People Management Skills, Employee Attrition, and Manager Rewards: An Empirical Analysis*

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Abstract

How much do a manager's interpersonal skills, what we call *people management skills*, affect employee outcomes, and are managers rewarded for having such skills? We analyze these questions using personnel data and surveys of employees about their managers at a large high-tech firm. Survey-measured people management skills have a strong negative relation to employee turnover. Results are robust to designs exploiting new workers joining the firm and manager moves. People management skills also raise employee engagement, but do not consistently improve employee subjective performance, salary growth, or probability of promotion. Better people managers are themselves more likely to be promoted and receive other rewards.

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1 Introduction

The relationship between managers and employees is fundamental to the success of firms, and has recently gained traction in labor and organizational economics research. As scholars have sought to explore if and how management plays a role in exploring large productivity differences across firms and countries (Bloom and Van Reenen, 2011; Syverson, 2011), increasing attention is being devoted to the managers themselves. It seems evident that good managers matter. Many people pay handsomely to attend business school to become better managers, and scores of books are written every year on how to become a better manager. Unfortunately, little empirical evidence exists regarding the managerial production function, particularly regarding the influence of managers on their employees (or what is sometimes called "people management").

How much does good people management by managers matter? Is good people management rewarded inside the firm? We seek to answer these and related questions using rich employee surveys conducted by a multinational technology and services firm. Employees in our firm are asked to evaluate their managers on a number of dimensions, e.g., whether they are trustworthy or whether they provide adequate coaching. We use these surveys to measure each manager's people management skills.

Progress has been made recently in examining how much managers matter using a "value-added" approach. For example, Bertrand and Schoar (2003) examine how much CEOs matter for various decisions in firms by regressing various firm outcomes on CEO fixed effects, an approach that has been pursued by a large subsequent finance literature. In a recent important paper, Lazear et al. (2015) use data from one firm to examine to what extent low-level managers (specifically, front-line supervisors) matter for productivity, finding that they matter a great deal. Bender et al. (2016) analyze interactions between employees/managers and management practices in Germany. Hoffman et al. (2017) use data from several firms to examine the determinants of low-level manager productivity around the world.

While these studies are of great interest, the value-added approach faces two main limitations. First, these studies require good objective data on worker productivity. However, in many firms, direct data on individual worker productivity is often scarce, and sometimes impossible to measure, particularly in high-skill, collaborative environments. When data are available, productivity metrics may be subject to various shocks (e.g., business generated by a law-firm partner could be adversely affected by the exit of a single prominent client, who decided to leave the firm for reasons having nothing to do with the partner). Second, value-added estimates provide researchers with the overall impact of a given manager on individual outcomes, not the separate impact of people management skills. A manager may appear to have desirable fixed effects for various reasons unrelated to interpersonal skills, such as ability to bring in high-value clients, thereby making his or her employees look more productive.

We take a different approach. Rather than calculate value-added, we create a measure of people management skills using employees' survey responses about their manager. We then proceed to explore the extent to which people management skills relate to employee outcomes, with the greatest focus on employee attrition. The data from the firm cover thousands of managers and tens of thousands of employees. The data contain a large number of knowledge workers, as well as a large number of lower-skill workers. In high-tech firms, employee turnover is believed to be a key way by which knowledge and ideas are acquired and lost (e.g., Shankar and Ghosh, 2013; Stoyanov and Zubanov, 2012). As such, many high-tech firms, including ours, are deeply interested in what can be done to reduce turnover, particularly turnover of their highest performers.

A central task for managers is to enhance the productivity of their employees and to help them succeed in their jobs. Asking employees about what managers do to improve their performance thus seems like a natural way to measure people management skills, and is one that is been pursued by many firms. Brutus et al. (2006) report that over one third of US and Canadian organizations in their survey reported using "multi-source assessments" (as opposed to only assessing individuals based on their managers) and Pfau et al. (2002) report that 65%

of firms use 360-degree performance evaluation.[1] Indeed, our approach of analyzing managers using employee surveys thus appears to align closely to the data practices of many firms.

There are several challenges in using employee surveys to measure people management. First, there is concern about non-response bias, but the response rate at our firm is over 95%. Second, one may worry that employees may not be truthful. Workers generally care about what their managers think about them, and may be highly averse to saying something negative about them. This concern is mitigated in our data due to the confidential nature of the survey. Workers are told truthfully that their individual responses cannot and will never be observed by the firm. Instead, managers receive aggregated results, and even that occurs only for managers with a minimum number of employees responding. Our data is thus limited to manager-year averages for various qualities ascribed to them by their employees. This feature protects worker confidentiality, but does not limit our analysis, given our focus on understanding behavior at the manager level. Third, survey responses may contain measurement error for several reasons, e.g., inattentiveness, sampling error, or different employees treating different questions differently. We address this using an instrumental variable (IV) strategy where a manager's score in one wave is instrumented using his or her score in the other wave or waves.

Our main finding is that people management has a strong negative relation to employee attrition. Our main IV results imply that increasing a manager's people management skill from the 10th to 90th percentile predicts a 50% reduction in turnover. These results are quite strong in terms of retaining the firm's high performers, both defined in terms of classifying employees based on persistent subjective performance score differences and using the firm's definition of regretted voluntary turnover.

An important question is whether these results are causal. Even for our IV estimates, there are concerns about non-contemporaneous measurement error in measured people management skills that is correlated with employee attrition, as well as concern that the firm is

[1] Prominent examples of firms using such surveys include Google (Garvin et al., 2013) and Royal Bank of Canada (Shaw and Schifrin, 2015), as documented in business case studies.

optimally sorting managers or employees together. We address this concern using two identification strategies in the spirit of those in the "teacher fixed effects" literature (Chetty et al., 2014). Our first strategy analyzes outcomes of employees who join mid-way through our sample while using as instrument a manager's quality measured before an employee joins the firm. This addresses contemporaneous shocks affecting manager ratings and employee outcomes, as well as reduces concern that the results are driven by sorting managers and employees based on long-time information about the employee. Our second strategy studies managers moving across work teams and locations within the firm, measuring manager quality before the move takes place. This strategy addresses more permanent unobserved shocks (beyond what are already measured using our rich, baseline controls). Both strategies support people management having a causal effect on attrition.

Having examined attrition, we also examine the relation between people management and other employee outcomes. We find that people management has a positive relation to employee engagement. Interestingly, however, we do not find a consistent relation of measured people management skills of employee subjective performance, salary growth, or probability of promotion. Thus, good people management affects some outcomes, but not others.

Our secondary result is that better people managers do receive various "rewards" by the firm. In particular, better people managers attain somewhat higher subjective performance scores, are more likely to be promoted, are more likely to be designed key individuals by the firm, and are more likely to receive stock grants. However, controlling for a worker's subjective performance score (which he or she receives from his or her various superiors), most of these relations disappear. While our results on rewards have multiple interpretations, overall, what the higher-ups think of a manager appear substantially more important for a manager's rewards than what the manager's direct reports express.

Our paper contributes to several literatures. First, it is related to other work on the importance of individual managers. In addition to work on value-added (which we mentioned further above), Bandiera et al. (2017) classify CEOs into two types using machine learning techniques and time use data, finding that one type (representing a higher tendency to delegate) tends to significantly outperform the other. Friebel et al. (2017) conduct a field experiment where they send a letter from the CEO to store managers explaining that reducing turnover is important; they find that this intervention reduced turnover by a third. Arguably most related to our paper is the above-cited work of Lazear et al. (2015), who study the impact of lower-level managers in a low-skill setting. Relative to existing the work, the main contribution of our paper is to measure the importance of people management skills using employee surveys.

Second, it relates to work in general on knowledge-based employees. Much of empirical personnel economics focuses on relatively low-skilled jobs (e.g., truckers, retail, and farmworkers), partially because it is often relatively simple in those jobs to measure individual productivity.[2] In contrast, for high-skilled jobs for knowledge employees, production is often complex, multi-faceted, and involves teamwork. Our analysis sheds light on the managerial production function in such a high-skilled setting.

Third, it is related to work on subjective performance evaluation and workplace feedback. Employee surveys bring to bear an advantage often ascribed to subjective performance evaluation, namely, that they help account for difficult-to-measure aspects of performance (Baker et al., 1994b). Our paper brings forward a new aspect of performance evaluation, namely reports from a manager's employees, that has not been previously explored in economics.[3] Fourth, it relates to studies of compensation and reward within organizations (e.g., Baker et al., 1994a), providing novel evidence that people management skills are rewarded within the firm.

Section 2 describes the data. Section 3 describes our empirical strategy. Section 4 pro-

[2]For notable exceptions in personnel economics also using high-skilled workers, see, e.g., Bartel et al. (2017); Kuhnen and Oyer (2016).

[3]In economics, there are papers studying job satisfaction surveys (e.g., Clark, 2001; Frederiksen, forthcoming), thereby complementing our work which focuses on managers. In industrial psychology, there is work on 360 degree performance evaluation (e.g., Atkins and Wood, 2002). In economics, there is also a parallel with respect to a literature on student evaluations of teachers (e.g., Beleche et al., 2012). Carrell and West (2010) show that teacher evaluations positively correlate with contemporaneous student value-added, but negatively correlate with later achievement.

vides our main analyses on how managers' people management skills affect employee attrition. Section 5 analyzes how people management skills affect outcomes other than attrition. Section 6 analyzes to what extent people management is rewarded. Section 7 concludes.

2 Data and Institutional Setting

Our data, obtained from a technology and services company, covers a period of two years and five months, some time between January 2011 and December 2015. To preserve firm confidentiality, certain details regarding the firm cannot be provided. We refer to the three years of the data as Y_1, Y_2, and Y_3. Between January Y_1 and May Y_3, we observe several dozen thousands of employees and several hundreds of thousands of employee months. The data cover several business units.

About 63% of workers are in the US, with the remainder located abroad. An observation is a worker-month, and about 16% of observations are filled by individuals in managerial roles, so the majority of observations are for non-managers (often referred to in industry as individual contributors). While our data begin in Jan. Y_1, the majority of the workers are hired before that date. Still, 38% of the employees in the data were hired on or after Jan. Y_1. The data cover workers only, and do not cover applicants.[4]

The firm is divided into several broad business units. From a functional standpoint, roughly 32% of worker-months are in customer service/operations and 22% of worker-months are in engineering, with the remainder in other business functions (e.g., marketing, finance, sales, etc.). We next provide information on employee outcomes, manager assignment, and the employee surveys, with further details regarding the data in Appendix B.

[4]This is in contrast to recent papers such as Burks et al. (2015) and Hoffman et al. (2018), which also cover applicants.

2.1 Employee Outcomes

In knowledge-based firms such as the one we study (as well as in non-knowledge-based firms), employee performance often has multiple dimensions. There are several core employee outcomes in our data, the most important one for our purposes being employee attrition:

- **Turnover.** Employee turnover is a significant issue in many organizations, and in high-tech firms in particular, where the knowledge of employees represents a key asset. As noted above, employee turnover is a key means by which knowledge is transferred in high-tech firms, leading many firms to be keenly interested in reducing turnover.[5] This is particularly true for high-tech employees in states such as California, where non-compete agreements are essentially unenforceable and firms are concerned about losing key ideas to competitors (Balasubramanian et al., 2017). We separately observe dates of voluntary quits and involuntary fires.

- **Subjective performance.** The firm's subjective performance scores are set biannually on a scale from 1 to 5, as in the case in many organizations that use subjective performance evaluation (Frederiksen et al., 2017). Subjective performance scores are set in a process involving an employee's immediate manager as well as higher-up managers. While there are some broad guidelines for the distribution of subjective performance scores across various units within the firm, there is not a fixed "curve" across managers in the number of subjective performance scores that can be provided.[6]

- **Employee engagement.** Engagement is a number from 0-100 about how engaged the employee is feeling (via the same survey that is used to elicit information on employees' view of their manager), which is then normalized. Employee engagement is a variable that seems to have received limited attention within labor and organizational economics

[5] In fact, as is common in many firms, our firm has analysts who try to predict and reduce employee turnover.

