possible to accurately predict a manager's propensity to hoard talent using observable characteristics. Without a rigorous data collection and analysis effort it is difficult for firms to pin down which managers are hoarding talent because forgone promotions can be attributed to a range of different factors – including managers hoarding talent, workers not wanting to pursue promotions, or hiring managers choosing other candidates.[18]

Similarly, workers seem not be able to find out whether a manager that they have not worked with before is a talent hoarder. When assessing the number of workers who apply for an internal job opening, the talent hoarding propensity of the team's manager carries no predictive power for workers' application decisions. This finding is in line with the general application pattern that internal applicants only in rare cases have worked with anyone in the team before applying to a job opening, reducing worker ability to gather information about a manager's talent hoarding propensity. These results echo findings from the literature on asymmetric information in firms (Kahn and Lange, 2014) and help to rationalize why talent hoarding may persist, even if firms know that misaligned incentives exist.

In addition to manager characteristics, the impacts of talent hoarding likely differ by workers. Since talent hoarding has very different effects by gender, a first-order question is whether managers hoard women more or whether women react to talent hoarding more. Because the rotation effects on applications depend both on managers and workers, they cannot distinguish worker effects from manager effects. To isolate manager behavior, I use the two measures of managerial talent hoarding described in Section 4.1. Columns 3 and 4 of Table 8 document that worker gender does not significantly affect managers' talent hoarding behavior. I also find no gender difference in workers' likelihood of reporting fearing manager retaliation, which is a key dimension of talent hoarding (Figure 6). These findings suggest that managers do not hoard women more than men.

Instead, employees' survey responses suggest that men and women react differently to talent hoarding. In the survey, women are 29% more likely than similar men to mention the importance of manager support for their career development (Figure 6), suggesting that they rely more on

[18]In line with infrastructure constraints, the firm in this study is not able to assemble and analyze a dataset that would allow them to detect talent hoarding. Consequently, the findings in this research study represent the first empirical test of talent hoarding at the firm that is difficult for practitioners to implement.

managers' career guidance. In addition, women are 19% more likely to rank a good relationship with their supervisor as the most important feature of their job (Figure 6), indicating that women seem to place more value on preserving a good relationship with their manager. These findings are in line with the fact that talent hoarding typically occurs through direct interpersonal interactions and are consistent with a large body of research on gender differences in preferences (Bertrand, 2011). Taken together, my results suggest that despite being gender-neutral, talent hoarding produces disparate effects due to workers' underlying gender differences. Mitigating talent hoarding may thus allow organizations to reduce gender inequality.

8 Conclusion

This paper provides the first empirical evidence that talent hoarding is an important source of frictions in organizations. Using novel personnel records and internal application data from a large manufacturing firm in Germany, I show that talent hoarding leads to misallocation of talent and perpetuates gender inequality at the firm. While my results provide the first detailed empirical evidence on talent hoarding, additional evidence suggests that such talent hoarding behavior is endemic. In a survey of top publicly listed companies in Germany, 83% cite talent hoarding as crucial friction in their organization (hkp///, 2021). Firm surveys in the United States document that talent hoarding is also common in US firms (i4cp, 2016, KornFerry, 2015).

Because talent hoarding arises due to misaligned managerial incentives, a natural solution would be to more closely align the incentives of managers with those of the firm. Surveys of German firms suggest that accomplishing this realignment through financial incentives is infeasible (HKP 2021). However, policies that increase application rates — such as implementing regular application schedules and having other organizational agents, such as the human resources department, directly invite workers to apply for positions — could reduce the scope for managers to engage in talent hoarding. The worker level survey I conduct shows that for such policies to be effective, the firm must be able to deter managers from retaliating against workers, for instance by assuring full confidentiality for applicants.

While the costs of these policies are likely to be non-negligible, their potential benefits are substantial given the potential gains for firms. A key contribution of this analysis has been to provide the first empirical evidence showing that talent hoarding has meaningful efficiency costs in the form of talent misallocation. It is likely that organizations suffer additional efficiency costs through other channels. The employee survey suggests that talent hoarding leads managers to deter workers from pursuing training programs and from participating in high-profile projects in order to suppress worker visibility. These actions likely cause substantial underinvestment in human capital. In addition, workers who report being subject to talent hoarding are 30% more likely to report having searched for external jobs, indicating that talent hoarding may create unwanted turnover of high-quality workers the firm would like to retain. These findings suggest that the estimates in this study represent a lower bound for the efficiency costs of talent hoarding. Future research that

quantifies these costs will help provide a more complete picture of the impacts of talent hoarding.

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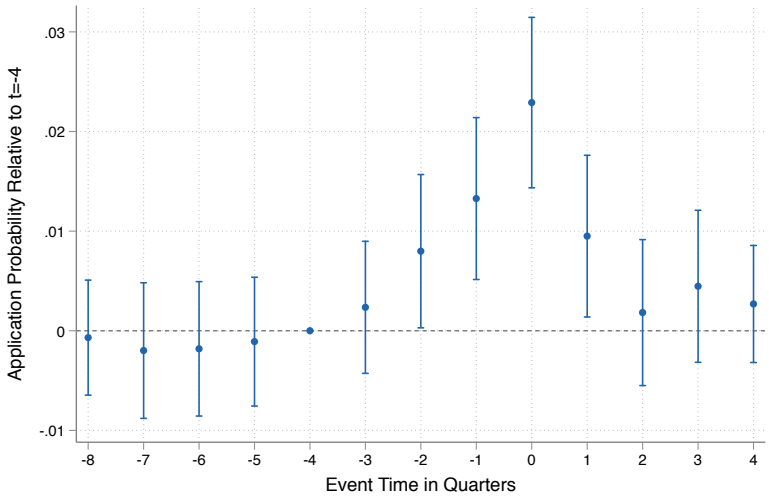
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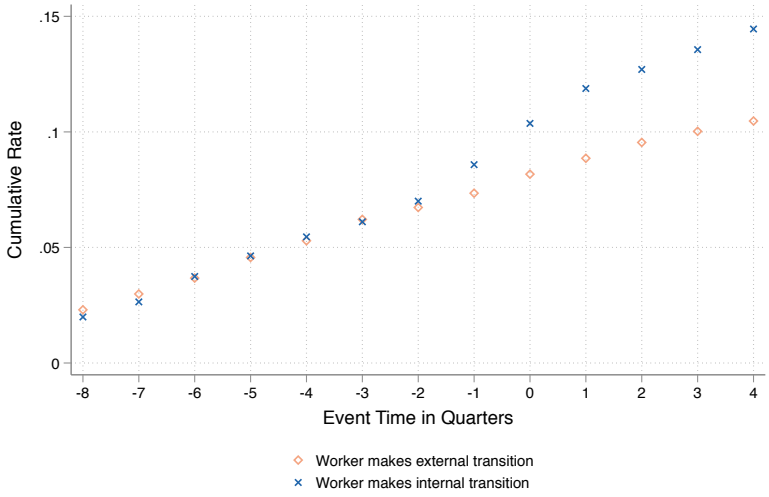
9 Figures and Tables

Figure 1: Effect of Manager Rotations on Applications and Job Transitions

Panel A. Application Probability



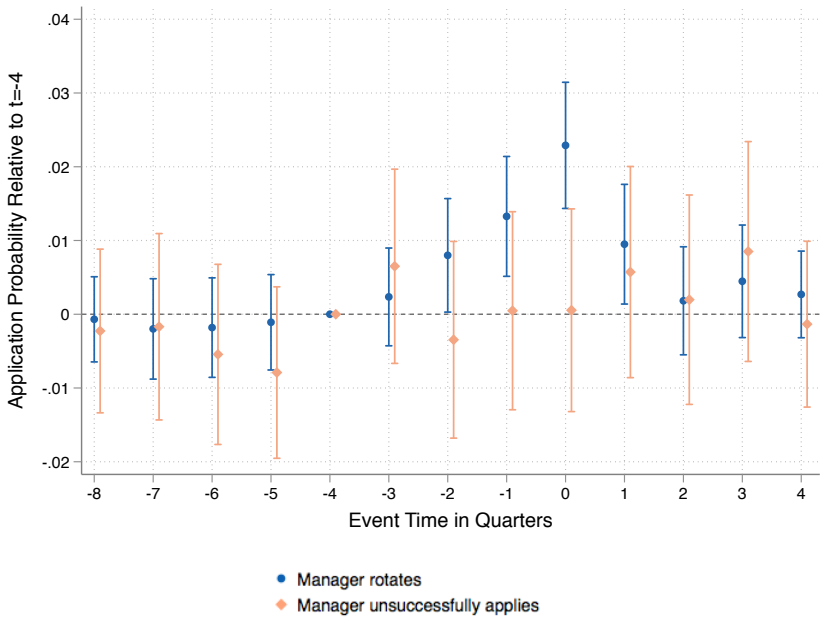
Panel B. Cumulative Transition Probability



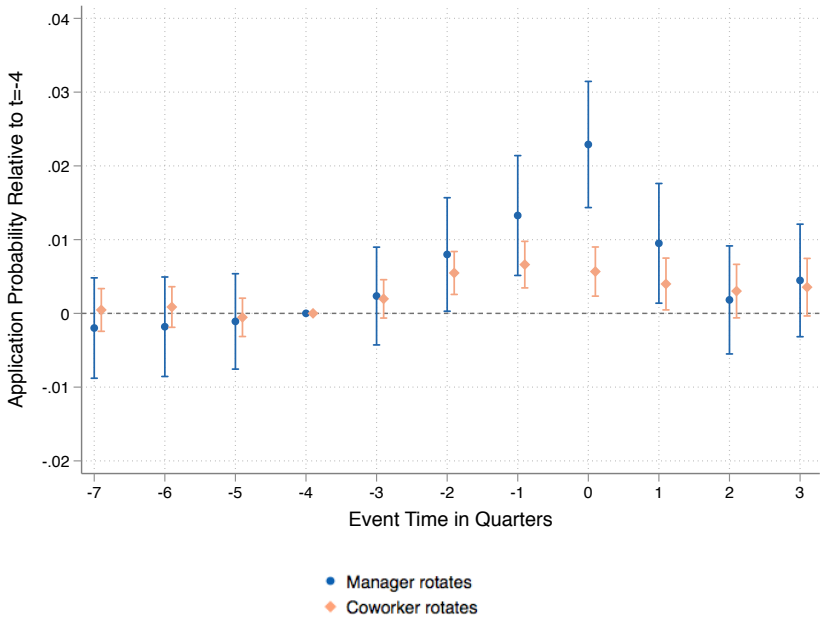
Notes: This figure documents internal applications (Panel A) and job transitions (Panel B) around a manager rotation. Panel A presents estimates from an event study regression, in which the outcome is an indicator that the worker applied in a quarter and event time is defined relative to the occurrence of a manager rotation. The specification includes worker and quarter fixed effects. I bin event time dummy variables at $t = -8$ and $t = 4$ and cluster standard errors at the worker level. The mean application rate as of $t = -4$ is 0.027. The sample of 3,xxx workers includes those who have not experienced a manager rotation (i.e. never-treated). Panel B plots the cumulative share of workers who have exited the team via internal (i.e. within the firm) and external (i.e. out of the firm) transitions around a manager rotation. Workers are assigned to their team as of ten quarters before the team experiences a manager rotation.

Figure 2: Placebo Test of Manager Rotations

Panel A. Results by Outcome of Manager Application

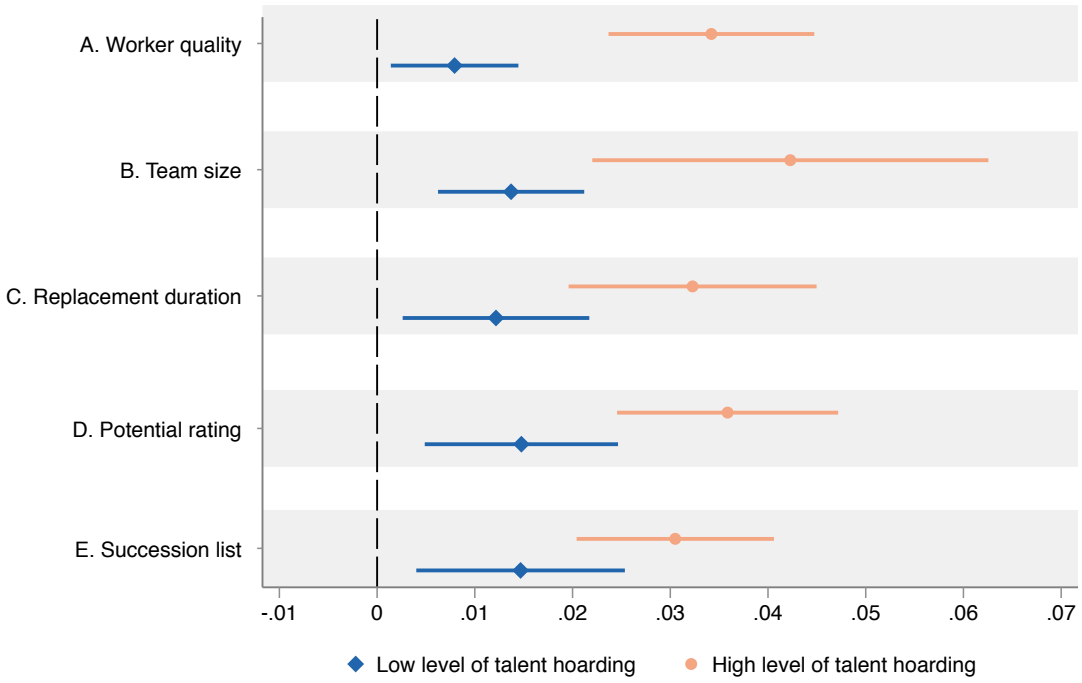


Panel B. Results by Type of Rotating Teammate



Notes: This figure presents placebo tests of manager rotations. Estimates stem from event study regressions, in which the outcome is an indicator that the worker applied in a quarter and event time is defined relative to the occurrence of a rotation event. The specification includes worker and quarter fixed effects. I bin event time dummy variables at $t = -8$ and $t = 4$ and cluster standard errors at the worker level. The mean application rate as of $t = -4$ is 0.027. The sample includes those who have not experienced a manager rotation (i.e. never-treated). Panel A compares a successful manager rotation (in blue, N=3, xxx) to a placebo event, in which a manager applied for an internal job rotation, but did not land the position and stayed in the team (in orange, N= 1,xxx). Panel B compares a manager rotation (in blue, N=3, xxx) to the rotation of the most senior coworker (in orange, N= 2x,xxx).