[6] At high levels of aggregation within the organization (that is, for top managers), there may be a curve with respect to subjective performance. To address this, we can examine the robustness of subjective performance results to excluding top managers.

(Blader et al. (2016) is a recent exception). However, within industrial psychology and management, employee engagement is an outcome of significant interest (Kahn, 1990).

- **Salary increases.** While it is difficult to measure the productivity of knowledge workers, we can attempt to proxy productivity improvements by the extent to which an employee's salary increases.

- **Promotions.** Another recent paper using promotions as a proxy for knowledge worker productivity is Brown et al. (2016).

Different employee outcomes are available at different frequencies, but are coded in our data at the monthly level. Attrition and promotion events are coded in our data at the monthly level using exact dates for these events. Subjective performance reviews occur twice per year, but are also coded month-by-month. The level of annual salary is tracked at the monthly level.

2.2 Assignment of Managers to Employees

Managers manage employees within their function and line of business, and this is reflected in the initial assignment of employees to managers. Assignment of employees to managers reflect the projects and functions that require employees at any given time. Geographic area needs also dictate the circumstances in which employees may experience the change of a manager. The company has an online system where managers post internal workforce needs, and new employee-manager matches can form based on these online postings. Managers are involved in hiring for vacancies and also have involvement with dismissals. Thus, it is clear that employees at the firm are not being randomly assigned to different managers. Instead, managers play a significant role in selecting employees for their teams. We further discuss manager assignment at the start of Section 3, as well as in Section 4.

On average across managers, a manager manages about 6 employees at one time in our data. However, the average number of employees per manager is 11 when managerial span is weighted by employee-months. Even though our dataset is not long, employees experience an average of 2.7 managers (and they experience about 3 managers when managers per employee is weighted by employee tenure). Conversations with several industry participants at this and other firms confirm that this level of internal movement is typical in the high tech industry.

2.3 Employee Surveys

Every year, employees are given a detailed survey. The goal of these type of surveys is for the firm's Human Resource (HR) department, and for company executives, to gain an accurate sense of employee opinions at the organization. Because the surveys are designed to ensure the anonymity of responses, survey information about one's managers is only collected on managers who manage a minimum number of individuals.[7] In the dataset provided to us by analysts at the firm, for managers who only manage a number of employees below the minimum for the survey, manager scores are imputed using information from a higher-ranked manager. About one-fifth of the observations have imputed manager scores. To increase power, most of our analyses use this dataset that includes imputations, but our main results are qualitatively robust to excluding imputed manager scores.

Surveys of this type are typically administered before year end, and consistent with this industry norm, the surveys in our data were performed in September in Y_1, Y_2, and Y_3. The survey had the same format and same manager questions in Y_1 and Y_2 whereas for Y_3, the survey format changed (some of the questions were the same and some changed). We focus our analysis using the two surveys in Y_1 and Y_2, and use the third survey for robustness.

For our main analysis, to match outcomes with their associated survey, observations from January Y_1-September Y_1 are assigned the survey information from the Y_1 survey, whereas other observations are assigned the survey information from the Y_2 survey.[8] For both the Y_1

[7]In the first year of the survey (Y_1), the threshold was 3 employees, whereas in the second year of the survey (Y_2), the threshold was 5 employees. Technically speaking, the survey is "3rd party confidential" instead of "anonymous," according to the firm. "Anonymous" means that it would be totally impossible to tie responses to employee attributes. "3rd party confidential" means the survey vendor, a third party independent firm, has access to responses so they can tie them to employee attributes to generate statistical information.

[8]In our robustness analysis using all three survey waves, we assign data from October Y_1 to September Y_2

and Y_2 surveys, the response rate was 95%.

Manager questions. Various survey questions are asked every year about what employees think about their managers. Employees are asked for each question whether they Strongly Disagree, Disagree, Neither Agree nor Disagree, Agree, or Strongly Agree. Specifically, we observe answers to the following survey items:[9]

1. My immediate manager communicates a clear understanding of the expectations from me for my job.
2. My immediate manager provides continuous coaching and guidance on how I can improve my performance.
3. My immediate manager actively supports my professional/career development.
4. My immediate manager consults with people for decision making when appropriate.
5. My immediate manager generates a positive attitude in the team, even when conditions are difficult.
6. My immediate manager is someone whom I can trust.

A manager's rating on an item is measured as the share of employees who marked Agree or Strongly Agree.[10] For example, if a manager has 8 direct reports, and 6 of them marked Agree or Strongly Agree for one of the items, the manager's score on that item would be 75 out of 100 in the data provided to us. If employees experience multiple managers over the survey period, they only rate their most recent manager.

to the Y_2 survey, and data after this to the Y_3 survey.

[9] To preserve firm confidentiality, the wording may be slightly modified from the original.

[10] This is how the data are prepared by the third party survey (presumably in part to protect anonymity of responses), and is thus also the form that the firm uses in its internal reporting. Therefore, it is impossible for us to analyze other moments of the data, such as the mean or standard deviation of manager scores. However, to our understanding, it is common practice in such surveys to break up the 5-answer scale into 2 or 3 parts. For example, exhibit 7 of Garvin et al. (2013) suggests that Google grouped the 5 answers into Unfavorable (Strongly Disagree or Disagree), Neutral (Neither Agree nor Disagree), and Favorable (Agree or Strongly Agree) in its own people management survey. Thus, using the share marking 4 or 5 (as we do) seems consistent with how many firms measure their managers on similar surveys.

A manager's overall rating (MOR) is the average of scores on the 6 items. For example, if a manager had score of 100 on the first 3 items and a score of 50 on the second 3 items, the manager's MOR is 75. The MOR is easy to compute and is used by the firm in its internal reporting and communications. We will use MOR as our main measure of employee-survey-based manager quality, and discuss this further below in Section 2.5.

Engagement questions. In the same survey as the manager questions are asked, employees also answer questions about their own level of engagement in the organization. Engagement scores combine information from a number of different items on the survey such as "I would recommend this company as a great place to work." Importantly, these questions concern the employee's overall satisfaction and engagement with the organization as opposed to focusing on the employee's manager. Like the manager scores, employee engagement scores are also only available at the manager level.

2.4 Sample Creation and Summary Statistics

To create our sample, we restrict attention to worker-months where an employee has a manager with a non-missing MOR for the current period, as well as a non-missing MOR in the other period. This sample restriction is required for our IV analysis, where we instrument manager MOR in the current period using MOR in the other period.

Table 1 provides summary statistics for our sample. The employee attrition rate is 1.35% per month. The majority of separations are voluntary ("quits"), but there are still a sizable number of involuntary separations ("fires"). There are a number of exits which are not classified in the data as voluntary or involuntary.

The average MOR is about 82 out of 100. About 85% of employees are co-located with their manager, whereas the remainder are managed remotely. While the number of observations cannot be shown to preserve firm confidentiality, note that the number of observations varies for the different variables, reflecting challenges in linking together many different dataset from within the firm.

2.5 Properties of MOR

Is MOR the right measure? A natural question is whether there is another way of combining the six manager questions that is more sensible than a simple average. We explore this question using principal component analysis. As seen in Table C2, the first component explains about 70% of the variation in manager scores. Interestingly, the first component is quite close to an equally weighted average of the 6 individual items. Thus, beyond being very simple, another justification for using MOR is that it is close to the first principal component of the six questions, a component that explains a large share of the variance.

Persistence. Table 2 shows that the manager scores are somewhat persistent over time on particular attributes. Each column takes one of the managerial quality questions from the Y_2 survey. The score is then regressed on the various manager quality questions from the Y_1 survey and various controls. For example, column 1 shows that a manager who perform one point better in the Y_1 survey in MOR is scored about one-third of a point higher on this same measure in the Y_2 survey. Columns 2-7 show that there is significant correlation over time in manager scores on particular attributes.[11]

These results are consistent with the view that managers have particular characteristics that are somewhat persistent over time. One challenge with this interpretation is that the various manager characteristics are correlated with one another.[12] To address this issue, we also regress each manager characteristics on all the six questions at once. Appendix Table C3 shows that each individual characteristic predicts the characteristic even while controlling for the other characteristics.[13]

[11]We restrict attention to non-imputed manager scores for Table 2. The predictiveness of the scores over time is moderate, but perhaps not as high as some readers might expect. Why is the coefficient far less than 1? First, if a manager scores badly on the scores multiple years in a row, the manager is invited to attend a "bootcamp" to improve manager effectiveness. Second, as with all surveys, it is possible that responses could reflect measurement error (e.g., an employee answering the questions quickly for one year), though we point out that the firm seems to take the surveys quite seriously. Third, manager's responsibilities, tasks, and projects change over time. A manager might be perceived has providing excellent coaching and guidance for one type of project, but not for another type of project.

[12]The correlation is relatively high, though still much less than 1. See Appendix Table C1.

[13]Another concern with interpreting managerial characteristics as relatively persistent is that manager scores

Appendix Table C4 shows that the result on the persistence of overall MOR (column 1 of Table 2) is qualitatively robust to including the Y_3 survey.

3 Empirical Strategy

While there are several parallels between the teacher value-added literature and our analysis, there are also key differences. First, we are estimating the impact of a survey-measured regressor (namely, survey-measured people management skills) instead of estimating manager fixed effects. Thus, we need to address the important issue of measurement error in our survey (as opposed to sampling error in estimating large numbers of fixed effects).

Second, unlike in schools (where teachers generally do not choose their students), managers at our high-tech firm play a critical role in hiring and selecting people for their team. Indeed, practitioners frequently argue that one of the most important parts of being a good people manager is selecting the right people (Harvard Management Update, 2008). Even if we could convince our firm to randomly assign employees to managers, such an experiment would not be informative of the overall impact of good people management skills since it would rule out better people managers selecting better people. Rather, differences across managers in employee quality might be viewed as a *mechanism* by which managers improve employee outcomes as opposed to a source of bias.

A more informative hypothetical experiment for our setting (and one we try to approximate in our design based on managers switching locations) would be to randomly assign managers to different parts of the firm and then observe employee outcomes, thereby reflecting the role of managers in selecting and motivating their teams.[14] Still, even if we do not wish to rule out better managers selecting better people, we need to address the possibility of the

could reflect persistence of worker characteristics or how workers answer the survey as opposed to manager characteristics. Thus, we have also repeated Table 2 while restricting attention to managers who move locations across the firm in the second period. In this robustness check, we continue to see substantial persistence of managerial characteristics across surveys.

[14]In addition, one would ideally wish to randomly assign differing levels of people management skills to different managers.

firm optimally sorting managers and employees together, which we discuss further below.[15]

3.1 Econometric Set-up

We wish to estimate how much the underlying people management skill of manager j, m_j, affects an outcome, y_{it}, of employee i:

$$y_{it} = \beta m_{j(i,t)} + \varepsilon_{it} \tag{1}$$

where $j(i,t)$ represents that j is the manager of employee i at time t, though we will henceforth abbreviate $j(i,t)$ simply by j. Given we are using an imperfect survey, one concern is that management quality, m is measured with error; instead of true underlying people management, we only observe the noisy survey measure, $\widetilde{m}$. In our data, we have the two main waves of the survey, giving us two manager scores $\widetilde{m}_1$ and $\widetilde{m}_2$, with $\widetilde{m}_{j,\tau} = m_j + u_{j,\tau}$, $\tau \in \{1, 2\}$. In our data, t is at the monthly level, whereas there are two values of τ.