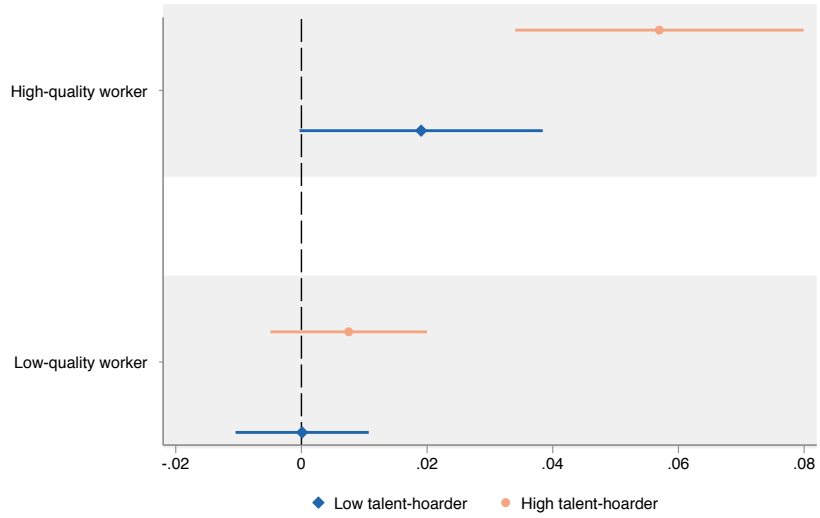
Figure 3: Heterogeneity in Application Effects by Predicted Level of Talent Hoarding



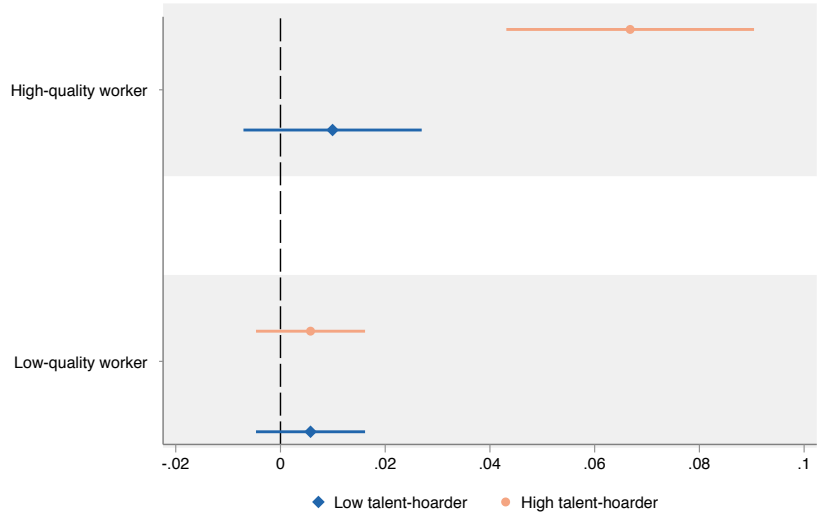
Notes: This figure demonstrates larger impacts of manager rotations on worker applications for subgroups that are expected to experience *high* instead of *low* predicted levels of talent hoarding. Each coefficient stems from a separate regression based on Equation 3 using robust standard errors. Panels A, B, and C focus on workers in the bottom and top quartile of the respective measure to distinguish between *high* and *low* levels of hoarding. Panel A uses a quality index, constructed using the predicted value from an OLS regression of workers' internal hiring probability on worker characteristics. Panel B uses team size (*high*: <4 teammates, *low*: >9 teammates). Panel C uses the average number of days it takes to replace a position (*high*: >174 days, *low*: <135 days). Panels D and E compare rotations of manager types with *high* versus *low* propensity to hoard based on systematic discrepancies in worker visibility. Panel D uses the mean deviation between actual and predicted potential ratings. Panel E uses mean deviations in subordinates' probability to be nominated to succession lists. Baseline application rates are very similar across subgroups and are therefore not separately reported. Controls: Female, age, German citizenship, educational qualification, marital status, family status, parental leave, firm tenure, position type, division, functional area, location, full-time, hours, team leadership, number of direct reports, performance and potential rating, time on position, and quarter fixed effects.

Figure 4: Heterogeneity in Application Effects by Hoarding Propensity and Worker Quality

Panel A. Potential Ratings as Measure of Talent Hoarding Propensity



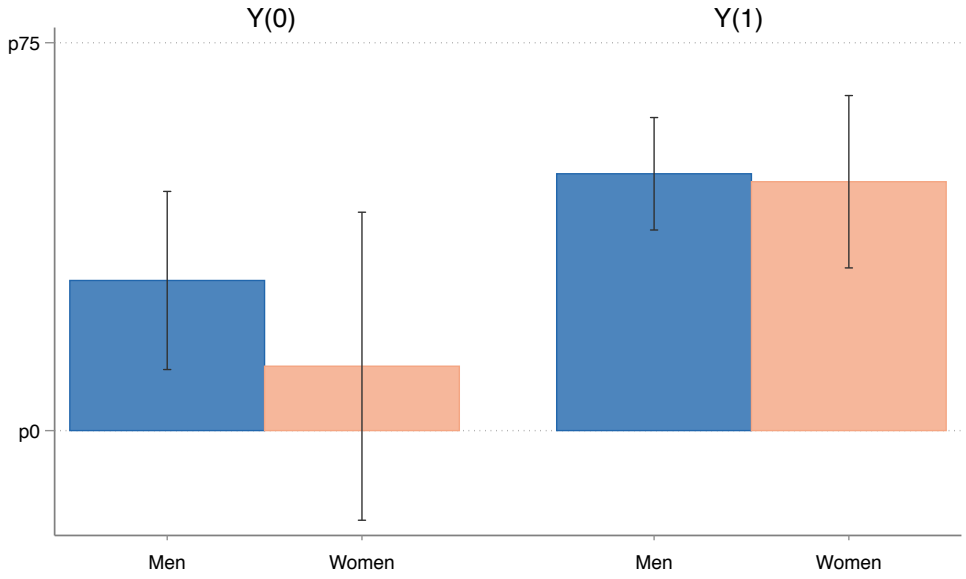
Panel B. Succession Lists as Measure of Talent Hoarding Propensity



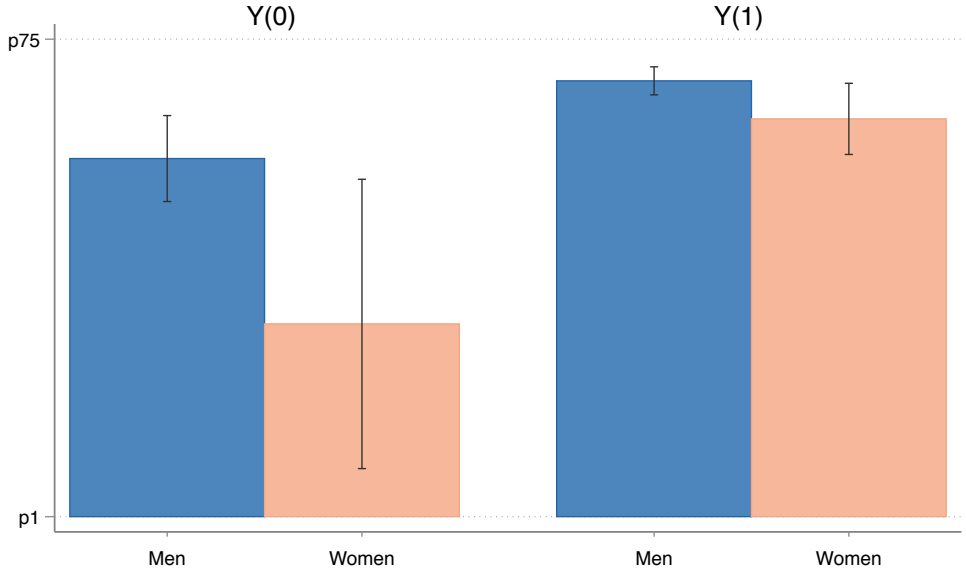
Notes: This figure demonstrates larger impacts of working under a manager with a high talent hoarding propensity for high-quality workers than low-quality workers. Each coefficient stems from a separate regression based on Equation 3 using robust standard errors. High-quality (low-quality) workers represent workers in the top (bottom) quartile of quality. Panel A uses the mean deviation between actual and predicted potential ratings to compare rotations of manager types with *high* versus *low* propensity to hoard. Panel B uses mean deviations in subordinates' probability to be nominated to succession lists. Controls: Female, age, German citizenship, educational qualification, marital status, family status, parental leave, firm tenure, position type, division, functional area, location, full-time, hours, team leadership, number of direct reports, performance and potential rating, time on position, and quarter fixed effects.

Figure 5: Potential Outcomes by Application Status for Marginal Applicants

Panel A. Hierarchy Level at $t+4$

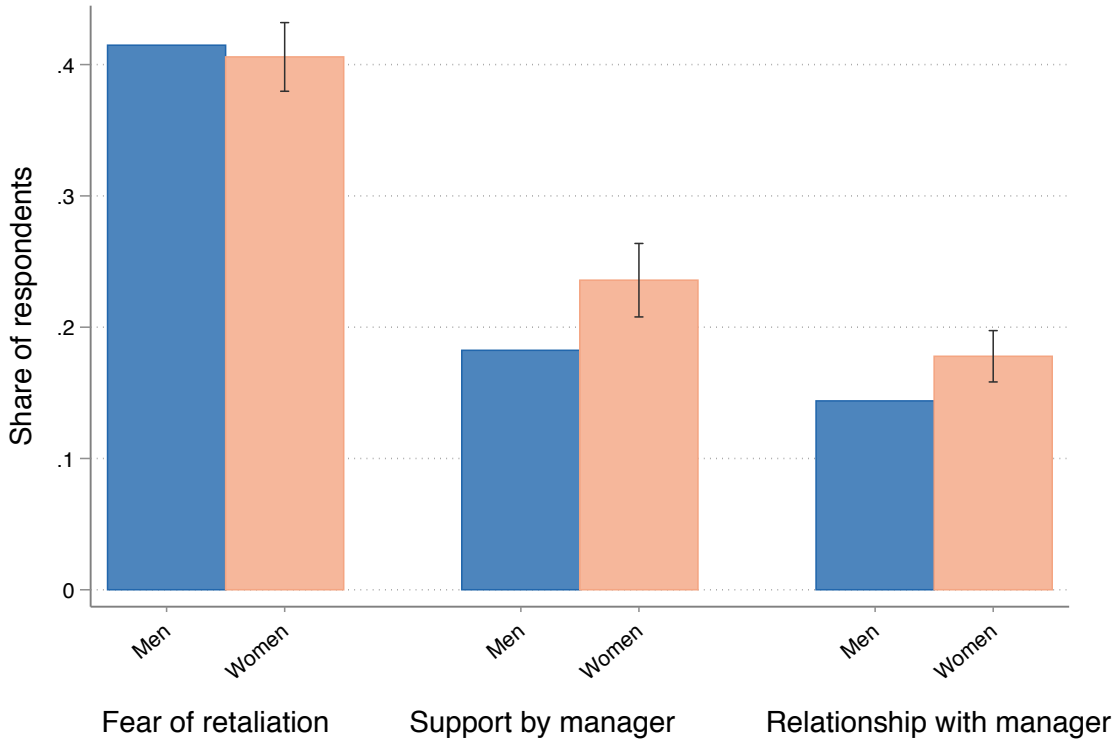


Panel B. Log Real Annual Earnings at $t+4$



Notes: This figure displays marginal applicants' potential outcomes in quarter $t+4$, measured in percentiles. The left two bars in each panel represent the potential outcomes for marginal applicants in the untreated state $Y(0)$ (i.e. had they not applied). The right two bars represent the potential outcome for marginal applicants in the treated state $Y(1)$ (i.e. had they applied). Panel A presents workers' hierarchy level in quarter $t+4$. Panel B presents workers' log real annual earnings in quarter $t+4$. The total number of observations is 3xx,xxx. Standard errors are robust. Controls: Female, age, German citizenship, educational qualification, marital status, family status, parental leave, firm tenure, position type, division, functional area, location, full-time, hours, team leadership, number of direct reports, performance and potential rating, time on position, and quarter fixed effects.