Perhaps the simplest approach to analyzing the impact of people management skills is to estimate OLS regressions of the form:

$$y_{i,t} = b\widetilde{m}_{j,\tau(t)} + \theta_{i,t} \tag{2}$$

where $\theta_{i,t}$ is an error term; and where $\tau(t) = 1$ if $t \leq$ month 9 of Y_1 and $\tau(t) = 2$ if $t >$ month 9 of Y_1.[16] However, OLS models may be biased by measurement error. An alternative approach (e.g., Ashenfelter and Krueger, 1994; Ashenfelter and Rouse, 1998) is to instrument

[15] Beyond a manager selecting employees for his or her team, and beyond the firm sorting employees and managers, another situation that could arise is one where a person has a reputation as a great people manager. For such managers, strong job applicants (or good existing employees at the firm) may make an effort to sort onto his or her team. While we try to reduce concerns about sorting below, it is not clear that one would want to control for this either. Indeed, having a "brand" as being a good people manager and thus attract strong hires is a key way by which good people managers may matter, particularly in high-skilled settings, such as the one we study.

[16] That is, $\tau(t)$ corresponds calendar months to survey periods. Recall that the Y_1 survey was administered in m9 of Y_1. Thus, we analyze employee outcomes during period 1 as a function of their manager's rating during period 1. This assignment of calendar dates to survey periods is also used by the firm for their internal reporting.

one survey measure with the other one:

$$y_{i,t} = b\widetilde{m}_{j,\tau} + \theta_{i,t} \tag{3}$$
$$\widetilde{m}_{j,\tau} = c\widetilde{m}_{j,-\tau} + \eta_{j,t}$$

where $\widetilde{m}_{j,-\tau}$ is the measured people management score of manager j in the period other than the current one, and $\theta_{i,t}$ and $\eta_{j,t}$ are error terms.

Instead of assuming that the measurement error is classical, we will consider the possibility that the measurement error could be correlated with unobserved determinants of employee outcomes, e.g., that being on a good project could affect how an employee rates their manager, as well as whether that employee attrites. That is, compared to most empirical studies where there is measurement error, we make fewer assumptions. However, like most studies, we do assume that measurement error is uncorrelated with a manager's true people management skill:[17]

Assumption 1 *$cov\left(m_j, u_{j,\tau}\right) = 0$ for $\tau \in \{1, 2\}$.*

While we do not expect Assumption 1 to be literally true (given there are caps of the management score at 0 and 100), we believe that it is approximately true in our setting, particularly because people are not selecting their own management score.[18]

We now compare OLS and IV estimators for this setting. For ease of exposition, we suppress i and j subscripts. For OLS, we use $\text{plim}(\widehat{b}_{OLS}) = \frac{cov(y_t, \widetilde{m}_\tau)}{var(\widetilde{m}_\tau)}$ plus Assumption 1 to get the below (derivation in Appendix A.1):

$$\text{plim}(\widehat{b}_{OLS} - \beta) = \underbrace{-\frac{\sigma_u^2}{\sigma_m^2 + \sigma_u^2}\beta}_{\text{Attenuation Bias}} + \underbrace{\frac{cov(\varepsilon_t, u_\tau)}{\sigma_m^2 + \sigma_u^2}}_{\text{Contemp. Corr. ME}} + \underbrace{\frac{cov(\varepsilon_t, m)}{\sigma_m^2 + \sigma_u^2}}_{\text{Assignment Bias}} \tag{4}$$

In (4), the first term or *Attenuation Bias*, is standard under OLS when there is classical measurement error on the right-hand side. In the second term or inconsistency from *Contemporaneously Correlated Measurement Error*, the numerator, $cov\left(\varepsilon_t, u_\tau\right)$, is the covariance

[17]Our analysis of measurement error draws heavily (in content and notation) from Pischke (2007).

[18]Assumption 1 seems most likely to be systematically violated when people are answering surveys about themselves and there are social pressures such as conformity bias, e.g., someone with a low amount of actual schooling or earnings might feel social pressure to report that they have more schooling or earnings than they actually have (as in Bound and Krueger (1991)).

between the measurement error from the survey and unobservables that affect employee outcomes. We believe that such measurement error is likely to be positive, but it is not necessarily the case. For example, one issue for analyzing attrition as an outcome is that there are individuals who quit before they get to take the survey. A manager may appear to have a better score on the survey than if the employee was allowed to take part in the survey. In the third term or *Assignment Bias*, the numerator, $cov(\varepsilon_t, m)$, represents the correlation of worker-level unobservables with manager quality. This could be positive or negative.

Next, consider the IV estimator where we instrument a manager's score during one period with the manager's score in the other period (as in equation (3) above). Note that different employees may evaluate the same manager during two different periods. Using $\text{plim}(\widehat{b}_{IV}) = \frac{cov(y_t, \widetilde{m}_{-\tau})}{cov(\widetilde{m}_{\tau}, \widetilde{m}_{-\tau})}$, we get:

$$\text{plim}(\widehat{b}_{IV} - \beta) \quad = \quad \underbrace{-\frac{cov\,(u_\tau, u_{-\tau})}{\sigma_m^2 + cov\,(u_\tau, u_{-\tau})}\beta}_{\text{Attenuation Bias}} + \underbrace{\frac{cov\,(\varepsilon_t, u_{-\tau})}{\sigma_m^2 + cov\,(u_\tau, u_{-\tau})}}_{\text{Asynchronously Corr. ME}} + \underbrace{\frac{cov\,(\varepsilon_t, m)}{\sigma_m^2 + cov\,(u_\tau, u_{-\tau})}}_{\text{Assignment Bias}} \qquad (5)$$

As for OLS, the expression for the consistency of IV (equation 5) has three terms. The first term has $cov\,(u_\tau, u_{-\tau})$ in place of σ_u^2. Thus, if the measurement errors are uncorrelated across the two surveys, there is no attenuation bias. This assumption seems reasonable for certain types of measurement error, such as sampling error due to small numbers of subjects, one-time data imputation, or people being in a good mood because the current project is going well. Other types of measurement error might be more persistent, e.g., there might be persistence if people on a manager's team have a general tendency to rate managers highly on surveys. As we discuss more later, such correlations though can be avoided by looking at managers who are rated by mostly different employees in the first and second periods, e.g., managers who move across locations within the firm. In such circumstances, we would expect substantially less attenuation bias than in OLS.

The second term of (5) has $cov\,(\varepsilon_t, u_{-\tau})$ instead of $cov\,(\varepsilon_t, u_\tau)$ in the numerator. That is, it involves the covariance between measurement error in the *other* period and the unobserved determinants of performance in the current period (instead of the covariance between measurement error in the *current* period and the performance equation error in the current period). For measurement error due to inattention or non-response, this correlation may be quite small or zero. For things like being on a good project, this correlation may depend on how persistent is the shock over time.

The third term of (5) still has $cov\,(\varepsilon_t, m)$ has in the numerator, but it is divided now by $\sigma_m^2 + cov\,(u_\tau, u_{-\tau})$ instead of $\sigma_m^2 + \sigma_u^2$. Thus, IV can amplify assignment bias if $cov\,(u_\tau, u_{-\tau}) < \sigma_u^2$.

We will also present reduced form results, i.e., OLS regressions of y_t on $\widetilde{m}_{-\tau}$:

$$\text{plim}(\widehat{b}_{RF} - \beta) \;=\; \underbrace{-\frac{\sigma_u^2}{\sigma_m^2 + \sigma_u^2}\beta}_{\text{Attenuation Bias}} + \underbrace{\frac{cov(\varepsilon_t, u_{-\tau})}{\sigma_m^2 + \sigma_u^2}}_{\text{Asynchronously Corr. ME}} + \underbrace{\frac{cov(\varepsilon_t, m)}{\sigma_m^2 + \sigma_u^2}}_{\text{Assignment Bias}}$$

Relative to the IV, a disadvantage of the reduced form is that there is still the same attenuation bias as for OLS. A potential advantage is that assignment bias is scaled by $\sigma_m^2 + \sigma_u^2$ in the denominator instead of $\sigma_m^2 + cov\,(u_\tau, u_{-\tau})$.

Throughout the empirical analysis, standard errors are clustered by manager, reflecting the main level of variation for our key regressor.

3.2 Additional Remarks

- **What if underlying people management quality varies within a manager over time?** This could occur for several reasons, including that a manager's effort may change over time; certain managers may be better with some projects or teams than others; and the firm may help a manager to improve their people management skills over time. Appendix A re-does the above formulas allowing manager quality to vary over time. For the IV, possible attenuation depends now on the size of the covariance of people management skills over time relative to the covariance of measurement error over time. The other results are qualitatively similar.

- **What happens if people management has persistent effects?** The key identification assumptions for IV are that $cov(\widetilde{m}_{j,-\tau}, \theta_{it}) = 0$ and that the only way that $\widetilde{m}_{j,-\tau}$

affects $y_{i,t}$ is through its influence on $\widetilde{m}_{j,\tau}$. One way this can fail is there are persistent effects of good people management. Similar to having had a good teacher in the past, it is possible that good people management could have a persistent effect over time. We have two responses. First, existing evidence on manager effects suggests that they are not very persistent: in Lazear et al. (2015), 2/3 of boss effects disappear after 6 months, and 3/4 disappear after one year.[19] Second, some of our identification strategies rule out persistent effects. For example, when we analyze new workers joining the firm in period 2, their current manager is interacting with them for the first time at the firm, so there is no concern about the manager's quality having a persistent effect. Persistent effects can also be addressed by looking at individuals who switch managers. That we reach qualitatively similar conclusions with these identification strategies is consistent with people management having primarily a contemporaneous effect.

- **Control variables.** While the above set-up ignored control variables, control variables can also be added. These help address the possibility that MOR and employee outcomes may differ systematically within the large firm we study. We control for the firm's different business units, as well as for work type (or occupation) within those business units. We also control for year of hire, current year dummies, and a 5th order polynomial in employee tenure. We control for location (as the firm has many offices), employee salary grade (or level), and an employee manager's span of control.

- **Adding fixed effects.** Beyond control variables, worker fixed effects can be added to an IV specification. The key is for some workers to experience multiple managers during the period for which output is being analyzed. For example, suppose that worker Alan experiences both managers Beth and Collin in period 2. The manager scores of Beth

[19] This evidence differs from ours in several respects. First, we analyze people management skill as opposed to overall boss effects. Second, we primarily analyze attrition whereas Lazear et al. (2015) primarily analyze output per hour. Third, we study a high-skill firm, whereas Lazear et al. (2015) study a firm where workers do a routine job. It is not whether such differences would lead to boss effects being more or less persistent, though we might imagine that the identity and skills of one's current manager would be particularly important for our outcome of attrition. Unfortunately, we cannot separately test whether people management is persistent using our IV strategy.

and Collin will be instrumented with the manager scores that they received in period 1.

4 Manager Quality and Employee Attrition

Section 4.1 presents our baseline results on the relationship between MOR and employee attrition. Next, we present our three research designs: new joiners (Section 4.2), employees switching managers (Section 4.3), and managers switching locations (Section 4.4). Exploiting different variation (and requiring different identifying assumptions) and addressing different threats to identification, the three designs provide complementary evidence supporting that people management skill substantially reduces employee attrition. Section 4.5 addresses additional threats to identification. Section 4.6 estimates manager value-added.

4.1 Baseline Results

Panel A of Table 3 shows our baseline results. Column 1 shows a strong first stage ($F > 200$). In column 2, the OLS coefficient of -0.118 means that increasing MOR by 1σ is associated with a monthly reduction in attrition of 0.118 percentage points (hereafter "pp"), which is a 9% reduction relative to the mean of 1.35pp per month. Column 3 presents the IV estimate where MOR in one period is instrumented with a manager's MOR in the other period. Here, the coefficient is substantially larger at -0.382, implying that increasing MOR by 1σ corresponds to a 28% reduction in turnover. By the difference of two Sargan-Hansen statistics, we reject that the IV and OLS estimates are the same ($p < 0.01$). That IV is substantially larger in magnitude than OLS is consistent with OLS being significantly biased downward in magnitude due to attenuation bias. Still, as discussed above, IV may be biased due to asynchronously correlated measurement error (i.e., measurement error from the non-current period which is correlated with unobserved determinants of turnover or $cov(\varepsilon_t, u_{-\tau}) \neq 0$) or assignment bias by the firm ($cov(\varepsilon_t, m) \neq 0$). We address those possibilities further below.

Our IV estimate implies that moving from a manager in the 10th percentile of MOR to one in the 90th percentile of MOR is associated with a reduction in quitting of roughly 50 percent (under the assumption of normality).[20] To further assess the IV magnitude, we compare it to estimates in other studies analyzing turnover, particularly those related to management. Bloom et al. (2014a) show that randomly assigning call-center employees to work from home reduces turnover by 50%. Friebel et al. (2017) show that randomly sending letters from the CEO highlighting the firm's turnover problem causes store managers to reduce turnover by one-third. Thus, having a manager in the 90th percentile of the people management distribution instead of one in the 10th percentile has a similar impact on turnover as letting employees work from home, and a slightly larger one than sending a letter to managers highlighting that there is a turnover problem.[21]

Panel A analyzes overall attrition, but not all attrition is the same. Some attrition is voluntary ("quits") and some is involuntary ("fires").[22] However, one might imagine that good managers are ones who prevent voluntary quitting, but who are willing to also sometimes remove individuals who are not contributing. Thus, Panels B and C perform the same analyses as Panel A, but separately for quits and fires. We observe highly significant IV results for both quits and fires. The coefficient is larger in absolute magnitude for quits, but is larger in percentage terms for fires, reflecting that fires are rarer in quits.[23]

Of course, the distinction between voluntary and involuntary turnover is often not clear-cut (e.g., in order to get rid of someone, you can ask them to resign), and there is no theoretical distinction in many models of turnover (e.g., Jovanovic, 1979); further, it is not immediately

[20]The 10th percentile of a standard normal distribution is 1.28σ below the mean, corresponding to a monthly attrition rate of 1.349-1.28*(-.382)=1.84. The 90th percentile corresponds to a monthly attrition rate of 1.349+1.28*(-.382)=0.86, a reduction of slightly more than 50%.

[21]In another example, Madrian (1994) analyzes the impact of turnover of having a spouse with health insurance to study the impacts of "job lock." She finds that job lock reduces employee turnover by 25%. Thus, our IV estimate from increasing MOR from the 10th to 90th percentile has roughly twice the impact on turnover as does one's spouse having health insurance in the US, and a larger impact on turnover than enforcing non-compete agreements. More generally, Manning (2011) reports wage-turnover elasticities of 0.5-1.5 in his survey of the literature.

[22]In the data field on the attrition event, attrition events are marked as 'voluntary,' 'involuntary,' or 'missing.' We don't use the 'missing' events in this auxiliary analysis here, but one can also classify the missing data fields as voluntary turnover events.

[23]For voluntary quits, the company classifies them as regretted or non-regretted (i.e., quits the firm wished it had avoided or not). Appendix Table C5 shows that results are robust and qualitatively similar when looking only at regretted quits.

clear whether it is "better" for managers to avoid quits or fires. Another way to delve further into turnover is to look at turnover separately for higher and lower productivity workers. To classify workers as high or low productivity, we residualize workers' subjective performance scores on the controls in Table 3, and then regress the residuals on worker fixed effects. Fixed effects that are above the median are classified as higher-productivity workers and those below as lower productivity workers.

Panels D and E of Table 3 analyze turnover separately for higher- and lower-productivity employees. The IV coefficients are large and significant in both cases. As has been been found in many studies, there is strong selection on productivity in turnover (e.g., Hoffman and Burks, 2017), with the higher-productivity workers having a substantially lower base probability of attrition. While the IV coefficient is larger in absolute magnitude for lower-productivity workers, it is larger in percentage terms for higher-productivity workers. Thus, it is not the case that high-MOR managers are simply preventing low-productivity workers from leaving.

4.2 Research Design based on New Workers Joining the Firm

Repeating our IV analysis while using only new workers who join the firm in the second period, Table 4 also finds a strong negative relation between a worker's manager's MOR and turnover. This "joiners" analysis has several advantage relative to our baseline analysis and allows us to address a couple concerns. First, in the joiners analysis, the survey responses of the workers under analysis do not influence the instrument (i.e., the MOR that their current manager received during period 1) because they are new to the firm. For example, one concern could be that employees who have a cheery personality might be both more likely to rate their manager highly and less likely to quit, i.e., that a worker's cheeriness could lead to a positive correlation between ε_t and $u_{-\tau}$. However, that issue is avoided here.[24]

[24]The joiners analysis also eliminates concern about events in period 1 that would lead workers to rate their managers more highly, as well as affect their quitting in period 2. For example, if an employee got to work on a very enriching project in period 1 that improved their general human capital, this could lead them to rate their manager in period 1, as well as to be less likely to quit in period 2. It is important to note, however, that our new joiners analysis does not help with persistent shocks, e.g., a very successful or exciting project that would make current employees rate a manager highly in period 1, as well as make new workers less likely

Second, our analysis reduces concerns about assignment bias. When an employee joins a very large firm, they are unlikely to have substantial information about differences across managers in people management skills that would enable them to sort into managers based on people management skills. Furthermore, the firm overall seems unlikely to have substantial information beyond the manager that was involved in hiring them.[25] This reduces the concern that ε_t is correlated with m separate from the possible role of better managers in selecting better employees for their team.

Results. Table 4 shows a sizable negative relation between MOR and attrition among joiners. The IV coefficient of -0.558 slightly misses statistical significance (the standard error is larger, reflecting the smaller sample for the joiners analysis), but is economically quite sizable, implying that a 1σ increase in MOR corresponds to a 0.56pp (30%) reduction in monthly turnover. We cannot reject that the IV estimate in the joiners analysis differ from the IV estimate in the baseline analysis in Table 3. Thus, while we have much less statistical power here than for our full sample, the relationship between MOR and attrition in Table 4 is qualitatively similar to that in the baseline analysis.

4.3 Research Design based on Workers Changing Managers

While the joiners analysis has several clear benefits, it also has limitations. First, it is based only on new workers, so there are potential concerns about external validity. Second, the sample size is small relative to our full sample. Third, it is difficult to do certain statistical tests regarding assignment bias. In this section, we instead analyze what happens after employees experience a change in manager (a "switchers" design). This analysis addresses these limitations, and we continue to find a strong negative relation between a worker's manager's MOR and turnover.

to quit. The joiners analysis is useful, however, if people differ in their opinions about whether a project is exciting, as the joiners analysis looks at different people in period 2 compared to the raters in period 1.

[25] Lazear et al. (2015) use new joiners as a research design for estimating manager fixed effects. Our argument that new employees have limited private information, and that the firm has limited information (separate from the manager), closely follows a similar argument in Lazear et al. (2015).

Manager switches occur for many reasons at the firm we study, such as new projects, manager turnover, and promotions, as well as several re-organizations ("re-orgs") that occurred for exogenous reasons. To preserve firm confidentiality, we cannot provide detailed accounts of the re-orgs, but they were events driven by external conditions or business conditions that affected many parts of the organization at once, and therefore caused numerous changes in who was managing whom.

Analysis of switchers is useful for multiple reasons. First, the sample is broader than only new joiners. Second, we can do a Rothstein (2010, 2017) test for non-random sorting.[26] Third, we can make "event study" graphs analyzing how impacts of MOR on turnover vary with how long a person has been with a manager; such a graph would be hard to interpret in the joiners design, where time since manager is collinear with tenure. Fourth, analyzing what happens to employees after changes in manager is generally useful for reducing concern about assignment bias. While matching of managers and employees is not random, one might believe that matching occurring for reasons such as manager turnover or re-orgs might reflect less active involvement or deliberate matching of the firm, particularly when there are many individuals being moved at the same time. It is presumably harder for a firm to do sophisticated matching when it has to make many personnel changes in a short amount of time.

Results. Table 5 re-produces Panel A of Table 3 while restricting to managers after their first switch in manager during our sample period.[27] The IV coefficient of -0.577pp implies that a 1σ increase in MOR predicts a 41% reduction quitting, which is slightly larger but qualitatively similar to our baseline estimates in Panel A of Table 3.

A concern with the switchers analysis is that the firm may be matching unobservedly

[26] We test whether the MOR of one's future manager predicts employee outcomes prior to a manager switch. This test is not possible for new joiners, as employee outcomes are unobservable prior to joining the firm.

[27] Many workers switch managers multiple times during our sample period. Our goal in restricting to time after first manager switch is to avoid concerns related to people experiencing multiple events. Another question is whether we should restrict to employees who experience their first manager in period 2 or not. We avoid doing so because doing so substantially limits whether workers can be observed with their manager for four or more quarters. To check that our results are not driven by an employee's contribution to their new manager's rating during the first period, we re-did Table 5 while restricting attention to employee-months when managers have an above median span of control, and obtained qualitatively similar results.

high-quality managers and workers together. While this is hard to test for in terms of attrition unobservables, we can examine whether the MOR of an employee's *future* manager predicts employee non-attrition outcomes in the current period, following Rothstein (2010, 2017). Table 6 shows that there is no relation between a future manager's MOR and three key non-attrition outcomes (subjective performance, salary, and promotion propensity). Note that we cannot use attrition for the Rothstein (2010, 2017) test because workers who will experience a new manager in the future do not attrite before they experience the new manager.

Figure 1 takes the IV regression in Table 5, but interacts MOR with quarter since receiving a new manager. When workers receive a new manager, they are less likely to quit when the manager has high MOR compared to when the manager has low MOR. However, there is little relation between MOR and quitting in the first quarter after a manager change. Rather, the quit benefit builds gradually, with much of the reduction in quitting only occurring in quarter 3 after a manager change (i.e., months 10-12 since the manager change).

The time path of results in Figure 1 seems consistent with a causal impact of people management on attrition. The impact of a good or bad manager may not be felt immediately after they become a worker's manager. Rather, it may take some time for workers to get to know their manager and to be affected by their manager's behavior. If the results in Figure 1 were instead driven by assignment bias (e.g., the firm decides to match unobservedly better workers with better managers), one might imagine that quit impacts would be observed immediately instead of growing over time.[28]

4.4 Manager Moves across Locations

Another type of shock that we have not yet discussed is a geographic shock. While our analyses already include location fixed effects, there could be shocks on smaller levels of geography. Imagine that one sub-section of an office is always darker than another sub-section (or has

[28] We have also made the graph separately for quits and fires. For quits, the impacts are decreasing over time, consistent with the impacts on overall attrition. In contrast, for fires, the impacts are fairly flat over time.

worse amenities in some other respect). The darkness could be correlated with measurement error in the first period survey, as well as with measurement error in the second period survey and/or with unobserved determinants of employee attrition in the second period.[29]

To address such concerns, we turn to instances where managers move across locations during the second period. This way, MOR is measured at one location of the firm in the first period, and will be measured at a different location in the second period.

Manager moves across locations may also be useful for addressing concerns about assignment bias. When manager moves take place within a firm location, higher managers may have private information about the types of employees and managers who will work well together. The firm may have less information when managers are moving across locations. Our notion that moves across locations helps reduce concerns about matching on unobservables builds on the work of Chetty et al. (2014), who use teacher moves across schools as a source of quasi-experimental variation in estimating the impact of teacher value-added.

Results. Table 7 shows results exploiting managers moving across locations. We restrict our analysis sample here to observations after the new manager has arrived at the firm, and we also restrict attention to a manager's first move in the second period time frame (There are some managers who move multiple times in the second period). [30]

As in our main results, the IV estimate is larger in magnitude than the OLS estimate. The IV estimate implies that a 1σ increase in a manager's MOR decreases employee attrition by 0.40pp or 21% in our sample. This is slightly lower than our benchmark estimate in Table 4.1, but is broadly similar.