Figure 6: Gender Differences in Survey Responses



Notes: This figure displays survey responses separately estimated by gender using robust standard errors. Bars 1 and 2 represent the share of respondents who report fearing retaliation if their manager were to find out about internal applications. Bars 3 and 4 represent the share of respondents who rank manager support as most important for their career progression. Bars 5 and 6 report the share of respondents who rank a good relationship with their manager as the most important feature of their job. While men and women are similarly likely to report fearing negative repercussions, women are 29% more likely to value manager support and 19% more likely to value a good relationship with their manager than similar men. Controls: Age, tenure, schooling, nationality, children, functional area, location, full-time, hours, and team leadership. The total number of observations is 1x,xxx.

Table 1: Summary Statistics of Analysis Sample

	Mean	Std. deviation	p25	p75
Demographics				
Female	0.21	0.40	0.00	0.00
German citizen	0.89	0.31	1.00	1.00
Age (years)	43.41	10.03	35.00	51.50
Tenure at firm (years)	13.34	9.65	5.00	19.25
Schooling (years)	15.81	2.74	12.00	18.00
Married	0.62	0.49	0.00	1.00
Children	0.75	0.43	0.00	1.00
On parental leave	0.03	0.17	0.00	0.00
Position Characteristics				
Technical position	0.63	0.48	0.00	1.00
Full-time	0.92	0.27	1.00	1.00
Weekly hours	41.15	4.56	40.75	43.50
Team leadership	0.19	0.39	0.00	0.00
Number of direct reports	5.00	3.89	2.00	7.00
Career Progression				
High performance rating	0.54	0.50	0.00	1.0
High potential rating	0.27	0.44	0.00	1.00
Time in position (quarters)	13.34	9.74	5.00	21.00
Internal application	0.03	0.17	0.00	0.00
Internal job transition	0.01	0.09	0.00	0.00
Observations		3xx ,xxx		

Notes: This table reports summary statistics for the quarterly analysis sample. This sample consists of over 300,000 employee-by-quarter observations from 2015 to 2018. A technical position is defined as a job related to engineering, IT, quality management, or production. The number of direct reports is only calculated for employees with team leadership. A high performance rating is defined as *sometimes exceeds expectations* or *often exceeds expectations*. High potential rating refers to supervisors' assessment that workers have future potential for higher-level positions. Internal application and job transition rates are at the quarterly level.

Table 2: Application Effects of Manager Rotations by Position Selectivity

	Application to			
	Any position	Lateral transition	Small promotion	Major promotion
	(1)	(2)	(3)	(4)
Manager Rotation	0.0224***	0.0030**	0.0115***	0.0065***
	(0.003)	(0.001)	(0.002)	(0.001)
Outcome Mean	0.0290	0.0049	0.0118	0.0053
Size of Effect in %	76	61	98	123
Observations	3xx,xxx	3xx,xxx	3xx,xxx	3xx,xxx

Notes: This table illustrates the effect of manager rotations on worker applications in the same quarter. Column 1 shows the effect of manager rotations for any positions, Column 2 represents lateral transitions. Column 3 focuses on small promotions, defined as an increase in the hierarchy index between 10 and 20. Column 4 focuses on applications for major promotions, which are defined as an increase in the hierarchy index of 20 or more and represent large career jumps, such as transitions from specialist to team leader positions. Controls: Female, age, German citizenship, educational qualification, marital status, family status, parental leave, firm tenure, position type, division, functional area, location, full-time, hours, team leadership, number of direct reports, performance and potential rating, time on position, and quarter fixed effects. Robust standard errors in parentheses. *p< 0.10, **p< 0.05, ***p< 0.01.

Table 3: Misallocation Effects of Talent Hoarding

	OLS	IV	IV
	Applied to major promotion	Hired for major promotion	Perform>team average if land major promotion
	(1)	(2)	(3)
Manager Rotation	0.0065***	-	-
	(0.001)	-	-
Applied	-	0.1511***	0.0840**
	-	(0.034)	(0.026)
Outcome Mean	0.0053	0.0009	0.3673
Observations	3xx,xxx	3xx,xxx	3xx,xxx

Notes: This table reports the effects of manager rotations on workers' career progression. Each coefficient is based on a separate regression. Column 1 reports the first-stage effect of manager rotation on applications for major promotions based on Equation 3. Column 2 reports the estimate from a two-stages least squares regression on landing a major promotion that instruments for applying with manager rotation based on Equation 5 which represents the LATE. Column 3 estimates a similar two-stages least squares regression, but uses an indicator for landing a major promotion *and* performing better than the leave-out team average one year later as outcome variable. Controls: Female, age, German citizenship, educational qualification, marital status, family status, parental leave, firm tenure, position type, division, functional area, location, full-time, hours, team leadership, number of direct reports, performance and potential rating, time on position, and quarter fixed effects. Robust standard errors in parentheses.*p< 0.10, **p< 0.05, ***p< 0.01.

Table 4: Characteristics of Marginal Applicants (in %)

	All workers (1)	Always taker (2)	Marginal applicant (3)
German citizen	89.8	87.2	86.4
Age >=40yrs	60.4	39.2	50.6
Married	61.7	54.8	49.5
Children	73.3	68.6	63.6
Tenure at firm <2yrs	37.5	53.4	49.2
Tenure at firm 2-5yrs	40.5	38.0	38.5
Tenure at firm >=5yrs	21.9	8.6	12.3
Graduate degree	47.6	48.6	63.3
Full-time	92.5	94.4	97.1
High performance	54.0	56.9	65.2
High potential	28.2	44.0	43.0
Technical position	63.2	56.7	59.1
Low-level position	68.9	73.6	77.7
First-level leadership position	11.5	9.7	7.4
Time in position <2yrs	37.1	38.3	39.3
Time in position 2-5yrs	36.2	40.9	42.1
Time in position >=5yrs	26.7	20.8	18.5
Nominated to succession list	1.6	2.4	5.7
Applied 12 months before	2.6	11.2	2.6

Notes: This table illustrates results from a complier analysis as described in Section 6. Each number is based on a separate regression including controls and represents an adjusted mean (in %). Column 1 shows means for all workers, Column 2 represents always takers, and Column 3 represents marginal applicants, who only apply if managers rotate and talent hoarding temporarily subsides. Each number represents the share of workers in a given group that exhibit the respective characteristic. A technical position is defined as a job related to engineering, IT, quality management, or production. Low-level positions are defined as positions at low hierarchy levels without leadership responsibility (i.e. individual contributors). First-level leadership represents positions with limited leadership responsibility, such as team leaders. Controls: Female, age, German citizenship, educational qualification, marital status, family status, parental leave, firm tenure, position type, division, functional area, location, full-time, hours, team leadership, number of direct reports, performance and potential rating, time on position, and quarter fixed effects.

Table 5: Misallocation Effects of Talent Hoarding by Gender

	OLS		IV		IV	
	Applied to major promotion		Hired for major promotion		Perform>team average if land major promotion	
	Men	Women	Men	Women	Men	Women
	(1)	(2)	(3)	(4)	(5)	(6)
Manager Rotation	0.0055***	0.0105***	-	-	-	-
	(0.001)	(0.003)	-	-	-	-
Applied	-	-	0.1278***	0.2578**	0.0638**	0.1766**
	-	-	(0.036)	(0.106)	(0.026)	(0.086)
Outcome Mean	0.0056	0.0041	0.0009	0.0009	0.3817	0.3572
Observations	3xx,xxx	8x,xxx	3xx,xxx	8x,xxx	3xx,xxx	8x,xxx

Notes: This table reports the effects of manager rotations on workers' career progression by gender. Each coefficient is based on a separate regression. Columns 1 and 2 report first-stage effects of manager rotation on applications for major promotions based on Equation 3. Columns 3 and 4 report estimates from a two-stages least squares regression on landing a major promotion that instruments for applying with manager rotation based on Equation 5. Columns 5 and 6 estimate a similar two-stages least squares regression, but use an indicator for landing a major promotion *and* performing better than the leave-out team average one year later as outcome variable. Controls: Female, age, German citizenship, educational qualification, marital status, family status, parental leave, firm tenure, position type, division, functional area, location, full-time, hours, team leadership, number of direct reports, performance and potential rating, time on position, and quarter fixed effects. Robust standard errors in parentheses.*p< 0.10, **p< 0.05, ***p< 0.01.

Table 6: Characteristics of Marginal Applicants by Gender (in %)

	Men			Women		
	All worker	Always takers	Marginal applicants	All workers	Always takers	Marginal applicants
	(1)	(2)	(3)	(4)	(5)	(6)
German citizen	90.7	87.9	85.1	84.4	84.8	91.4
Age >=40yrs	63.6	43.2	50.9	59.4	25.6	49.2
Married	64.5	60.1	51.4	55.8	36.9	43.0
Children	76.0	72.9	60.0	68.8	54.3	80.2
Tenure at firm <2yrs	36.1	51.0	51.6	35.2	61.3	37.9
Tenure at firm 2-5yrs	41.1	40.2	38.0	41.5	30.7	41.8
Tenure at firm >=5yrs	22.8	8.7	10.4	23.3	8.0	20.3
Graduate degree	51.5	51.4	61.0	48.4	39.0	74.7
Full-time	97.4	97.9	100.0	73.2	82.4	79.9
High performance	56.1	57.8	63.6	55.4	53.8	73.6
High potential	28.7	44.3	36.1	27.7	43.1	73.4
Technical position	71.0	64.9	66.3	45.5	29.1	32.3
Low-level position	67.8	72.5	76.4	68.8	77.4	83.6
First-level leadership position	12.8	10.8	8.0	12.4	5.8	4.9
Time in position <2yrs	36.7	37.7	43.8	37.3	40.7	20.0
Time in position 2-5yrs	36.2	40.0	37.2	36.2	43.8	63.0
Time in position >=5yrs	27.1	22.4	19.0	26.4	15.5	17.0
Nominated to succession list	1.6	2.3	5.0	1.6	2.9	8.7
Applied 12 months before	2.6	11.7	2.4	2.4	9.4	4.3

Notes: This table illustrates results from a complier analysis by gender. Each number is based on a separate regression including controls and represents an adjusted mean (in %). Columns 1 and 4 show means for all workers, Columns 2 and 5 represent always takers, and Columns 3 and 6 reflect marginal applicants, who only apply if managers rotate and talent hoarding temporarily subsides. A technical position is defined as a job related to engineering, IT, quality management, or production. Low-level positions are defined as positions at low hierarchy levels without leadership responsibility (i.e. individual contributors). First-level leadership represents positions with limited leadership responsibility, such as team leaders. Controls: Female, age, German citizenship, educational qualification, marital status, family status, parental leave, firm tenure, position type, division, functional area, location, full-time, hours, team leadership, number of direct reports, performance and potential rating, time on position, and quarter fixed effects.

Table 7: Application Effects of Manager Rotation by Manager Characteristics

Dependent variable: Workers' internal applications

Panel A: Manager Attributes

	Manager Gender		Manager vs Worker Gender		Age	
	Male	Female	Opposite	Same	Old	Young
	(1)	(2)	(3)	(4)	(5)	(6)
Manager Rotation	0.0211***	0.0315***	0.0268***	0.0210***	0.0226***	0.0234***
	(0.003)	(0.009)	(0.006)	(0.003)	(0.003)	(0.006)
Outcome Mean	0.028	0.028	0.028	0.028	0.028	0.028
Adj R-squared	0.013	0.012	0.012	0.012	0.012	0.013
P-value of t-test	0.2612		0.6329		0.8956	
Observations	3xx,xxx	3xx,xxx	3xx,xxx	3xx,xxx	3xx,xxx	3xx,xxx

Panel B: Manager Quality

	Experience as manager		Manager performance		Team absenteeism	
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
Manager Rotation	0.0193***	0.0238***	0.0206***	0.0181***	0.0207***	0.0201***
	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)
Outcome Mean	0.028	0.028	0.028	0.028	0.028	0.028
Adj R-squared	0.012	0.013	0.013	0.012	0.012	0.012
P-value of t-test	0.5487		0.7240		0.9353	
Observations	3xx,xxx	3xx,xxx	3xx,xxx	3xx,xxx	3xx,xxx	3xx,xxx

Notes: This table illustrates heterogeneity in the effect of rotations on worker applications by manager characteristics. Each coefficient stems from a separate regression based on Equation 3, where the rotation event is restricted to managers with a given characteristic. Panel A compares application effects by manager gender (Columns 1 and 2), manager vs worker gender (Columns 3 and 4), and age split at the sample median of 40 years (Columns 5 and 6). Panel B compares application effects by manager quality as measured by experience as manager at the firm (Columns 1 and 2), managers' own performance rating (Columns 3 and 4), as well as absenteeism rates (Columns 5 and 6). All splits in Panel B are with respect to the top and bottom quartile of the respective measure. In both panels, I find no statistical difference in the effect between each pair-wise comparison as indicated by the p-value of the corresponding t-test. Controls: Female, age, German citizenship, educational qualification, marital status, family status, parental leave, firm tenure, position type, division, functional area, location, full-time, hours, team leadership, number of direct reports, performance and potential rating, time on position, and quarter fixed effects. *p< 0.10, **p< 0.05, ***p< 0.01.