Paralleling the teacher value-added literature, one concern is whether manager moves are truly exogenous. In our setting, a concern might be one where excellent managers are promoted to interact with unobservedly strong employees at a different location. However,

[29] In conversation with us, one manager mentioned the possibility of free food as a shock. For example, at various times, to increase morale, the firm will prioritize giving free food to certain segments within the company. Free food provision can be for short periods of time, or it can be more persistent.

[30] In addition, we exclude moves to three locations, where moves tended to occur in the same month, and which appear to reflect a re-naming of the string location in the data, as opposed to actual moves across locations.

in our data, only about 3% of manager moves correspond to a promotion in that particular month, and only about one-quarter of manager moves are associated with a salary increase in that month (though we caveat this by pointing out that promotions and salary might not adjust immediately). Rather, many of the moves appear to be lateral moves, which are common in large firms (Jin and Waldman, 2016).

4.5 Additional Threats to Identification and Robustness

Non-monotonic relationship between MOR and Employee Quality. In our analyses, we have analyzed the linear relationship between manager quality and employee outcomes. However, it could be that manager quality has a non-linear impact on employee outcomes. In particular, one could imagine that some managers are "superstars" (Rosen, 1981), and have potentially very large impacts on employees, whereas the difference between a low and middling manager is immaterial. To examine this hypothesis, we split MOR into 5 quintiles and re-run Panel A of Table 3. We failed to find a special importance of very high ranked managers.[31]

Heterogeneity analysis. Above, we provided evidence across different research designs that MOR appears to have a strong causal negative relation on employee turnover. Furthermore, our baseline IV estimates were qualitatively similar to IV estimates exploiting the different research designs. Having provided this evidence, we now examine heterogeneity in the IV estimates by occupation, geography, and hierarchy.

Appendix Tables C8-C10 shows that negative IV relation between MOR and turnover is qualitatively robust across occupation, geography, and hierarchy. In terms of occupation, we observe that the IV estimates are relatively similar across workers in engineers, customer service, marketing, and finance.

In terms of geography, there has been a lot of recent interest in how management varies across countries, particularly in rich vs. poor countries. Bloom et al. (2014b) document that

[31] Specifically, the coefficients on the top 2 quintiles (compared to the worst quintile) are not very different. NEED TO RE-DO.

management practices are substantially better in richer countries than in poorer countries. Hoffman et al. (2017) document that front-line supervisors appear to matter more in rich countries than in poor countries for the case of employee attrition. Most of the workers we study are in rich countries (particularly the US), but there are roughly 10% of employee records in "poor countries" (China, India, and Malaysia). In our setting, MOR has a stronger negative relation for non-US workers than US workers, though relatively large standard errors make our comparisons only suggestive.

In terms of hierarchy, Appendix Table C10 shows that the negative relation between MOR and attrition is actually slightly larger for individuals toward the upper part of the firm hierarchy. We divide individuals at the firm into three levels of hierarchy according to their salary grade, following how the firm does such divisions in its internal communications. It is natural to analyze heterogeneity in manager effects by hierarchy, as theories of managers emphasize different roles for managers at different levels of hierarchy. For example, in knowledge based theories of the firm (Garicano, 2000), managers solve increasingly complex problems as they ascend the firm hierarchy. Of the 5 outcomes studied, log salary growth is an exception, where associations are higher at lower levels.

4.6 Value-Added Approach

We can also use our data to perform a value-added analysis of managers, similar to as in Lazear et al. (2015) and Hoffman et al. (2017). By computing manager value-added, we will later examine to what extent managers are rewarded for their MOR scores, for their value-added, or for their own subjective performance scores received from their own superiors.

In line with our focus on attrition, we estimate manager value-added regressions of the form:

$$attrition_{it} = \alpha + \gamma_j + X_{it}\gamma + \epsilon_{it} \tag{6}$$

where $attrition_{it}$ is a dummy for whether person i attrites in month t; γ_j is a manager effect; and X_{it} are various controls.

As discussed in Lazear et al. (2015) and Hoffman et al. (2017), as well as the literature on teacher value-added, an important issue is accounting for random noise in the estimation in the variation of manager fixed effects. Specifically, if manager fixed effects are measured from a finite number of observations per manager, our estimate of the standard deviation of manager fixed effects may be biased upward.

An approach taken in Lazear et al. (2015) is to present standard deviations weighted by the number of observations in the data per manager. An alternative approach is to estimate a random effects model. We pursue both these approaches.

Appendix Table C11 shows that there is significant variation in manager effects for the outcome of employee attrition. In a random effect model predicting employee attrition as a function of manager effects, we find that the standard deviation of manager effects is about 0.007, which while smaller than the fixed effect standard deviation, is still quite sizable relative to the monthly attrition rate of about 0.018.

5 Manager Quality and Non-Attrition Outcomes

This section analyzes the relation between MOR and various non-attrition outcomes.

Employee subjective performance. Columns 1-2 of Table 8 shows that managers appear to have only a modest positive relationship (if any) to employee performance as measured with subjective performance reviews. On the left-hand side, we use employee's subjective performance review on a 1-5 scale, which we then normalize. Column 1 of Table 8 presents a baseline estimate without employee fixed effects. A 1σ increase in MOR is associated with 0.03σ increase in employee subjective performance under OLS, as well as a 0.09σ increase under IV. As for the attrition results, the OLS coefficients are likely biased downward due to attenuation bias.

In column 2, we add employee fixed effects. It is not clear *a priori* whether the results with or without fixed effects should be preferred. The results without employee fixed effects examine the relationship between MOR and employee outcomes inclusive of managers possibly being able to select better employees. Results with employee fixed effects tell us how MOR relates to various outcomes *within an employee*, which may be useful to know if some managers happen to receive better or worse employees as a result of luck or other factors unrelated to their managerial quality. We therefore will often present results with and without employee fixed effects. In column 2, when employee fixed effects are included, the relationship between MOR and subjective performance shrinks toward 0 in magnitude and becomes statistically insignificant. This suggests that the estimate in column 1 reflects some aspect of how managers and workers are sorted together (such as better managers hiring better workers).

Employee engagement. Columns 3-4 of Table 8 shows that people management does appear to matter for employee engagement. A 1σ increase in MOR corresponds to a 0.08σ increase under IV within employee (i.e., while including employee fixed effects), which is larger than the corresponding OLS estimate of 0.04σ.

Employee salary increases. Columns 5-6 of Table 8 shows managers also appear to matter for salary increases. The outcome variable is the increase in salary 12 months from now relative to the present. That is, for an employee in May Y_1, the outcome variable is log(salary) in May Y_2 minus log(salary) in May Y_1. A 1σ increase in MOR is associated with roughly a 0.2% increase in employee salary in the OLS in column 5 of Panel A, as well as a 0.6% increase in column 5 of Panel B. The average salary increase per year in our data is confidential, but is between 4% and 8%, so these impacts are relatively small in comparison to that. When employee fixed effects are added, the coefficients diminish substantially.

Employee promotions. Columns 7-8 of Table 8 shows that there is a significant positive relationship between MOR and whether an employee experiences a promotion in the OLS, but not in the IV. In column 7, the OLS coefficient indicates that a 1σ increase in MOR is associated with a 0.09 percentage point increase in the probability of receiving a promotion. This association is fairly similar either when employee fixed effects are controlled for. Given the average monthly promotion rate at the firm of between 1.5% and 2%, these coefficients imply roughly that a 1σ increase in MOR is associated with roughly a 5% increase in promotion probability. This implies roughly that moving from a manager who is 2σ below the mean to one who is 2σ above the mean is associated with a 20% increase in monthly chance of promotion. While the coefficient in column 9 is larger than that in column 8, the 95% confidence intervals on the coefficients overlap, suggesting that the two estimates are not statistically distinguishable.

5.1 Additional Remarks on Non-Attrition Outcomes Results

Research designs. Appendix Tables C6 and C7 repeat our research designs for the non-attrition outcomes. Compared to attrition, the results on the non-attrition outcomes are much less robust across the different research designs. Thus, while the different designs provide strong evidence that better people management reduces attrition, they fail to do so for other outcomes.

Differential Attrition. In Section 4, we provided evidence that higher MOR lowers employee attrition. However, such differential attrition could potentially bias estimation of the relation between MOR and non-attrition outcomes. For example, if a very good manager successfully retains all of their employees (both the stars and the mediocre ones), this might lead to the very good manager getting lower average achievement on an employee outcome variable than had the mediocre employees left. To address this concern, we repeated our analysis in Table 8 while restricting to employees who are with the firm for the full duration of the dataset. This "balanced panel" analysis yielded qualitatively similar results to those in Table 8.[32]

Why did we see large impacts of people management on attrition but not on most non-attrition outcomes? There are several possible answers. First, it could be that good people management naturally matters most for attrition and employee engagement, outcomes which importantly reflect issues such as whether an employee feels respected and

[32]Restricting to a balanced panel is a common way to address differential attrition concerns when there are differences in groups of employees in terms of attrition (e.g., Brown et al., 2016; Burks et al., 2015).

motivated. The people management skills of one's manager may matter less for subjective performance, salary growth, or promotions, for which technical talent and knowledge may be more important. Second (and related to the first answer), it could reflect that some outcomes are "stickier" and harder to change. It might be easier for a manager to affect whether someone feels engaged and motivated, and harder to affect subjective performance. Third, it could be that certain outcomes take longer time and more interaction to be affected. Ultimately, it is hard for us to definitively distinguish these possibilities in our data. The primary contribution of our paper is how people management skill relates to different outcomes.

6 How does the Firm Reward Good Managers?

So far, we have presented evidence that a manager's people management skills, as measured by MOR, reduce employee turnover. We now examine whether MOR is "rewarded" by the firm in terms of how it evaluates, compensates, and promotes its managers. In large high-skill firms such as the one we study, the concept of *reward* may be complex and multi-faceted. Individuals can be rewarded through higher salary, promotions, or stock grants. The firm could also respond to managers in other ways such as changing their span of control so that better managers become responsible for managing better people.[33]

To examine how managers are rewarded, it is instructive to include two additional measures of managerial performance. First, beyond evaluations from their employees (measured by MOR), managers also receive evaluations from their own supervisors, i.e., a traditional subjective performance score. Second, we also examine a manager's attrition value-added fixed effect. We normalize the fixed effects and multiple by -1 to create a manager fixed effect in terms of retention. We use these two measures as control variables in the regressions.

[33] Another outcome to examine is whether a manager attrites. Our IV analysis is not ideally suited for analyzing manager attrition because it requires observing a manager score for a manager in both periods. If one performs the analysis in Table 9 but using manager attrition as an outcome, one finds a statistically significant negative relation between a manager's MOR and their turnover.

6.1 Evidence on Manager Rewards

Manager Subjective Performance. Before evaluating to what extent MOR is rewarded by the firm, we first examine the relation of MOR to subjective performance. As seen in column 1 of Table 9, a 1σ increase in MOR is associated with a 0.07σ increase in subjective performance in OLS, but a 0.43σ increase in subjective performance in IV. The IV coefficient is substantial both statistically and also in terms of economic magnitude. As in our main results on attrition above, we suspect that OLS is subject to attenuation bias.

Promotions. Table 9 additionally shows that better people managers are substantially more likely to get promoted, with a 1σ increase in MOR predicting a 0.9pp increase in promotion probability each month. However, once the manager's subjective performance is controlled for in Table 10, the IV coefficent on MOR follows by three-quarters, and is no longer statistically significant.

The promotion results present different interpretations. On one hand, it may be desirable to promote the most capable people to highest levels of the organization where they may have greater impact. On the other hand, if someone is doing a great job in their present position, the firm may not wish to promote them to another type of position that might be qualitatively different. For a manager who is performing well in their current position with respect to people management, the latter consideration may be more important.