Table 8: Impact of Manager and Worker Gender on Talent Hoarding Propensity

	Manager-level		Worker-level	
	Potential rating	Succession nomination	Potential rating	Succession nomination
	(1)	(2)	(3)	(4)
Female	-0.003	-0.118	-0.013	0.054
	(0.217)	(0.228)	(0.012)	(0.036)
Outcome Mean	0.2875	0.3135	0.3768	0.0160
Av ME for Women	-0.0007	-0.0239	-0.0019	0.0010
Gender Gap in %	-0	-8	-1	6
Prob > chi2	0.398	0.341	0.000	0.000
Observations	1,xxx	1,xxx	3xx,xxx	3xx,xxx

Notes: This table examines the impact of gender on managers' decisions to make worker talent visible. Each column is based on a separate logit regression where the regressor of interest is whether the manager is female (Columns 1 and 2) or the worker is female (Columns 3 and 4). Columns 1 and 2 are at the manager-level and estimate the propensity that managers manipulate worker visibility through suppressing potential ratings or nominations to succession lists. Controls include manager age, marital and family status, and experience at the firm, division, function, and location. Columns 3 and 4 are at the worker-level and estimate the propensity that workers' talents are made visible through rating them as potentials or nominating them to a succession list. Controls include age, tenure, schooling, nationality, married, kids, parental leave, position title, division, function, location, full time, hours, leadership, direct reports, past mobility, quarter, and performance. Robust standard errors in parentheses. *p< 0.10, **p< 0.05, ***p< 0.01.

Appendices

A Appendix Tables

Table A1: Workers' Quotations from Survey on Talent Hoarding

Form of Talent Hoarding	Quotations by Workers
Informal underrating	"[My] former boss made me look bad at the potential new superiors behind my back in order to keep me on the team."
Formal underrating	"Supervisors suppress potential ratings because of fear that employees will leave their current position for a promotion." "Out of fear that workers will leave the team, supervisors tend to underrate employees." "My supervisor would certainty find out if I applied to another position at the firm and that would have a negative impact on my assessment"
Suppressed development	"[Supervisors] keep employees in their positions by preventing further development, rejecting training courses, and increasing workloads to prevent capacity for new tasks and development measures." "Career development is not supported by direct supervisors, instead it is actively blocked with the goal of keeping people in their current positions."
Soft pressure	"I decided not to apply internally...because the message communicated to me in the employee dialogue was that I can't leave the team within three years of joining." "My boss strongly hinted that in order for my success until now to be considered I need to follow through on my project until the very end otherwise my efforts will not be fully taken into account."
Threats	"...my supervisor communicated very openly in a workshop that if one of his employees applied and was not hired, his career in his current department would also be at an end."
Retaliation	"The position should fit exactly so that negative effects of applying regarding the current manager are worthwhile." "Fear of negative reactions from the supervisor: I have seen it from many colleagues who openly stated that they were applying. These colleagues then received no further training and no more interesting projects. The supervisor had written them off. This made the months leading up to the final change of job very difficult."

Notes: This table displays worker quotations regarding talent hoarding at the firm. The quotations are based on workers' free text responses to questions on internal career development at the firm.

Table A2: Managers' Quotations from Survey on Talent Hoarding

Statement	Quotations by Managers
Acknowledgment	"Many managers are not necessarily interested in developing workers or helping them to get a better job within the firm, because they would lose a good worker. Switches to other areas at the firm are not encouraged, even if it would have been the right move for the worker." "If you are good in what you are doing, it is very unlikely that you will be proposed for a higher position especially if that particular higher position is in a different team." "Supervisors have the policy to do whatever it takes to keep the people in their team, even if this means ignoring the development of the team members."
Misaligned incentives	"Managers have no interest in developing talents because they have no direct benefit from it." "Managers pursue their own goals and often prevent further development of workers, because they are not rewarded for developing talent." "Selfish managers are not willing to promote or recommend subordinates to other areas of the firm, even if that would add value to the firm." "[Middle] Managers can't improve the situation themselves since they depend on the upper management. That is why they block the development of their subordinates." "Regarding the development of your subordinates, there often is a conflict of interests for managers, since the employee then usually leaves the team and the position will not be approved to be refilled again."
Departure costs	"I observe that managers are not interested in letting good workers leave their current position or develop them, otherwise they would have to fill the current position again." "Managers don't actively support workers in switching positions because the vacant position is usually not (immediately) filled again."
Improvement	"Make sure that supervisors at all levels are incentivized to get their employees to the next stage of their career." "Positions are cut if an employee takes on a new job or even dies, so managers are afraid that their team will shrink and they don't know how to do all the work with the rest of the team. Managers would be more open to talk to employees about developing them if they would know that they can fill the vacant position again."

Notes: This table displays manager quotations regarding talent hoarding at the firm. The quotations are based on managers' free text responses to questions on internal career development at the firm.

Table A3: Comparison of Analysis Sample to Respondents of Employee Survey

	Sample (1)	Survey (2)
Demographics		
Female	0.22	0.24
German	0.91	0.94
Age <30 yrs	0.09	0.12
Age 30-39 yrs	0.29	0.32
Age 40-49 yrs	0.26	0.26
Age ≥50 yrs	0.35	0.28
Tenure ≤2 yrs	0.14	0.14
Tenure 3-5 yrs	0.16	0.18
Tenure 6-9 yrs	0.15	0.17
Any children	0.57	0.58
Position Characteristics		
Weekly hours	37	40
Location small	0.16	0.15
Location medium	0.12	0.17
Location large	0.72	0.68
Engineering	0.45	0.41
Finance	0.05	0.05
Marketing and Sales	0.08	0.07
Observations	3x,xxx	1x,xxx

Notes: This table compares average characteristics of the analysis sample (Column 1) to the subset of employees who responded to the employee survey (Column 2). The sample of survey respondents is restricted to only contain responses who took at least five minutes to respond and have no missing observations.

Table A4: Selection into Survey Response by Gender

	Survey Response before Reminder
	(1)
Female	0.023
	(0.0503)
Outcome mean	0.607
Av ME for Women	0.005
Gender Gap in %	0.9
Observations	1x,xxx

Notes: This table tests differential selection into survey responses by gender. Estimates stem from a logit regression of completing the survey before reminders were sent out on gender and employee controls. Controls: Age, tenure, nationality, children, team leadership, full-time, hours, location, functional area. Robust standard errors in parentheses. * p < 0.10, ** p< 0.05, p< 0.01.

Table A5: Comparison of Analysis Sample to Representative Survey of German Workforce

	Analysis sample	Large manufacturer	German workforce
	(1)	(2)	(3)
Female	0.21	0.21	0.45
German	0.89	0.85	0.88
Age (years)	43.3	44.4	43.9
Tenure (years)	14	11	7
Schooling (years)	16	12	12
Married	0.61	0.60	0.54
Children	0.54	0.63	0.62
Weekly hours	41	41	38
Manager	0.18	0.26	0.29
Observations	2x,xxx	1,848	13,791

Notes: This table compares average employee characteristics of my main analysis sample to representative survey measures for employees in Germany in 2018. Column 1 reports statistics for my main analysis sample. Column 2 uses data from the BiBB survey on white-collar employees at manufacturing firms with at least 100 employees in West Germany. Column 3 uses data from the BiBB survey for all labor force participants in West Germany. Columns 2 and 3 are weighted to achieve representativeness of the German population.

Table A6: Effect of Manager Rotations on Applications by Incoming Manager's Characteristics

	Characteristics of Incoming Manager					
	Female	Male	Old	Young	Married	Unmarried
	(1)	(2)	(3)	(4)	(5)	(6)
Manger Rotation	0.0109**	0.0149***	0.0144***	0.0148***	0.0140***	0.0161***
	(0.004)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
Outcome Mean	0.012	0.012	0.012	0.012	0.012	0.012
P-value of t-test	0.3707		0.9207		0.5523	
Observations	3xx,xxx	3xx,xxx	3xx,xxx	3xx,xxx	3xx,xxx	3xx,xxx

	Characteristics of Incoming Manager					
	Firm Tenure		Division		Functionl Area	
	Long	Short	Same	Different	Same	Different
	(1)	(2)	(3)	(4)	(5)	(6)
Manger Rotation	0.0149***	0.0126***	0.0140***	0.0158***	0.0132***	0.0149***
	(0.002)	(0.004)	(0.002)	(0.003)	(0.002)	(0.002)
Outcome Mean	0.012	0.012	0.012	0.012	0.012	0.012
P-value of t-test	0.6220		0.6257		0.5582	
Observations	3xx,xxx	3xx,xxx	3xx,xxx	3xx,xxx	3xx,xxx	3xx,xxx

Note: This table tests the influence of incoming managers' characteristics for the impacts of manager rotations on worker applications. Each coefficient stems from a separate regression based on Equation 3, where I restrict the rotation event to transitions to incoming managers with the respective characteristics. Worker controls: Female, age, German citizenship, educational qualification, marital status, family status, parental leave, firm tenure, position type, division, functional area, location, full-time, hours, team leadership, number of direct reports, performance and potential rating, time on position, and quarter fixed effects. Robust standard errors in parentheses.*p< 0.10, **p< 0.05, ***p< 0.01.

Table A7: Effect of Manager Rotations on Job Transitions and Applications

	Job Transition		Internal Application	
	Internal	External	Incumbent	Newly hired
	(1)	(2)	(3)	(4)
Manager Rotation	0.0109***	0.0009	0.0146***	0.0175***
	(0.002)	(0.001)	0.0146***	0.0175***
Outcome Mean	0.007	0.007	0.027	0.030
P-value of t-test	0.0000		0.4018	
Observations	3xx,xxx	3xx,xxx	1xx,xxx	1xx,xxx

Notes: This table provides evidence in support of talent hoarding as underlying mechanism. Columns 1 and 2 illustrate the effect of manager rotations on workers' job transitions within the firm (Column 1) and out of the firm (Column 2). Consistent with talent hoarding, only internal transitions are affected by rotations. Columns 3 and 4 documents the application effects of manager rotations for workers who have been in the team before the manager arrived (Column 3) and workers who were hired by the rotating manager (Column 4). In contrast to match effects, rotations do not affect workers more who the manager was able to select herself. Controls: Female, age, German citizenship, educational qualification, marital status, family status, parental leave, firm tenure, position type, division, functional area, location, full-time, hours, team leadership, number of direct reports, performance and potential rating, time on position, and quarter fixed effects. Robust standard errors in parentheses.*p< 0.10, **p< 0.05, ***p< 0.01.

Table A8: Effect of Manager Rotations by Destination of Application

	Division		Functional Area		Location	
	Same	Different	Same	Different	Same	Different
	(1)	(2)	(3)	(4)	(5)	(6)
Manager Rotation	0.01557***	0.00716***	0.01407***	0.00818***	0.01769***	0.00438***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Outcome Mean	0.01438	0.01434	0.01575	0.01310	0.01777	0.00963
P-value of t-test	0.0021		0.0307		0.0000	
Observations	3xx,xxx	3xx,xxx	3xx,xxx	3xx,xxx	3xx,xxx	3xx,xxx

Notes: This table illustrates heterogeneity in the effect of manager rotations on worker applications by the destination of applications. Under talent hoarding, workers should disproportionally hold off on applications about which managers are likely to find out (e.g. because of proximity to the hiring manager). I assess three dimension of proximity compared to worker's current position: same versus different division (Columns 1 and 2), same versus different functional area (Columns 3 and 4), and same versus different location (Columns 5 and 6). Each coefficient stems from a separate regression based on Equation 3. Controls: Female, age, German citizenship, educational qualification, marital status, family status, parental leave, firm tenure, position type, division, functional area, location, full-time, hours, team leadership, number of direct reports, performance and potential rating, time on position, and quarter fixed effects. Robust standard errors in parentheses.*p< 0.10, **p< 0.05, ***p< 0.01.

Table A9: Testing for Instrument Relevance and Independence

Panel A: Application Effects of Manager Rotation

	All	All	Men	Women
	(1)	(2)	(3)	(4)
Manager Rotation	0.0222***	0.0224***	0.0227***	0.0203***
	(0.003)	(0.003)	(0.003)	(0.006)
Outcome Mean	0.029	0.029	0.029	0.027
Quarter Fixed Effects	X	X	X	X
Other Controls	-	X	X	X
Observations	3xx,xxx	3xx,xxx	3xx,xxx	8x,xxx

Panel B: Balance Across Worker Characteristics by Manager Rotation

	No Rotation	Rotation	Difference (in %)
	(1)	(2)	(3)
German citizen	0.90	0.88	2
Age (years)	43.42	42.83	1
Tenure at firm (years)	13.35	12.75	5
Schooling (years)	15.81	15.98	-1
Married	0.62	0.61	2
Children	0.75	0.73	3
On parental leave	0.03	0.03	0
Full-time	0.92	0.93	-1
Weekly hours	41.15	41.12	0
Number of teammates	9.01	8.96	1
Quarters worked with manager	9.68	9.32	4
Performance rating	2.72	2.70	1
Past earnings growth	0.05	0.05	0
Past share absent	0.09	0.09	0
Past share applied	0.03	0.03	0
Past share internal switch	0.01	0.01	0
Observations			3xx,xxx

Notes: This table illustrates relevance (Panel A) and independence (Panel B) of manager rotations as instrument for worker applications. Panel A reports the first-stage effect of manager rotations on applications, based on Equation 3. Columns 1 and 2 contain the full sample, Columns 3 and 4 focus on male and female workers, respectively. I estimate δ_1 by OLS regression and assess instrument relevance by testing the hypothesis that δ_1 is significantly different from zero. Controls: Female, age, German citizenship, educational qualification, marital status, family status, parental leave, firm tenure, position type, division, functional area, location, full-time, hours, team leadership, number of direct reports, performance and potential rating, time on position, and quarter fixed effects. Robust standard errors in parentheses. *p< 0.10, **p< 0.05, ***p< 0.01. Panel B compares average characteristics of workers, who do not experience a manager rotation (Column 1), and workers, who do experience a manager rotation (Column 2), in a given quarter. Column 3 represents the differences between Column 1 and Column 2 as % share of Column 1. Variables that refer to the past represent worker characteristics 12 months before.

Table A10: Testing for Instrument Exclusion

Panel A: IV Estimates on Hiring by Rotating Manager's Ties to Destination

	Rotating Manager Has Worked in the Job Opening's ...					
	Division		Functional Area		Location	
	Ever	Never	Ever	Never	Ever	Never
	(1)	(2)	(3)	(4)	(5)	(6)
Applied	0.488***	0.277***	0.548***	0.317***	0.445***	0.590***
	(0.066)	(0.084)	(0.074)	(0.093)	(0.062)	(0.181)
Outcome Mean	0.005	0.002	0.004	0.002	0.005	0.002
Observations	3xx,xxx	3xx,xxx	3xx,xxx	3xx,xxx	3xx,xxx	3xx,xxx

Panel B: IV Estimates on Hiring by Rotating Manager's Quality

	Promotion		Turnover		Absenteeism	
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
Applied	0.479***	0.471***	0.518***	0.463***	0.486***	0.537***
	(0.111)	(0.063)	(0.137)	(0.060)	(0.113)	(0.111)
Outcome Mean	0.007	0.007	0.007	0.007	0.007	0.007
Observations	3xx,xxx	3xx,xxx	3 xx,xxx	3xx,xxx	3xx,xxx	3xx,xxx

Panel C: IV Estimates on Hiring by Rotating Manager's Exposure to Workers

	Exposure Length in Quarters					
	≤1	2-3	4-6	7-8	9-10	11-14
	(1)	(2)	(3)	(4)	(5)	(6)
Applied	0.4429**	0.3177**	0.5593***	0.4367***	0.5135**	0.4227**
	(0.199)	(0.140)	(0.193)	(0.138)	(0.211)	(0.167)
Outcome Mean	0.009	0.008	0.008	0.008	0.008	0.007
Observations	3x,xxx	6x,xxx	7x,xxx	3x,xxx	3x,xxx	4x,xxx

Notes: This table finds no violation of the exclusion restriction regarding manager rotations as instrument for worker applications. Each panel presents two-stages least squares estimates of applying on getting hired based on Equation 5. Panel A estimates hiring outcomes for applications to which rotating managers have varying degrees of formal ties. Each column uses a different split of applications based on whether the rotating manager has ever worked in the same area as the job opening the worker applies to, where area is defined as division (Columns 1 and 2), functional area (Columns 3 and 4), and location (Columns 5 and 6). Panel B estimates hiring outcomes by rotating managers' quality using past leave-out means for three outcomes: promotions (Columns 1 and 2), turnover (Columns 3 and 4), and absenteeism (Columns 5 and 6). Each column uses a different manager type to define the rotation event. Panel C estimates hiring outcomes by manager's length of exposure to workers. Each column uses a different split of workers based on the number of quarters the worker has been with the manager. Controls: Female, age, German citizenship, educational qualification, marital status, family status, parental leave, firm tenure, position type, division, functional area, location, full-time, hours, team leadership, number of direct reports, performance and potential rating, time on position, and quarter fixed effects. Robust standard errors in parentheses. *p< 0.10, **p< 0.05, ***p< 0.01.

Table A11: Testing for Instrument Monotonicity

Panel A: Application Effects of Manager Rotations by Subgroup

Sample	Observations	Baseline application rate	First-stage effect	Standard error
(1)	(2)	(3)	(4)	(5)
Age $\leq$ 40 years	1xx,xxx	0.0389	0.0244***	(0.005)
Age $>$ 40 years	2xx,xxx	0.0204	0.0213***	(0.003)
Tenure $\leq$ 5 years	1xx,xxx	0.0348	0.0282***	(0.006)
Tenure $>$ 5 years	2xx,xxx	0.0255	0.0226***	(0.003)
Schooling $\leq$ 13 years	1xx,xxx	0.0203	0.0130***	(0.005)
Schooling $>$ 13 years	2xx,xxx	0.0305	0.0258***	(0.003)
Married	2xx,xxx	0.0259	0.0203***	(0.003)
Not married	1xx,xxx	0.0322	0.0268***	(0.005)
Parent	2xx,xxx	0.0265	0.0220***	(0.003)
Non-parent	1xx,xxx	0.0337	0.0246***	(0.005)
German citizen	3xx,xxx	0.0272	0.0232***	(0.003)
Non-German citizen	4x,xxx	0.0338	0.0194**	(0.009)
Team leadership	8x,xxx	0.0242	0.0164***	(0.006)
No team leadership	2xx,xxx	0.0287	0.0242***	(0.003)
High performance	2xx,xxx	0.0283	0.0284***	(0.004)
Low performance	1xx,xxx	0.0289	0.0172***	(0.004)

Panel B: Application Effects of Manager Rotations by Predicted Application Propensity

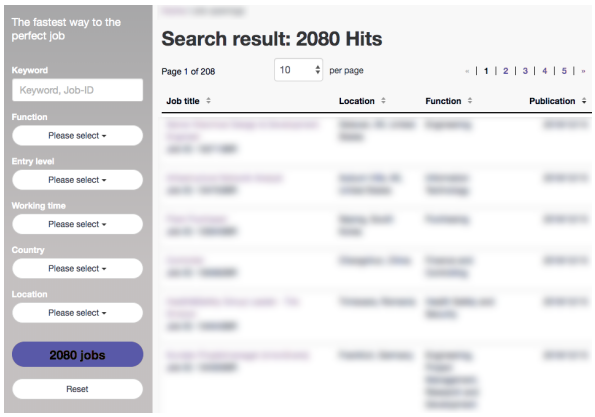
	Never applied	Applied before	Low-application team	High-application team
	(1)	(2)	(3)	(4)
Manager Rotation	0.0183***	0.0407***	0.0216***	0.0145*
	(0.003)	(0.013)	(0.003)	(0.008)
Outcome Mean	0.017	0.067	0.019	0.067
Observations	3xx,xxx	4x,xxx	2xx,xxx	8x,xxx

Notes: This table finds no violation of the monotonicity assumption regarding manager rotation as instrument for worker applications. Panel A presents first-stage effects of manager rotation on applying for several subpopulations of interest, as indicated by Column 1. Estimation is based on Equation 3 and conducted separately in each subpopulation. Column 2 contains the number of observations, Column 3 presents baseline application rates, Column 4 provides first-stage effects, and Column 5 contains robust standard errors. I find that manager rotation has a positive and statistically significant first-stage effect (Column 4) for each subpopulation. Panel B presents first-stage effects of manager rotation on applying by workers' predicted application propensity. I use two approaches to predict workers' unobserved application propensity. Columns 1 and 2 split the sample by workers' own past application activity. Columns 3 and 4 split the sample by whether teams' leave-out application rates in the past were high or low. I find a significant and positive first-stage effect even for the subsets of workers who previously had a high propensity to apply (Columns 2 and 4). Controls: Female, age, German citizenship, educational qualification, marital status, family status, parental leave, firm tenure, position type, division, functional area, location, full-time, hours, team leadership, number of direct reports, performance and potential rating, time on position, and quarter fixed effects. Robust standard errors in parentheses. *p< 0.10, **p< 0.05, ***p< 0.01.

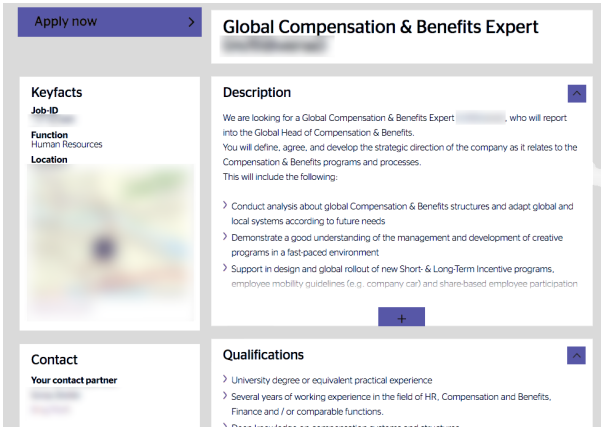
B Appendix Figures

Figure B1: Example of Firm's Internal Job Portal

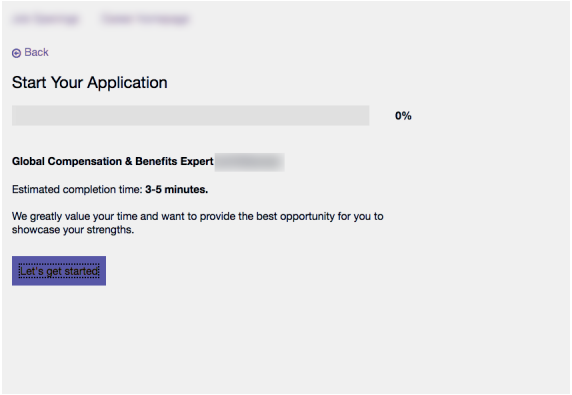
Panel A. Search Interface



Panel B. Typical Job Ad

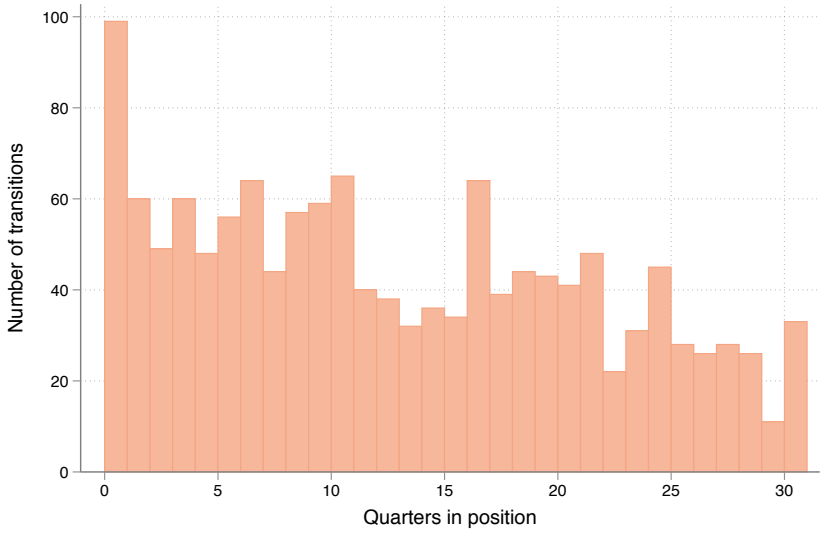


Panel C. Application Interface



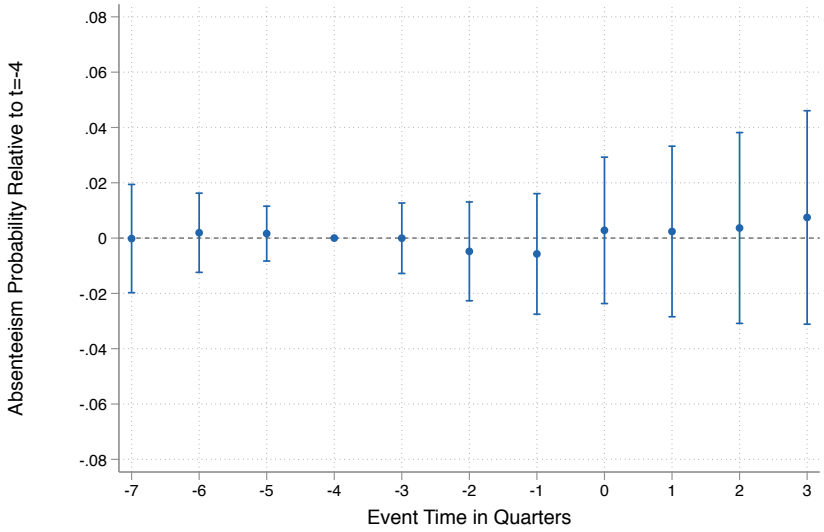
Notes: This figure provides an stylized example of the firm's internal job portal. Panel A displays the search interface, Panel B illustrates a typical job ad, and Panel C presents the application interface through which employees submit internal applications.

Figure B2: Number of Manager Rotations by Length in Position



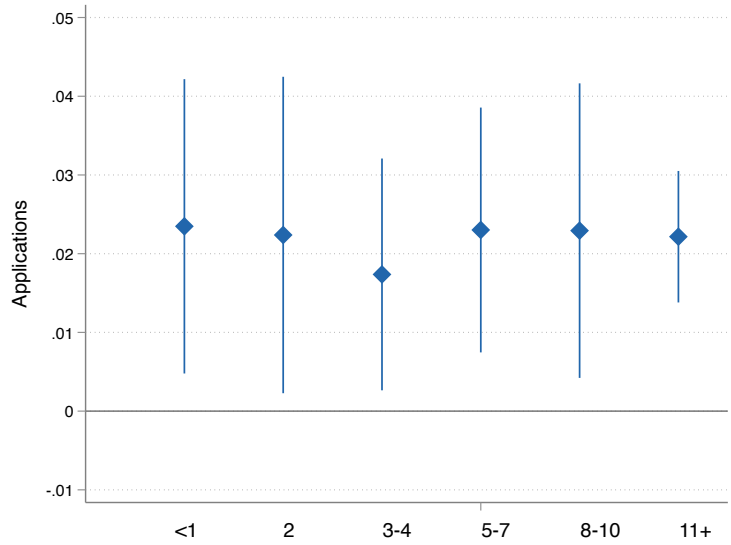
Notes: This figure illustrates the variation in the timing of manager rotations, as measured by the number of quarters a manager has been in their position at the time of rotation. The number of observations is 1,359, representing the total number of all internal job transitions in my sample.