Compensation. There is no significant relationship between MOR and log salary, both in terms of MOR by itself and in the context of the three-way horse race. In contrast, the manager's subjective performance (provided by higher-ups) is a strong predictor of higher salaries and promotions. Manager value-added also does not positively predict manager salary.[34]

For our analysis of manager salaries, beyond including a large number of rich controls, we also analyze an individual's "compensation ratio" (or "comp ratio"), which measures how

[34] One question is whether there is a required relationship between subjective performance and compensation or promotions, e.g., everyone with a certain number needs to receive a certain reward. There is not a mechanical relationship or absolute policy, but the firm certainly does look favorably on higher subjective performance scores in allocating rewards.

well paid the individual is relative to others in a similar position.[35] In Table 9, we see a positive relation between people management skill and comp ratio, but it is not statistically significant.

Span of Control. In models of optimal span of control such as Lucas (1978) and Garicano (2000), firms optimally assign better managers to manage larger teams. Empirically, we examine whether managers who achieve higher MOR become more likely to manage larger teams. Column 5 of Tables 9 and 10 shows that this is the case. Interestingly, managers who have better turnover fixed effects are also more likely to receive larger teams, but there is no relation between a manager's subjective performance score from his/her higher-ups and span of control.

Key individual designation. Individuals at the firm who are believed to be especially important can be designated by the firm as "key individuals." The data show that better people managers are significantly more likely to be designed as "key individuals." In Table 9, a 1σ increase in MOR predicts a 4pp increase in the probability of being designed a key individual.

Stock grants. High-skill firms often provide stock grants to reward and try to retain their most valued employees. Table 9 shows that better people managers receive larger stock grants, as can be seen in the columns analyzing holding power and the change in holding power.

Concern regarding the exclusion restriction. An issue in thinking about manager rewards is whether pay for past performance could constitute a violation of the exclusion restriction. To address, we re-do our compensation results while restricting attention to compensation in the first period (so that the instruemntal variable is a manager's people management score in the second period). The results are somewhat weaker (but are broadly qualitatively similar under this analysis).

[35] A comp ratio of 120 would mean that a manager is making 20% more in compensation than an individual doing a similar role in the industry, whereas a comp ratio of 90 would mean that a manager is making 10% less in compensation than an individual doing a similar role in the industry.

6.2 Discussion on Manager Rewards

Broadly speaking, Table 9 shows that better people managers do receive significant rewards from the firm in many dimensions. Interestingly, however, the manager's own subjective performance tends to be a stronger predictor of performance, as seen in Table 10.

There are multiple interpretations to this results. One interpretation is that because the subjective performance can incorporate information on people management, it is not surprising that subjective performance is a stronger predictor of rewards than people management.

A second interpretation is that managers only have a limited amount of time and thus managers can choose whether they want to specialize in people management or non-people management activities such as product development (Dessein et al., 2016). Thus, even though better people managers receive some rewards, the relationship may be relatively limited because better people managers are more likely to be unobservedly worse in terms of other behaviors. Because of these multiple interpretations, our analysis here is ultimately more speculation than our earlier analysis of attrition.[36]

7 Conclusion

Managers are at the heart of organizations, but measuring what managers do and the impact of people management skills is challenging. A common approach is to calculate a manager's value-added using performance metrics, but such an approach may be difficult in knowledge-based firms and other firm contexts where objectively measuring productivity is challenging. While subjective performance reviews are widely understood to be useful in measuring difficult-to-observe aspects of manager behavior, a potentially more direct way of measuring how managers affect their direct reports is to leverage employee surveys. This approach is pursued by many firms, but we have little hard evidence on the importance of people management skills for managers.

[36] Other interpretations are possible as well. For example, it could be for various reasons (such as having a strong engineering culture) that the firm we study is under-valuing good people management.

We find a strong negative relationship between people management skills and employee attrition, a critical outcome in high-skill firms. A causal interpretation is support for several complementary research designs. People management skills increase employee engagement, but do not seem to consistently improve other employee outcomes. Managers with better people management skills receive some rewards, but people management skill still does not seem strongly rewarded by the firm. Although our conclusions are specific to one firm, our results are robust across low-skill and high-skill workers within the firm, and our statistical conclusions seem confirmed by qualitative case studies in other firms (Garvin et al., 2013; Shaw and Schifrin, 2015).

By evidencing the importance of good people management, our paper highlights an aspect of managers that differs from that emphasized by most theories of managers. One tradition of management theories (e.g., Holmstrom, 1979) emphasizes the importance of managers for helping address employee moral hazard (such as by monitoring) or by making resource allocation decisions. Another tradition of theories of managers beginning with Garicano (2000) emphasizes the role of managers in problem-solving, i.e., a good manager is someone who can solve more complex problems than the people under them. We thus see an open role for theory in constructing models that incorporate good people management.

One direction in theoretical and empirical work that seems related is the growing literature on social skills, i.e., skills that are primarily interpersonal in nature. Scholars have shown that social skills play a critical role in determining wages and occupations, and that social skills command a rising return in the labor market.[37] Our work provides novel evidence on the importance of social skills in management, an area where they have received much less economic attention than others, but where new evidence is starting to emerge.[38]

[37]For example, Borghans et al. (2014) show that people skills are important determinants of occupations and wages. Deming (2017) show that workers with higher social skills earn higher wages, and that there is complementarity between social and cognitive skills. Social skills are generally thought of as one component of "soft skills;" see Heckman and Kautz (2012) for general discussion on soft skills.

[38]For example, Kuhn and Weinberger (2005) show that men who occupied leadership positions while in high school earn more in the labor market years later. Lazear (2012) presents theory and evidence on how the skillset of effective leaders is more general than what might be observed in hard measures like GPA. Schoar (2016) shows that a randomized intervention in Cambodian garment factories aimed at improving supervisors' communication skills and treatment of workers leads to productivity improvement.

Though our results indicate that people management matters to a significant degree, the precise mechanism by which people management matters remains an important area of research. Theories of managerial attention (e.g., Dessein et al., 2016) emphasize the importance of attention as a limited resource in determining productivity across managers. We hope to be able to examine such theories in future work.

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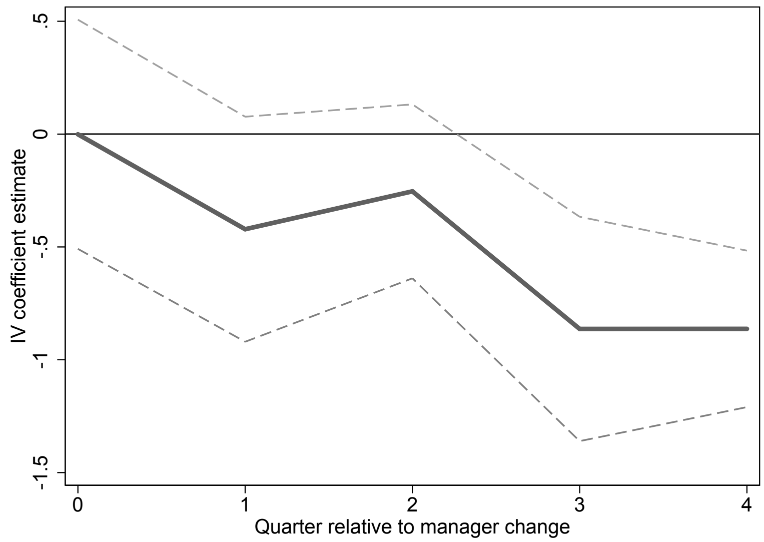
Figure 1: Impacts of MOR on Turnover by Quarter Since Getting New Manager



Notes: Dotted line shows 90% confidence interval on coefficients, with standard errors clustered by manager. This figure comes from an IV regression similar to that in Table 5, with one main difference. The difference is that instead of using MOR, we use MOR interacted with quarters since getting a new manager. "Quarter 0" is the month during which a worker gets a new manager, followed by the two months after (i.e., months 2 and 3). "Quarter 4" includes months 13, 14, and 15, as well as all months after that. Both current period MOR (the regressor) and other period MOR (the instrument) are interacted with quarters since getting a new manager.

Table 1: Summary Statistics

Panel A: Overall numbers

Share of records, employee in US	0.63
Share of records from managers	0.16
Share of records for engineers	0.22
Share of records for customer service	0.32
Share of employees hired in sample period	0.38
Co-located with manager	0.85
Manager span (employees/mgr)	5.97
Managers per employee	2.68
Managers per employee (weighted by tenure)	3.05

Panel B: Several outcomes and regressors of interest

Variable:	mean	sd	min	max
Attrition probability (monthly)	1.35	11.53	0	100
Subjective performance rating	3.3	0.82	1	5
Employee engagement score	83.89	5.03	58	100
Log salary	Confidential			
Promotion probability (monthly)	Confidential			
Manager overall rating	82.68	14.45	0	100
Manager gives clear expectations	85.25	15.58	0	100
Manager provides coaching	77.58	19.45	0	100
Manager supports career dev	79.6	17.88	0	100
Manager involves people	85.74	15.32	0	100
Manager instills poz attitude	83.8	17.53	0	100
Manager is someone I trust	83.49	16.41	0	100

Notes: This table presents important summary statistics regarding our sample. The data are at the monthly level. In Panel A, "Share of records, employee in US" refers to share of employee-months in the dataset where the employee is working in a US location. "Co-located with manager" refers to the share of employee-months where the employee and manager are working at the same location. For further detail on sample construction, see Appendix B.

Table 2: Managerial Characteristics are Persistent: Predicting Manager Ratings on Different Dimensions in the Y_2 Survey using Ratings from the Y_1 Survey

Dep. Variables:	(1) Overall MOR	(2) Clear expectations	(3) Coaching	(4) Career dev	(5) Involves people	(6) Positive attitude	(7) Someone I trust
Characteristic in Y_1	0.343***	0.281***	0.263***	0.265***	0.291***	0.316***	0.299***
	(0.0285)	(0.0306)	(0.0250)	(0.0272)	(0.0317)	(0.0293)	(0.0271)
R-squared	0.32	0.30	0.32	0.28	0.25	0.27	0.25

Notes: Robust standard errors in parentheses. An observation is a manager. Each column regresses a managerial score variable in Y_2 on the same variable in Y_1. For example, column 1 regresses a manager's overall rating (MOR) in Y_2 on a manager's MOR in Y_1 as well as control variables. The sample is restricted to managers for whom we have manager scores for both waves of the employee surveys. We include control variables corresponding to a manager's first observation in the data as a manager. All regressions include controls for business unit, for work type (engineer, customer service, marketing, finance, or other), dummies for year of hire (observations before 2001 lumped in one year), salary grade dummies, and location dummies. The questions from the survey are listed in the main text in Section 2.3. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 3: MOR and Employee Attrition: Baseline Results

Specification:	1st Stg	OLS	IV	Reduced Form
Panel A: Attrition				
MOR in other period	0.225***			-0.086***
	(0.016)			(0.019)
MOR in current period		-0.118***	-0.382***	
		(0.020)	(0.087)	
Mean dep. var.		1.349	1.349	1.349
F-stat on excl instrument			208.5	
Panel B: Quits				
MOR in other period	0.225***			-0.044***
	(0.016)			(0.013)
MOR in current period		-0.072***	-0.194***	
		(0.014)	(0.060)	
Mean dep. var.		0.795	0.795	0.795
F-stat on excl instrument			208.5	
Panel C: Fires				
MOR in other period	0.225***			-0.033***
	(0.016)			(0.009)
MOR in current period		-0.028***	-0.145***	
		(0.008)	(0.039)	
Mean dep. var.		0.293	0.293	0.293
F-stat on excl instrument			208.5	
Panel D: All attrition, higher-productivity employees				
MOR in other period	0.219***			-0.047***
	(0.016)			(0.017)
MOR in current period		-0.068***	-0.216***	
		(0.019)	(0.081)	
Mean dep. var.		0.663	0.663	0.663
F-stat on excl instrument			182.5	
Panel E: All attrition, lower-productivity employees				
MOR in other period	0.230***			-0.105***
	(0.016)			(0.026)
MOR in current period		-0.072***	-0.456***	
		(0.026)	(0.114)	
Mean dep. var.		1.387	1.387	1.387
F-stat on excl instrument			214.9	