Figure B3: Effect of Manager Rotations on Team-Level Absenteeism Rates



Notes: This figure documents team-level absenteeism rates around a manager rotation. Estimates stem from an event study regression, in which the outcome is the team average of absenteeism rates in a given quarter and event time is defined relative to the occurrence of a manager rotation. The specification includes team and quarter fixed effects. I bin event time dummy variables at $t = -8$ and $t = 4$ and cluster standard errors at the team level. The mean absenteeism rate as of $t = -4$ is 0.085. I find no evidence that manager rotations are preceded by changes in absenteeism. The sample of 6,xx teams includes those who have not experienced a manager rotation (i.e. never-treated).

Figure B4: Application Effects of Manager Rotations by Exposure Length



Notes: This figure assesses heterogeneity in the impact of manager rotation on applications by workers' length of exposure to the rotating manager. Each coefficient stems from a separate regression based on Equation (3) using standard errors. Worker subgroups are defined by the number of quarters a worker has worked under the manager. Baseline application rates are 0.031 (<1), 0.026 (2), 0.027 (3-4), 0.029 (5-7), 0.030 (8-10) and 0.026 (11+). The total number of observations are 3x,xxx (<1), 3x,xxx (2), 6x,xxx (3-4), 5x,xxx (5-7), 3x,xxx (8-10) and 1xx,xxx (11+). Controls: Female, age, German citizenship, educational qualification, marital status, family status, parental leave, firm tenure, position type, division, functional area, location, full-time, hours, team leadership, number of direct reports, performance and potential rating, time on position, and quarter fixed effects.

C Theoretical Appendix

In this section, I provide the formal derivations for predictions 4 and 5 referenced in Section 2.

Prediction 4. If $\beta_1 < \beta_2 \implies \Pr[i \text{ applies}|\beta = \beta_1] > \Pr[i \text{ applies}|\beta = \beta_2]$
This prediction implies that greater levels of talent hoarding reduce the number of workers who apply for a promotion.

Workers apply if $q(\alpha_i, \beta)b \geq c + \varepsilon_i$, where $\varepsilon_i \sim \Psi$ captures worker-specific heterogeneity. A worker's probability to apply can be expressed as $\Pr[i \text{ applies}|\beta_m] = \Psi\big(\mathrm{q}(\alpha_i,\beta_m)b - c\big)$. Because workers' promotion probability is decreasing in talent hoarding ($\frac{\partial q}{\partial \beta} < 0$), if $\beta_1 < \beta_2$:

$$
\begin{aligned}
q(\alpha_i, \beta_1) &> q(\alpha_i, \beta_2) \\
\Psi\big(q(\alpha_i, \beta_1)b - c\big) &> \Psi\big(q(\alpha_i, \beta_2)b - c\big) \\
\implies \Pr[i \text{ applies}|\beta = \beta_1] &> \Pr[i \text{ applies}|\beta = \beta_2]
\end{aligned}
$$

Prediction 5. If $\alpha_1 < \alpha_2$ and $\beta_1 < \beta_2 \implies \frac{\Pr[i \text{ applies}|\alpha_2,\beta_1]}{\Pr[i \text{ applies}|\alpha_1,\beta_1]} > \frac{\Pr[i \text{ applies}|\alpha_2,\beta_2]}{\Pr[i \text{ applies}|\alpha_1,\beta_2]}$
This prediction implies that greater levels of talent hoarding change the composition of applicants, causing a lower share of workers with high productivity in the applicant pool.

Let $r(\alpha_i, \beta_m)$ be $\Pr[i \text{ applies}|\alpha_i, \beta_m] = \Psi\big(\mathrm{q}(\alpha_i,\beta_m)b - c\big)$. We have assumed that $\frac{\partial^2 q}{\partial\beta\partial\alpha} < 0$, $\frac{\partial q}{\partial \beta} < 0$, $\frac{\partial q}{\partial \alpha} > 0$. We want to show that $\frac{\partial}{\partial \beta}\frac{r(\alpha_1,\beta)}{r(\alpha_2,\beta)} < 0$ for $\alpha_2 > \alpha_1$.

$$
\begin{aligned}
\frac{\partial}{\partial \beta}\frac{r(\alpha_2,\beta)}{r(\alpha_1,\beta)} &= \frac{\partial}{\partial \beta}\frac{\Psi(q(\alpha_2,\beta))}{\Psi(q(\alpha_1,\beta))} \\
&= \frac{\Psi(q(\alpha_2,\beta))\psi(q(\alpha_1,\beta))\frac{\partial q(\alpha_1,\beta)}{\partial \beta} - \Psi(q(\alpha_1,\beta))\psi(q(\alpha_2,\beta))\frac{\partial q(\alpha_2,\beta)}{\partial \beta}}{\big[\Psi(q(\alpha_1,\beta)\big]^2}
\end{aligned}
$$

Omitting the denominator since $\big[\Psi(q(\alpha_1,\beta)\big]^2 > 0$ leaves to show that

$$
\Psi(q(\alpha_1,\beta))\psi(q(\alpha_2,\beta))\frac{\partial q(\alpha_2,\beta)}{\partial \beta} < \Psi(q(\alpha_2,\beta))\psi(q(\alpha_1,\beta))\frac{\partial q(\alpha_1,\beta)}{\partial \beta}
$$

Rearranging leads to following expression

$$
\underbrace{\frac{\frac{\partial q(\alpha_2,\beta)}{\partial \beta}}{\frac{\partial q(\alpha_1,\beta)}{\partial \beta}}}_{<0} < \underbrace{\frac{\Psi(q(\alpha_2,\beta))\psi(q(\alpha_1,\beta))}{\Psi(q(\alpha_1,\beta))\psi(q(\alpha_2,\beta))}}_{>0}
$$

Since the left-hand side of the equation is below zero and the right-hand side of the equation is above zero, it holds that $\frac{\partial}{\partial \beta}\frac{r(\alpha_1,\beta)}{r(\alpha_2,\beta)} < 0$ for $\alpha_2 > \alpha_1$.

D Data Appendix

This section provides additional information on how I construct my main analysis sample. I illustrate how I merged personnel records and job application data. I then discuss the validity of my measure of managers' talent hoarding propensity. Finally, I provide details on the new measure of internal job hierarchy I use in order to test for misallocation of talent.

D.1 Merging Personnel Records and Application Data

In order to relate internal application and hiring decisions to employees' career progression at the firm, I use a five-step matching algorithm to merge personnel records to application data. The algorithm uses exact matches based on names and date of birth. I estimate a match quality of over 90% for both men and women.

Before beginning the matching process, I prepare names and birth dates to be matched. I standardize the names in both data sources. In order to be able to use date of birth in the matching algorithm, I need to impute birth dates for applicants since it is not contained in the main application data. I therefore parse 180,000 applicant CVs to isolate the date of birth for applicants mentioned on the CV and add it to the application data using a unique applicant identifier. This procedure allows me to capture birth dates for 33% of applicants in my sample. The remaining applicants will be merged using exact matches based on their names in later steps of the algorithm.

The matching algorithm follows an iterative process over five steps. In each step, individuals are only considered for matching if they have not been matched in previous rounds. The steps are constructed as follows:

- Step 1: Exact match on last name, first name, and birth date
- Step 2: Exact match on last name, first name, and year of birth
- Step 3: Exact match on last name, first three letters of first name, and birth date
- Step 4: Exact match on last name, first three letters of first name, and year of birth
- Step 5: Exact match on last name and first name

Note that Step 2 allows for the fact that there are different norms of whether to list month or day first when stating birth dates on a CV. Step 3 and 4 accommodate that some applicants add their middle name to their first name. I only keep exact matches. Disambiguous matches are either resolved by using additional information on occupations, locations, and employees' work history. Since it is not clear how many applicants should be matched to the personnel records in the first place, a simple comparison of applicants and employees is not possible. Instead, I evaluate the match rate by checking how many applicants who got hired and therefore should appear in the personnel records are matched by the algorithm. This test represents a valid alternative to assess match quality, since the algorithm does not contain any specific treatment of hired applicants compared

to applicants who are not hired. I find a match rate of over 90%. The match rate does not differ by gender.

D.2 Validity of Talent Hoarding Measure

This section demonstrates the validity of my measure of talent hoarding, which infers managers' propensities to hoard talent based on systematic deviations between the potential and performance rating managers assign to workers in their teams. Intuitively, a manager that decides to hoard talent should give workers lower (public) potential ratings than (private) performance ratings. Section 4.1 describes the construction of the measure in detail.

The comparison between performance and potential ratings is intuitive. Even though performance and potential ratings are designed to capture different objects, potential ratings are highly predictive of future performance ratings on average. Managers' mean deviation between actual and predicted potential ratings is reasonably stable over time, supporting the systemic notion of talent hoarding my measure is meant to capture. When I split my sample and use earlier years to estimate a manager's mean deviation, its correlation with the manager's deviation based on later years is 0.64.

I find strong evidence against the possibility that the low potential ratings my measure identifies as underrating result from managers' accurate assessment of worker potential. When managers with a high propensity to hoard talent rotate, underrated workers not only experience increases in applications and promotions, but are also likely to perform well in higher-level positions, demonstrating that the low potential rating was inaccurate.[19] In addition, while low potential ratings could in theory stem from the fact that managers have an incentive to hire low-potential workers to avoid the possibility of losing talent, this is not confirmed in the data. For instance, I find that talent hoarding effects occur both for incumbent workers and workers who are newly hired by a rotating manager (Columns 3 and 4 of Appendix Table A7) .

The measure of talent hoarding is highly correlated with workers' realized visibility at the firm, confirming that managers' suppression of public signals has a meaningful impact. I measure worker visibility by collecting data on workers' nominations to succession lists. As in many large organizations, the firm compiles lists of three to five candidates as potential successors for about one-fifth of positions in my sample. The lists are assembled by HR employees who search for suitable candidates across the firm. Workers' appearance on such a list represents a measure of their visibility outside of the team. If a manager is successful at hoarding talent, worker visibility should be low, and thus their likelihood of appearing as a nominee on a succession list should also be low. I estimate a version of Equation 2 to compute the difference between actual nominations and predicted nominations, then classify managers as high- and low-propensity talent hoarders, defined as those in the bottom and top terciles of this difference.

The underrating of potential my measure captures does not appear to result from managers'

[19] My 2SLS results demonstrate that these workers face a marginal probability of 0.15 (p-value 0.001) to land a position and a marginal probability of 0.08 (p-value 0.018) to perform in higher-level positions.

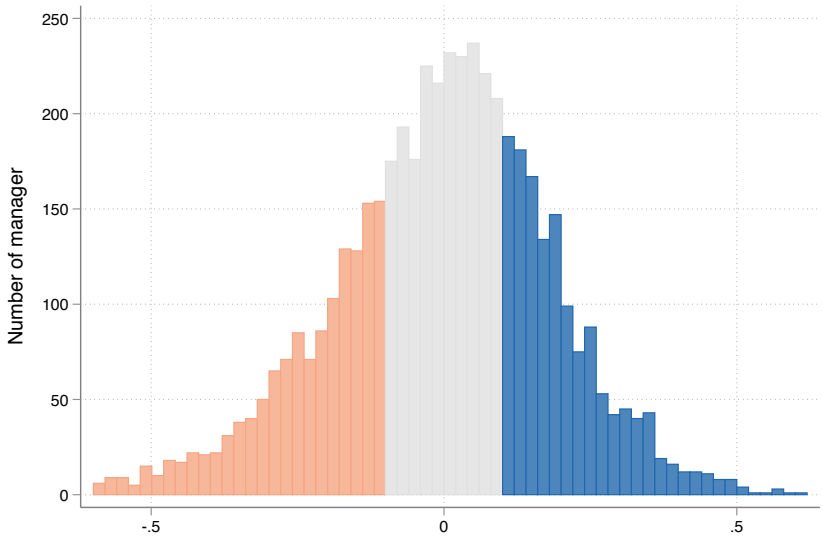
involuntary mistakes. The deviation between performance and potential ratings signals is not driven by managers' ability to assess talent, as measured by the experience of leading a team, or other key manager attributes, such as gender, age, and experience. While Table 8 only reports the coefficient on gender for brevity, the coefficients on age and experience are not statistically significant. A F-test of all manager characteristics included in this logit regression—which besides gender include age, marital and family status, tenure and experience as a manager at the firm, division, function, and location— further rejects their joint significance. Moreover, survey evidence from employees in my sample documents that managers purposefully underrate potential (Appendix Table A1).

I do not find evidence for alternative channels that would explain why managers suppress potential ratings. For instance, managers may be reluctant to rate a worker as high potential (despite high performance) if the worker has expressed disinterest in promotions. In contrast, under talent hoarding managers have less incentives to suppress potential ratings for workers who are less likely to leave the team. I use two different measures for workers' willingness to switch jobs to distinguish between these competing explanations: (i) workers' past internal applications and (ii) workers' consent that the firm can include the worker in their internal recruiting pool.[20] Appendix Table D1 demonstrates that managers' are more likely to suppress potential ratings for workers who have signaled their willingness to switch position using either measure, which is in line with talent hoarding as underlying mechanism but in contrast with alternative explanations.

A placebo test provides further evidence against the importance of alternative channels. In the internal labor market managers are generally likely to learn about workers' unsuccessful applications and have some power to diminish workers' application probability. However, it is unlikely that managers will be able to observe or intervene with respect to applications outside of the firm. Consequently, under talent hoarding, comparing managers with a high and low propensity to hoard talent should lead to differential effects with respect to workers' internal career progression, but to zero impacts on transitions to jobs outside of the firm. However, if managers' suppression of potential ratings is not a sign for talent hoarding, but reflects other types of manager-specific behavior that affect workers, we would not necessarily expect the effect on external transitions to be zero and the effect under both high and low propensity talent hoarders to be similar. I use this intuition to conduct a placebo test, comparing rotation effects for managers with a high versus low propensity to hoard for internal applications, internal job transitions within the firm, and external job transitions out of the firm. Panel C of Appendix Figure D2 documents that I find a zero effect on external transitions for both managers with a high and low propensity to hoard talents, which contrasts my findings on internal applications (Panel A) and internal job transitions (Panel B).