Notes: Standard errors clustered by manager in parentheses. An observation is an employee-month. The dependent variable is whether an employee attrites in a given month. All regressions include controls for business unit, for work type (engineer, customer service, marketing, finance, or other), dummies for year of hire (observations before 2001 lumped in one year), salary grade dummies, current year dummies, location dummies, the span of control for an employee's manager, and a 5th order polynomial in employee tenure. Locations with less than 2,000 employee-months are lumped into a separate location category. Higher productivity and lower productivity employees are classified based on subjective performance scores, as described in Section 4.1. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 4: MOR and Employee Attrition: Exploiting New Joiners

Specification:	1st Stg	OLS	IV	Reduced Form
MOR in other period	0.182***			-0.101
	(0.026)			(0.072)
MOR in current period		-0.277***	-0.558	
		(0.079)	(0.385)	
Mean dep. var.		1.852	1.852	1.852
F-stat on excl instrument			48.25	

Notes: This table is similar to Panel A of Table 3, but restricts to new employees joining the firm after the administration of the second survey. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 5: MOR and Employee Attrition: Exploiting Workers Experiencing their First Change in Manager

Specification:	1st Stg	OLS	IV	Reduced Form
MOR in other period	0.219***			-0.126***
	(0.018)			(0.038)
MOR in current period		-0.119***	-0.577***	
		(0.040)	(0.179)	
Mean dep. var.		1.411	1.411	1.411
F-stat on excl instrument			142.1	

Notes: This table is similar to Panel A of Table 3, but restricts to employees who experience their first change (during our data period) in manager. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 6: Rothstein Test: Predicting Employe Outcomes Before Manager Switch as a Function of Period 1 MOR of Future Manager

Dep var:	Subjective performance (1)	Log Salary (x100) (2)	Promotion (x100) (3)
MOR of Future Mgr	0.007	-0.269	-0.035
	(0.008)	(0.183)	(0.032)

Notes: Standard errors clustered by manager in parentheses. The baseline controls are the same as in the base analyses. * significant at 10%; ** significant at 5%; ***significant at 1%

Table 7: MOR and Employee Attrition: Exploiting Managers Moving Across Locations

Specification:	1st Stg	OLS	IV	Reduced Form
MOR in other period	0.332***			-0.213**
	(0.045)			(0.093)
MOR in current period		-0.155	-0.642**	
		(0.099)	(0.284)	
Mean dep. var.		1.675	1.675	1.675
F-stat on excl instrument			54.32	

Notes: This table is similar to Panel A of Table 3, but restricts to employees who experience a manager who changes locations. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 8: MOR and Non-Attrition Outcomes

Dep. Var.	Subjective performance (normalized)		Employee engagement (normalized)		Log Salary Growth (x100)		Promotion (x100)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: OLS								
MOR (normalized)	0.030***	-0.008*	0.061***	0.051***	0.206***	0.115*	0.097***	0.126
	(0.004)	(0.004)	(0.006)	(0.008)	(0.043)	(0.063)	(0.023)	(—)
Panel B: IV								
MOR (normalized)	0.091***	-0.000	0.117***	0.081***	0.529**	-0.023	-0.087	-0.013
	(0.019)	(0.008)	(0.030)	(0.017)	(0.212)	(0.126)	(0.117)	(0.090)
Panel C: Red. Form								
MOR (normalized)	0.021***	-0.001	0.028***	-0.033***	0.119**	0.017	-0.019	0.001
	(0.004)	(0.004)	(0.007)	(0.008)	(0.047)	(0.061)	(0.026)	(0.000)
Employee FE	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Standard errors clustered by manager in parentheses, with the exception of the even columns of Panel B, where standard errors are calculated via block bootstrap, with subsampling over managers. Because it is computationally demanding, the bootstrap is done with 10 replications only. The controls are the same as Table 3, except that locations with less than 10 employee-months are lumped into a separate location category. "Subjective performance" is an employee's subjective performance on a 1-5 scale. "Employee Engagement" is normalized employee engagement. In columns 7-8, the outcome is whether an employee receives a promotion, with coefficients multiplied by 100 for readability. In column 8 of Panel A, Stata did not provide standard errors. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 9: What are Managers Rewarded For? Employees Survey Scores (MOR)

Dep var:	Subjective performance (normalized)	Promoted (x100)	Log Salary (x100)	Comp ratio	Change in span of control	Key individual (x100)	Holding power	Change in holding power
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: OLS								
MOR in current period	0.0721***	0.108***	-0.107	0.229	0.213***	0.374	0.00922	0.00393
	(0.00814)	(0.0329)	(0.146)	(0.199)	(0.0425)	(0.257)	(0.00578)	(0.0169)
Panel B: IV								
MOR in current period	0.426***	0.887***	-0.623	1.415	0.423**	4.116***	0.0746**	0.138*
	(0.0535)	(0.173)	(0.812)	(1.196)	(0.208)	(1.572)	(0.0341)	(0.0808)
Panel C: Red. Form								
MOR in other period	0.0870***	0.184***	-0.135	0.250	0.0966**	0.823***	0.0143**	0.0262*
	(0.00907)	(0.0318)	(0.162)	(0.239)	(0.0472)	(0.304)	(0.00651)	(0.0152)

Notes: Standard errors clustered by manager in parentheses. The controls are the same as Table 3, except that locations with less than 10 employee-months are lumped into a separate location category. "Subjective performance" is an employee's subjective performance on a 1-5 scale. "Employee Engagement" is normalized employee engagement. In columns 7-8, the outcome is whether an employee receives a promotion, with coefficients multiplied by 100 for readability. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 10: What are Managers Rewarded For? Employees Survey Scores vs. Subjective Performance Score vs. Value-Added

Dep var:	Subjective performance (normalized)	Promoted (x100)	Log Salary (x100)	Comp ratio	Change in span of control	Key individual (x100)	Holding power	Change in holding power
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: OLS								
MOR in current period	0.0714***	-0.0172	-0.144	0.164	0.218***	-0.0449	0.00439	-0.00708
	(0.00816)	(0.0341)	(0.149)	(0.200)	(0.0445)	(0.266)	(0.00576)	(0.0171)
Subj performance		1.721***	0.748***	0.858***	-0.0247	5.777***	0.0794***	0.161***
		(0.0422)	(0.124)	(0.179)	(0.0480)	(0.256)	(0.00472)	(0.0106)
Manager FE in retention	0.0142	-0.00553	-0.724***	0.455	0.0899*	0.183	-0.0108	6.16e-05
	(0.00896)	(0.0350)	(0.232)	(0.280)	(0.0535)	(0.323)	(0.00672)	(0.0130)
Panel B: IV								
MOR in current period	0.428***	0.221	-1.028	0.658	0.458**	1.745	0.0488	0.0744
	(0.0540)	(0.167)	(0.841)	(1.226)	(0.226)	(1.588)	(0.0349)	(0.0822)
Subj performance		1.698***	0.784***	0.871***	-0.0435	6.014***	0.0830***	0.155***
		(0.0461)	(0.148)	(0.207)	(0.0528)	(0.308)	(0.00570)	(0.0125)
Manager FE in retention	-0.00645	-0.0391	-0.703***	0.561*	0.0817	-0.0604	-0.00566	-0.00401
	(0.0111)	(0.0392)	(0.272)	(0.332)	(0.0556)	(0.386)	(0.00750)	(0.0148)
Panel C: Red. Form								
MOR in other period	0.0867***	0.0466	-0.212	0.0979	0.102**	0.326	0.00901	0.0132
	(0.00909)	(0.0320)	(0.162)	(0.237)	(0.0498)	(0.304)	(0.00650)	(0.0152)
Subj performance		1.708***	0.729***	0.900***	-0.0237	6.110***	0.0853***	0.159***
		(0.0443)	(0.138)	(0.196)	(0.0493)	(0.285)	(0.00509)	(0.0113)
Manager FE in retention	0.00840	-0.0244	-0.708***	0.576*	0.0929*	-0.0150	-0.00458	-0.00230
	(0.0102)	(0.0380)	(0.266)	(0.324)	(0.0551)	(0.374)	(0.00723)	(0.0139)

Notes: Standard errors clustered by manager in parentheses. The controls are the same as Table 3, except that locations with less than 10 employee-months are lumped into a separate location category. "Subjective performance" is an employee's subjective performance on a 1-5 scale. "Employee Engagement" is normalized employee engagement. In columns 7-8, the outcome is whether an employee receives a promotion, with coefficients multiplied by 100 for readability. * significant at 10%; ** significant at 5%; *** significant at 1%

"People Management Skills, Employee Attrition, and Manager Rewards: Evidence from a High-Tech Firm": Online Appendix

Mitchell Hoffman and Steven Tadelis

The Online Appendix is organized as follows. Appendix A provides derivations and additional results. Appendix B gives more details on the data. Appendix C presents additional tables and figures.

A Additional Results

A.1 Econometric Derivations

OLS Derivation.

$$
\begin{aligned}
\operatorname{plim}(\widehat{b}_{OLS}) &= \frac{cov\left(y_t, \widetilde{m}_\tau\right)}{var\left(\widetilde{m}_\tau\right)} \\
&= \frac{\beta\sigma_m^2 + \beta cov\left(m, u_\tau\right) + cov\left(\varepsilon_t, m\right) + cov\left(\varepsilon_t, u_\tau\right)}{\sigma_m^2 + 2cov\left(m, u_\tau\right) + \sigma_u^2} \\
&= \frac{\sigma_m^2}{\sigma_m^2 + \sigma_u^2}\beta + \frac{cov(\varepsilon_t, u_\tau)}{\sigma_m^2 + \sigma_u^2} + \frac{cov(\varepsilon_t, m)}{\sigma_m^2 + \sigma_u^2} \\
\operatorname{plim}(\widehat{b}_{OLS} - \beta) &= \underbrace{-\frac{\sigma_u^2}{\sigma_m^2 + \sigma_u^2}\beta}_{\text{Attenuation Bias}} + \underbrace{\frac{cov(\varepsilon_t, u_\tau)}{\sigma_m^2 + \sigma_u^2}}_{\text{Contemp. Corr. ME}} + \underbrace{\frac{cov(\varepsilon_t, m)}{\sigma_m^2 + \sigma_u^2}}_{\text{Assignment Bias}} \qquad (7)
\end{aligned}
$$

where we used $cov\left(m, u_\tau\right) = 0$ (Assumption 1) to go from the second line to the third line.

IV Derivation.

$$
\begin{aligned}
\operatorname{plim}(\widehat{b}_{IV}) &= \frac{cov\left(y_t, \widetilde{m}_{-t}\right)}{cov\left(\widetilde{m}_\tau, \widetilde{m}_{-\tau}\right)} \\
&= \frac{\beta\sigma_m^2 + \beta cov\left(m, u_{-\tau}\right) + cov\left(\varepsilon_t, m\right) + cov\left(\varepsilon_t, u_{-\tau}\right)}{\sigma_m^2 + cov\left(m, u_\tau\right) + cov\left(m, u_{-\tau}\right) + cov\left(u_\tau, u_{-\tau}\right)} \\
&= \frac{\sigma_m^2}{\sigma_m^2 + cov\left(u_\tau, u_{-\tau}\right)}\beta + \frac{cov\left(\varepsilon_t, u_{-\tau}\right)}{\sigma_m^2 + cov\left(u_\tau, u_{-\tau}\right)} + \frac{cov\left(\varepsilon_t, m\right)}{\sigma_m^2 + cov\left(u_\tau, u_{-\tau}\right)} \\
\operatorname{plim}(\widehat{b}_{IV} - \beta) &= \underbrace{-\frac{cov\left(u_\tau, u_{-\tau}\right)}{\sigma_m^2 + cov\left(u_\tau, u_{-\tau}\right)}\beta}_{\text{Attenuation Bias}} + \underbrace{\frac{cov\left(\varepsilon_t, u_{-\tau}\right)}{\sigma_m^2 + cov\left(u_\tau, u_{-\tau}\right)}}_{\text{Asynchronously Corr. ME}} + \underbrace{\frac{cov\left(\varepsilon_t, m\right)}{\sigma_m^2 + cov\left(u_\tau, u_{-\tau}\right)}}_{\text{Assignment Bias}} \qquad (8)
\end{aligned}
$$

Reduced Form. For the reduced form expression in equation (5), the derivation is very similar to those above for OLS and IV, so it is omitted for brevity.