[20]While this internal feature is very recent, it represents a public signal of the desire to switch positions.

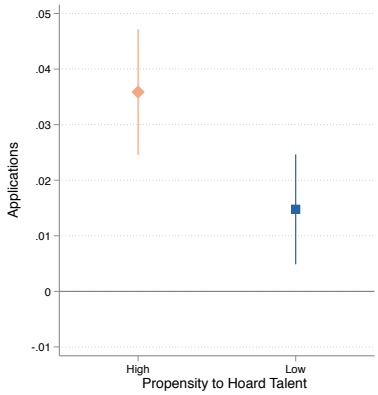
Figure D1: Mean Deviation Between Actual and Predicted Potential Ratings as Measure for Managers' Talent Hoarding Propensity



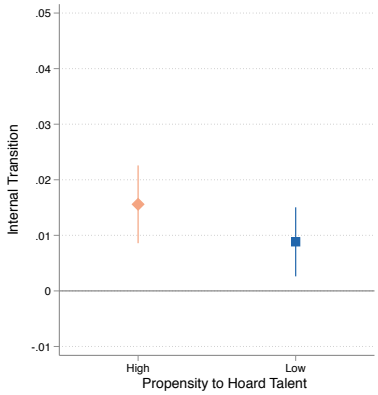
Notes: This figure documents the mean deviation by manager between actual and predicted potential ratings, which captures systematic discrepancies in the workers' visibility, and thus serves as a measure of managers' talent hoarding propensity. The y-axis reports the number of unique managers with a given deviation. Each year, managers simultaneously conduct a performance rating (i.e. private signal of worker talent only shared with worker) and potential ratings (i.e. public signal of worker talent that is widely circulated) for each worker in their team. I assess managers' systematic underreporting of public potential ratings by comparing managers' actual potential rating to the predicted potential rating based on managers' own assessment of worker performance and worker characteristics. Values below zero represent managers who on average lower their public signal below their private signal of worker talent, which captures one likely dimension of talent hoarding. I use the bottom (marked in orange) and top (marked in blue) tercile of this distribution to classify managers as high versus low propensity to hoard talents. The total number of observations is 7,xxx.

Figure D2: Placebo Test for Talent Hoarding Measure

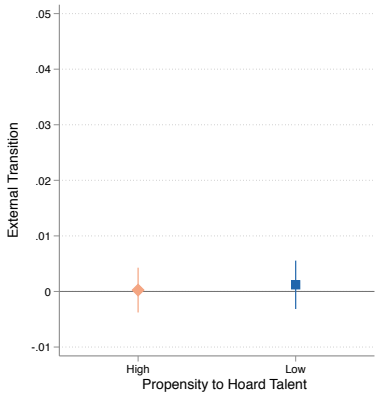
Panel A. Internal Applications



Panel B. Internal Transitions



Panel C. External Transitions



Notes: This figure provides a placebo test for the measure of managers' talent hoarding propensity based on the mean deviation between actual and predicted potential ratings. Each coefficient stems for a separate regression based on Equation 3 using robust standard errors. Each panel compares rotations of manager types with high versus low propensity to hoard. The outcomes of interest are internal applications (Panel A), internal job transitions within the firm (Panel B), and external job transitions out of the firm (Panel C). Controls: Female, age, German citizenship, educational qualification, marital status, family status, parental leave, firm tenure, position type, division, functional area, location, full-time, hours, team leadership, number of direct reports, performance and potential rating, time on position, and quarter fixed effects.

Table D1: Impact on Talent Hoarding Propensity at the Worker-Level

	Underrated Potential		Undernominated for Succession	
	(1)	(2)	(3)	(4)
Applied in past 12 months	0.328***		0.157***	
	(0.015)		(0.039)	
Consent to be recruited		0.623***		0.270***
		(0.014)		(0.042)
Outcome Mean	0.3768	0.3768	0.0160	0.0160
Av ME for Women	0.0494	0.0913	0.0031	0.0057
Gender Gap in %	13	24	20	36
Observations	3xx,xxx	1xx,xxx	3xx,xxx	1xx,xxx

Notes: This table provides a robustness test for my measure of talent hoarding by examining the impact on managers' decisions to make worker talent visible. Each column is based on a separate logit regression at the worker level where the regressor of interest is whether the worker has applied internally in the past 12 months (Columns 1 and 3) or the worker has given their consent to be included in the firm's internal recruiting pool (Columns 2 and 4). Columns 1 and 2 estimate the propensity that managers manipulate worker visibility through suppressing potential ratings, Columns 3 and 3 focus on nominations to succession lists. Controls include age, tenure, schooling, nationality, married, kids, parental leave, position title, division, function, location, full time, hours, leadership, direct reports, past mobility, quarter, and performance. Robust standard errors in parentheses. *p< 0.10, **p< 0.05, ***p< 0.01.

D.3 Construction of Job Hierarchy

I follow Haegele (2021) and construct a novel measure of internal job hierarchy using the detailed position characteristics that are available in the personnel data. The main objective of this hierarchy measure is to provide granular distinctions between positions that are not based on employee pay, which allows me to test for misallocation effects of talent hoarding.

The internal labor market of the manufacturing firm is large and complex, consisting of 200 different position titles and multiple non-intersecting career paths, implying that institutional structures, such as the firm's organizational chart, are not sufficient to create a hierarchy measure that is comparable across different parts of the firm.

Advancing over previous measures that use position titles alone, I take advantage of the rich set of job characteristics in the personnel records. I collect characteristics that contain information on a job's position in the firm hierarchy that can be interpreted across career paths. Specifically, I use a position's managerial autonomy, the cumulative number of direct reports, and the reporting distance to the CEO. I use principal component analysis to combine these characteristics into a one-dimensional hierarchy ranking. The first component of the principal-component analysis alone explains 61% of variation. In order to construct a one-dimensional hierarchy index, I use the corresponding loadings on the first component. These loadings are very granular, capturing over 600 different values. The inputs load on the first component as follows: $0.5591 \times \{\text{cumulative reports}\} + 0.6336 \times \{\text{managerial autonomy}\} + 0.5348 \times \{\text{reporting distance to the CEO}\}$.

This ranking provides a consistent ordering of all positions at the firm, allowing me to identify promotions as increases in the job hierarchy independent of employees' career paths. The cardinality of the hierarchy ranking is also comparable across career paths. I define a major promotion as an increase in the hierarchy index of 20 or more. This definition captures significant increases in the hierarchy, such as a transition from an entry-level job to a team leader position. However, my findings are robust to alternative thresholds.

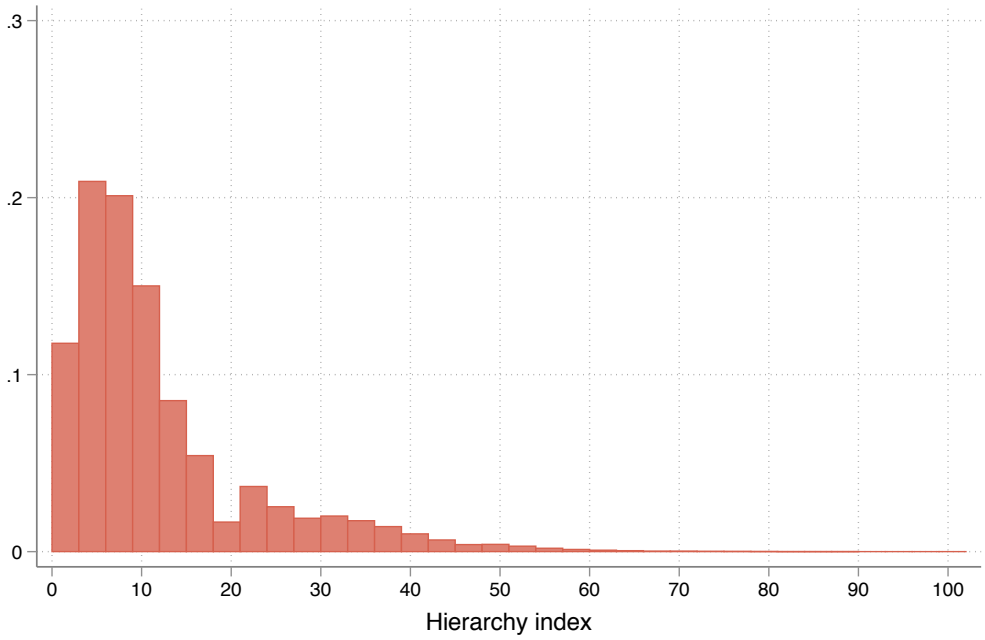
Appendix Figure D3 illustrates that the majority of employees (69%) are located at the bottom of hierarchy (index $\leq$20). Increases in hierarchy levels represent typical steps in the job ladder, as illustrated by the transition matrix for employees who switch positions (Appendix Table D2). Employees are most likely to move to adjacent hierarchy levels. Appendix Table D3 documents that hierarchy levels differ substantially in terms of characteristics not used to construct the hierarchy measure. As hierarchy levels increase, bonus payments represent larger shares of employees' total compensation (Column 1). Higher shares of bonus payments are usually associated with higher-level positions that have large autonomy. While the vast majority f positions with an hierarchy index of 20 or less do not entail leadership of a team, the number of direct reports substantially increases as hierarchy levels rise (Column 2). Positions at higher hierarchy levels are filled by employees with more work experience (Column 3) and higher educational qualifications (Column 4).

Average earnings are highly correlated with the hierarchy measure, implying that my measure successfully captures differences in position quality that are reflected in wages. Appendix Figure D4 documents the strong positive correlation of earnings with my measure of hierarchy. The figure

shows that the hierarchy index, which is not based on pay, corresponds closely to the earnings measure. However, particularly at the bottom of the hierarchy, there are many positions for which earnings are similar, but the hierarchy index substantially differs, suggesting that hierarchy measures solely based on earnings likely underestimates differences in hierarchy.

Appendix Figure D5 documents that the hierarchy measure correlates well with position titles, which were not used to construct the hierarchy measure. Even though position titles do not always reflect leadership responsibility, the share of position titles that reference leadership (e.g. "team lead", "head of department") rises as hierarchy levels increases. This finding suggests that the ordering of positions that the hierarchy measure induces is sensible, further supporting the validity of the hierarchy measure. However, Appendix Figure D5 also illustrates that using position titles alone likely fails to distinguish between leadership levels, as many position titles do not sufficiently reflect how much leadership responsibility a position entails. For instance, some positions at high hierarchy levels are labeled as engineering or specialist positions, even though they entail leadership over a department.

Figure D3: Distribution of Hierarchy Index



Notes: This figure displays the distribution of the continuous index of job hierarchy in my sample. Low values represent low-level positions, such as entry-level engineering jobs. The highest value of 100 represents the CEO. The majority of workers (69%) are situated at positions with a hierarchy index of 20 or below. The total number of observations is 4xx,xxx.

Table D2: Transition Matrix

	Hierarchy Index$_{t+1}$						
Index$_t$	0-10	10-20	20-30	30-40	40-50	50-60	60-100
0-10	83.1	16.0	0.6	0.2	0.0	0.0	0.0
10-20	9.4	73.0	14.3	2.7	0.3	0.3	0.1
20-30	0.0	12.9	65.6	16.4	4.3	0.8	0.0
30-40	0.0	3.1	8.5	65.9	19.4	3.1	0.0
40-50	0.0	0.0	12.5	20.0	55.0	7.5	5.0
50-60	0.0	0.0	10.0	0.0	40.0	50.0	0.0
60-100	0.0	0.0	0.0	25.0	0.0	50.0	25.0

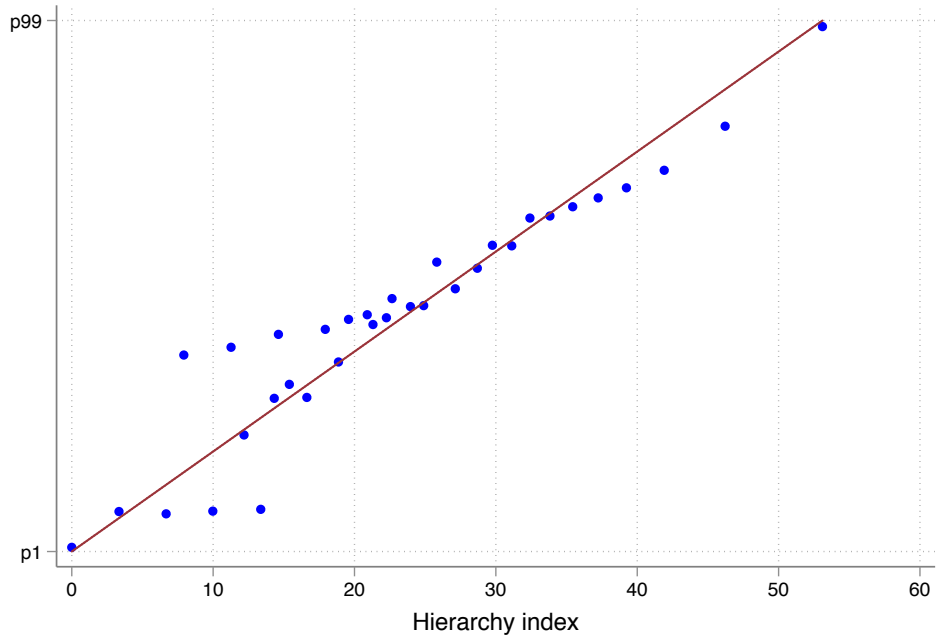
Notes: This table represents the transition matrix for employees who switch positions between year t and the subsequent year $t+1$. Each coefficient represents the share of employees (in %)who start out at a hierarchy decile in year t and transition to a respective decile in year $t+1$. For instance, 83.1% of employees from the first hierarchy decile transition to a position in the same decile. The total number of observations is 2,xxx.

Table D3: Characteristics by Hierarchy Index

Hierarchy index	Fraction bonus/pay (1)	Number reports (2)	Tenure (years) (3)	Share >= BA (4)	External hire (5)
0-10	0.11	0.03	11.7	0.42	0.024
10-20	0.13	0.32	13.5	0.56	0.017
20-30	0.16	3.04	16.2	0.72	0.007
30-40	0.22	5.61	17.6	0.77	0.003
40-50	0.30	7.74	17.3	0.79	0.003
50-60	0.43	9.69	16.8	0.79	0.002
60-100	0.45	14.98	17.2	0.78	0.001
N	4xx,xxx				

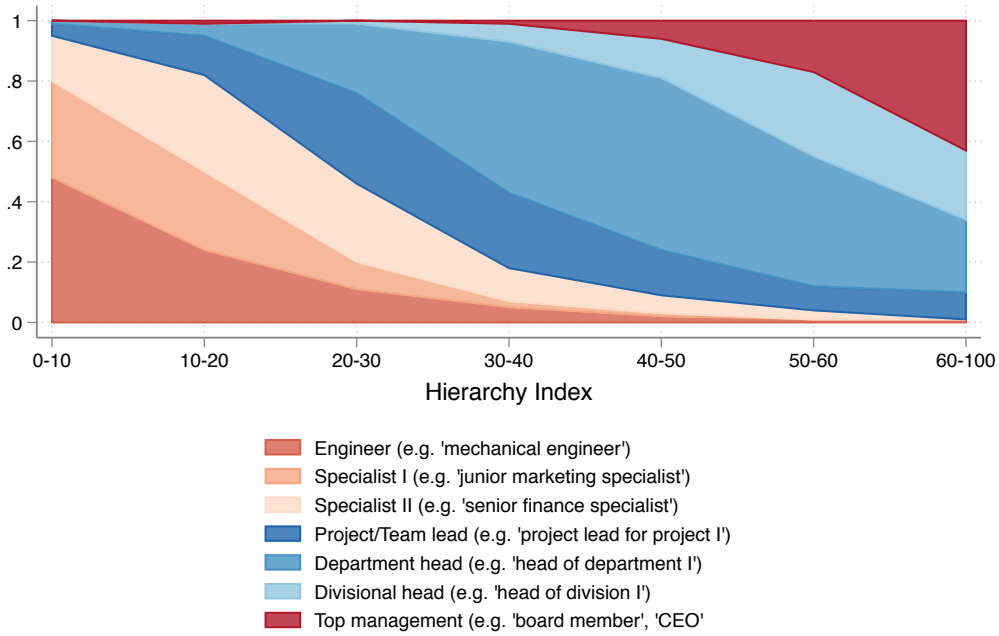
Notes: This table reports average characteristics by decile of hierarchy index: bonus pay as fraction of total pay (Column 1), number of direct reports (Column 2), firm tenure in years (Column 3), share with at least a Bachelor's degree (Column 4), share who are hired from externally in a given year (Column 5). Note that for the construction of the hierarchy measure the number of all reports is used, not the number of direct reports. The total number of observations is 4xx,xxx.

Figure D4: Fit of Hierarchy Index Compared to Earnings



Notes: This figure displays the fit of the continuous hierarchy index and the percentile of workers' log real annual earnings. The total number of observations is 4xx,xxx.

Figure D5: Composition of Position Titles by Hierarchy Level



Notes: This figure displays the composition of position titles by deciles of the hierarchy index. I extract key terms from position titles that likely indicate the type of leadership responsibility that the position entails (e.g. "engineer", junior specialist", "head of department"). The total number of observations is 4xx,xxx.

E Supplementary Results for Robustness

This section presents supplementary results that demonstrate the robustness of my main findings.

I verify that misallocation effects are not limited to major promotions. Instead, I show that similar misallocation patterns arise when considering other types of promotions. Appendix Table E1 presents two-stages least squares results for any type of promotion (Column 1), small promotions (Column 2), and very large promotions (Column 3), which complement my preferred outcome of major promotions.[21] For each of these different promotion types, I find that marginal applicants, who only apply in the event of a manager rotation, face statistically significant and economically meaningful marginal probabilities with respect to landing higher-level positions and performing well in them.

I demonstrate robustness of my measure of managerial talent hoarding propensity. Specifically, I verify that my finding, which states that rotations of managers with higher propensities to hoard talent lead to bigger application effects, is not sensitive to specific cutoff choices I made when constructing my measure of talent hoarding. While my preferred approach compares manager rotations of managers in the bottom and top tercile of the mean deviation between actual and predicted public signals, Appendix Table E2, Panel A, Columns 3 and 4 document very similar results when using bottom and top quartiles. Similarly, instead of assessing the effect of different manager rotations in the joint sample, Appendix Table E2, Panel A, Columns 1 and 2 show similar results when splitting the sample of workers by whether their manager is in the bottom and top tercile. I conduct the same robustness tests for nominations to succession lists as measure of talent hoarding (Appendix Table E2, Panel A, Columns 5 to 8), and also find very similar patterns.

I use a similar approach to verify the robustness of my measure of worker quality. While my preferred approach uses the bottom and top quartile of my quality index, Appendix Table E2, Panel B documents very similar results when using bottom and top halves (Columns 1 and 2) and terciles (Columns 3 and 4) of my quality index. I also use an alternative measure to distinguish between high and low quality workers using years of education and past performance ratings (Columns 5 and 6 and Columns 7 and 8, respectively). The resulting application patterns are very similar to my preferred measure of worker quality.

I document that my complier analysis in Section 6 is not sensitive to the controls that I use for covariate adjustments. Appendix Table E3 presents results from my complier analysis without the use of any controls. I find very similar patters with respect to the positive selection of marginal applicants compared to always takers and the worker population.

[21] While major promotions are defined as an increase of 20 or more in the hierarchy index, the cutoffs for small and very large promotions are 10 and 30, respectively.

Table E1: Misallocation Effects of Talent Hoarding by Promotion Types

Panel A: 2SLS Results for Landing a Promotion

	Any promotion	Small promotion	Large promotion
	(1)	(2)	(3)
Applied	0.3519***	0.2240***	0.0725**
	(0.053)	(0.043)	(0.017
Outcome Mean	0.0047	0.0024	0.0004
Observations	3xx,xxx	3xx,xxx	3xx,xxx

Panel B: 2SLS Results for Landing a Promotion and Outperforming the Team

	Any promotion	Small promotion	Large promotion
	(1)	(2)	(3)
Applied	0.4077***	0.1154***	0.0373*
	(0.058)	(0.032)	(0.017)
Outcome Mean	0.365	0.365	0.365
Observations	3xx,xxx	3xx,xxx	3xx,xxx

Notes: This table documents the robustness of my main misallocation effects by evaluating different types of promotions. Column 1 refers to any type of promotion, Column 2 refers to small promotions (10% increase in hierarchy index), while Column 3 refers to very large promotions (30% increase in hierarchy index). Panel A reports estimates from two-stages least squares regressions on landing a promotion, where applying is instrumented for by manager rotations based on Equation 5. Panel B reports estimates from similar two-stage least squares regressions, but for the outcome of landing a promotion and performing better than the leave-out team average one year later. These results suggests that the misallocation effects of talent hoarding arise with respect to range of transition types, not only with respect to my preferred outcome which is major promotions. Robust standard errors in parentheses.*p< 0.10, **p< 0.05, ***p< 0.01. Controls: Gender, age, tenure, schooling, nationality, married, kids, parental leave, position title, division, function, location, full time, hours, leadership, direct reports, past mobility, quarter, performance, and potential rating.

Table E2: Heterogeneity in Application Effects by Talent Hoarding Levels

Panel A: Robustness in Measure of Managerial Talent Hoarding Propensity

	Public Signal		Public Signal		Succession List		Succession List	
	Bottom $\frac{1}{3}$	Top $\frac{1}{3}$	Bottom $\frac{1}{4}$	Top $\frac{1}{4}$	Bottom $\frac{1}{3}$	Top $\frac{1}{3}$	Bottom $\frac{1}{4}$	Top $\frac{1}{4}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Manager Rotation	0.0345***	0.0187***	0.0367***	0.0137*	0.0295***	0.0150**	0.0341***	0.0171**
	(0.006)	(0.005)	(0.007)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
P-value of t-test	0.0361		0.0068		0.0442		0.0467	
Observations	1xx,xxx	1xx,xxx	3xx,xxx	3xx,xxx	1xx,xxx	1xx,xxx	3xx,xxx	3xx,xxx

Panel B: Robustness in Measure of Worker Quality

	Quality Index		Quality Index		Education		Performance	
	Top $\frac{1}{2}$	Bottom $\frac{1}{2}$	Top $\frac{1}{3}$	Bottom $\frac{1}{3}$	Top $\frac{1}{2}$	Bottom $\frac{1}{2}$	Top $\frac{1}{2}$	Bottom $\frac{1}{2}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Manager Rotation	0.0315***	0.0116***	0.0346***	0.0101**	0.0280***	0.0177***	0.0284***	0.0172***
	(0.004)	(0.003)	(0.006)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
P-value of t-test	0.0001		0.0002		0.0522		0.0484	
Observations	1xx,xxx	1xx,xxx	1xx,xxx	1xx,xxx	1xx,xxx	1xx,xxx	1xx,xxx	1xx,xxx

Notes: This table documents the robustness of the heterogeneity in application effects I find by predicted levels of talent hoarding. Each coefficient stems from a separate regression based on Equation 3. Panel A documents the robustness of my direct measure of talent hoarding based on deviations between managers' actual and predicted signals of worker talent. Columns 1 and 2 use the bottom and top tercile of this deviation, but conduct estimation in two separate samples of workers based on whether their manager is in the bottom or top tercile. Columns 3 and 4 use the same joint sample approach as my preferred measure, but split managers based on top and bottom quartiles instead of terciles. Columns 5 and 6 split workers into two samples based on whether their managers are in the top or bottom tercile of nominations to succession lists. Columns 7 and 8 use the same joint sample approach as my preferred measure, but split managers based on top and bottom quartiles instead of terciles. Panel B documents the robustness of my measure of worker quality. Columns 1 and 2 split workers into high versus low quality using the median of the quality index, while Columns 3 and 4 use top and bottom terciles. Columns 5 and 6 distinguish high versus low quality workers based on the median education level (having 18 or more years of schooling versus less than 18 years of schooling). Columns 7 and 8 make the quality distinction based on the median past performance rating. Using different cutoffs to make these distinctions leads to very similar patterns, highlighting the robustness of my heterogeneity analysis. Controls: Gender, age, tenure, schooling, nationality, married, kids, parental leave, position title, division, function, location, full time, hours, leadership, direct reports, past mobility, quarter, performance, and potential rating. Robust standard errors in parentheses. *p< 0.10, **p< 0.05, ***p< 0.01.

Table E3: Characteristics of Marginal Applicants (in %)

	All workers (1)	Always taker (2)	Marginal applicant (3)
German citizen	89.8	86.8	84.4
Age >=40yrs	60.4	38.7	50.6
Married	61.7	54.6	49.6
Children	73.3	68.1	63.5
Tenure at firm <2yrs	37.5	53.9	50.0
Tenure at firm 2-5yrs	40.5	37.7	38.2
Tenure at firm >=5yrs	21.9	8.4	11.9
Graduate degree	47.6	48.4	63.9
Full-time	92.5	94.4	97.5
High performance	54.0	56.7	63.5
High potential	28.2	44.2	43.4
Technical position	63.2	56.3	65.1
Low-level position	68.9	73.7	80.2
First-level leadership position	11.5	9.6	7.0
Time in position <2yrs	37.1	38.9	39.8
Time in position 2-5yrs	36.2	40.6	42.3
Time in position >=5yrs	26.7	20.6	17.9
Indicated desire to switch position	46.7	76.3	67.4
Nominated to succession list	1.6	2.4	5.6
Applied 12 months before	2.6	11.1	2.9

Notes: This table illustrates results from a complier analysis as described in Section 6. Each number is based on a separate regression *without* controls. Column 1 shows means for all workers, Column 2 represents always takers, and Column 3 represents marginal applicants, who only apply if managers rotate and talent hoarding temporarily subsides. Each number represents the share of workers in a given group that exhibit the respective characteristic (in %). A technical position is defined as a job related to engineering, IT, quality management, or production. Low-level positions are defined as positions at low hierarchy levels without leadership responsibility (i.e. individual contributors). First-level leadership represent positions with limited leadership responsibility, such as team leaders. I measure workers' indicated desire to switch position based on a recent internal feature at the firm that elicits workers' consent that the firm can include the worker in their internal recruiting pool. Controls: Female, age, German citizenship, educational qualification, marital status, family status, parental leave, firm tenure, position type, division, functional area, location, full-time, hours, team leadership, number of direct reports, performance and potential rating, time on position, and quarter fixed effects.