A.2 What happens when manager quality varies over time?

In Section 3, we present probability limits for OLS, IV, and reduced form estimators under the assumption that manager quality is fixed over time. Here, we derive the probability limits of the estimators while allowing underlying manager quality to vary across the two periods in our data. Suppose that $y_{it} = \beta m_{j,\tau(t)} + \varepsilon_{it}$ and write $\sigma_{12} \equiv cov(m_\tau, m_{-\tau})$. We further assume that $var(m_1) = var(m_2) = \sigma_m^2$. Under these assumptions, OLS is the same as when manager quality is fixed. However, for IV, we have:

$$
\begin{aligned}
\text{plim}(\widehat{b}_{IV}) &= \frac{cov\left(y_t, \widetilde{m}_{-\tau}\right)}{cov\left(\widetilde{m}_\tau, \widetilde{m}_{-\tau}\right)} \\
&= \frac{\beta cov(m_\tau, m_{-\tau}) + \beta cov(m_\tau, u_{-\tau}) + cov\left(\varepsilon_t, m_{-\tau}\right) + cov\left(\varepsilon_t, u_{-\tau}\right)}{cov(m_\tau, m_{-\tau}) + cov(m_\tau, u_{-\tau}) + cov(u_\tau, m_{-\tau}) + cov\left(u_\tau, u_{-\tau}\right)} \\
&= \frac{\beta\sigma_{12}}{\sigma_{12} + cov\left(u_\tau, u_{-\tau}\right)} + \frac{cov(\epsilon_t, u_{-\tau})}{\sigma_{12} + cov\left(u_\tau, u_{-\tau}\right)} + \frac{cov(\epsilon_t, m_{-\tau})}{\sigma_{12} + cov\left(u_\tau, u_{-\tau}\right)} \\
\text{plim}(\widehat{b}_{IV} - \beta) &= \underbrace{-\frac{cov\left(u_\tau, u_{-\tau}\right)}{\sigma_{12} + cov\left(u_\tau, u_{-\tau}\right)}\beta}_{\text{Attenuation Bias}} + \underbrace{\frac{cov\left(\varepsilon_t, u_{-\tau}\right)}{\sigma_{12} + cov\left(u_\tau, u_{-\tau}\right)}}_{\text{Asynchronously Corr. ME}} + \underbrace{\frac{cov\left(\varepsilon_t, m\right)}{\sigma_{12} + cov\left(u_\tau, u_{-\tau}\right)}}_{\text{Assignment Bias}}
\end{aligned}
$$

Relative to the version with constant people management over time, the difference is that σ_m^2 is replaced by σ_{12} in the denominator. This makes attenuation bias worse. For the reduced form, we have:

$$
\begin{aligned}
\text{plim}(\widehat{b}_{RF}) &= \frac{cov\left(y_t, \widetilde{m}_{-\tau}\right)}{var\left(\widetilde{m}_{-\tau}\right)} \\
\text{plim}(\widehat{b}_{RF} - \beta) &= \underbrace{\frac{\sigma_{12} - \sigma_m^2 - \sigma_u^2}{\sigma_m^2 + \sigma_u^2}\beta}_{\text{Attenuation Bias}} + \underbrace{\frac{cov(\varepsilon_t, u_{-\tau})}{\sigma_m^2 + \sigma_u^2}}_{\text{Asynchronously Corr. ME}} + \underbrace{\frac{cov(\varepsilon_t, m)}{\sigma_m^2 + \sigma_u^2}}_{\text{Assignment Bias}}
\end{aligned}
$$

Attenuation bias is also worsened here the larger the divergence between σ_{12} and σ_m^2. However, the formula is relatively similar.

B Data Appendix

Data assembly. The data were assembled for us by an analyst at the data provider. A variety of files were combined together during this process. The analyst also subjected the data to cleaning.

Manager survey variables. To create the manager survey variables used in the analysis sample, we begin with the variables as provided by the data analyst. Next, we fill in missing values using raw data from the manager surveys. If values are still missing, we will in missing values using "roll-up survey values." These are manager scores using all the individuals under a given manager in the organization. The manager overall rating ("MOR") is calculating by normalizing over all functions including all years in the data.

Salary. Workers at the firm are paid in different currencies. We convert salaries to US dollars using the exchange rate as of March 1, 2014, which falls in the middle of our data period. We avoid using a time-varying exchange rate because this would induce variation in a worker's salary over time that may be artificial from the standpoint of a worker located in a foreign country.[1]

Key individual. Persons at the firm who are recognized as an integral part of the company are designated "key individuals." The firm uses a slightly different term to refer to such persons, but we have modified it for the paper to preserve firm confidentiality.

B.1 Y_3 Survey Questions

The survey questions were slightly different for the Y_3. They are listed below.

1. My immediate manager provides ongoing coaching and guidance on how I can improve my performance.
2. My immediate manager actively supports my efforts regarding professional / career development.
3. My immediate manager extends influence and leadership across organizational boundaries.
4. My immediate manager creates the conditions that support stronger engagement at work.
5. I would recommend my manager to others.

[1]Another approach would be to restrict our analysis of salary to employees who get paid in US dollars, as in Baker et al. (1994a). However, this would require throwing out a lot of our sample.

C Additional Figures and Tables

Table C1: Manager Characteristics, Correlation Table

Variables:	Clear expectations	Coaching	Career dev	Involves people	Positive attitude	Someone I trust
Manager gives clear expectations	1.00					
Manager provides coaching	0.67	1.00				
Manager supports career development	0.59	0.71	1.00			
Manager involves people	0.59	0.57	0.59	1.00		
Manager instills positive attitude	0.59	0.58	0.60	0.68	1.00	
Manager is someone I trust	0.63	0.60	0.64	0.69	0.72	1.00

Notes: Correlation coefficients are reported. The analysis sample (including all data, non-imputed and imputed) has been collapsed to the manager-survey period level.

Table C2: Principal Component Analysis

Variables:	Component 1	Component 2	Component 3	Component 4
Eigenvalue	4.34	0.54	0.36	0.30
Proportion variance explained	0.72	0.09	0.06	0.05
Manager gives clear expectations	0.40	0.38	0.74	0.10
Manager provides coaching	0.41	0.55	-0.14	-0.12
Manager supports career development	0.41	0.27	-0.64	0.01
Manager involves people	0.41	-0.38	-0.04	0.80
Manager instills positive attitude	0.41	-0.44	0.09	-0.51
Manager is someone I trust	0.42	-0.37	0.02	-0.27

Notes: This table presents the results of the principal components analysis.

Table C3: Robustness Analysing on Persistence of Managerial Characteristics: Using all the Manager Characteristics as Regressors at the Same Time

Dep. Variables:	(1) Overall MOR	(2) Clear expectations	(3) Coaching	(4) Career dev	(5) Involves people	(6) Positive attitude	(7) Someone I trust
Manager sets clear expectations	0.07*	0.17***	0.06	0.04	0.07*	0.03	0.06
	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)	(0.04)
Manager gives coaching	0.04	0.04	0.15***	0.07*	-0.00	-0.01	-0.01
	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)
Manager promotes career development	0.07**	0.05	0.09**	0.13***	0.04	0.07*	0.05
	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)
Manager involves people	0.04	0.02	-0.00	0.03	0.18***	0.02	0.01
	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)
Manager instills a positive attitude	0.09**	0.02	0.04	0.09**	0.03	0.23***	0.11***
	(0.03)	(0.04)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)
Employees trust the manager	0.05	0.03	0.01	0.00	0.03	0.06	0.15***
	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)
R-squared	0.32	0.31	0.33	0.29	0.26	0.28	0.26

Notes: This table is a robustness check to Table 2. Instead of regressing a particular Y_2 characteristic on the same characteristic in Y_1 and various controls, we regress each Y_2 characteristics on all the Y_1 characteristics at once (plus controls). * significant at 10%; ** significant at 5%; *** significant at 1%

Table C4: Robustness Analysing on Persistence of Managerial Characteristics: Using the Y_3 Survey

	(1)	(2)
Variables:	Overall MOR	Overall MOR
Sample:	Y_3	Y_1, Y_2, Y_3
Lagged MOR	0.36***	0.32***
	(0.078)	(0.029)

Notes: This table is a robustness check to Table 2. The difference is that we use all three surveys (in Y_1, Y_2, Y_3) as opposed to just the Y_1 and Y_2 surveys. Column 1 analyzes MOR in Y_3 as a function of MOR in Y_2. Column 2 analyzes MOR in Y_2 and Y_3 as a function of the MOR in the previous period. * significant at 10%; ** significant at 5%; *** significant at 1%

Table C5: MOR and Employee Attrition: Regretted vs. Non-regretted Quits

Specification:	1st Stg	OLS	IV	Reduced Form
Panel A: Regretted Quits				
MOR in other period	0.225***			-0.035***
	(0.016)			(0.012)
MOR in current period		-0.048***	-0.157***	
		(0.012)	(0.053)	
Mean dep. var.		0.630	0.630	0.630
F-stat on excl instrument			206.1	
Panel B: Non-regretted Quits				
MOR in other period	0.225***			-0.010*
	(0.016)			(0.005)
MOR in current period		-0.012*	-0.043*	
		(0.006)	(0.024)	
Mean dep. var.		0.150	0.150	0.150
F-stat on excl instrument			206.1	

Notes: The panels in this table are similar to Panel B of Table 3. The difference is that they look separately at regretted and non-regretted quit events. * significant at 10%; ** significant at 5%; *** significant at 1%

Table C6: MOR and Non-Attrition Outcomes: Exploiting New Joiners

Dep. Var.:	Subjective performance (1)	Employee engagement (2)	Log Salary Growth (3)	Promotion (4)
Panel A: OLS				
MOR (normalized)	0.021	0.043***	-0.045	-0.011
	(0.018)	(0.010)	(0.143)	(0.043)
Panel B: IV				
MOR (normalized)	-0.094	0.087	-0.268	0.349
	(0.120)	(0.064)	(0.673)	(0.429)
Panel C: Reduced Form				
MOR (normalized)	-0.117	-0.117	-0.117	-0.117
	(0.073)	(0.073)	(0.073)	(0.073)
Employee FE	No	No	No	No

Notes: Standard errors clustered by manager in parentheses. The specifications are similar to the odd columns in Table 8, but restricts to new employees joining the firm after the administration of the second survey. * significant at 10%; ** significant at 5%; ***significant at 1%

Table C7: MOR and Non-Attrition Outcomes: Exploiting Workers Experiencing their First Change in Manager

Dep. Var.:	Subjective performance (1)	Employee engagement (2)	Log Salary Growth (3)	Promotion (4)
Panel A: OLS				
MOR (normalized)	0.032***	0.039***	0.204**	0.106**
	(0.009)	(0.007)	(0.088)	(0.041)
Panel B: IV				
MOR (normalized)	0.111***	0.158***	1.317***	0.183
	(0.042)	(0.041)	(0.477)	(0.238)
Panel C: Reduced Form				
MOR (normalized)	0.032***	0.035***	0.266***	0.034
	(0.009)	(0.009)	(0.092)	(0.050)
Employee FE	No	No	No	No

Notes: Standard errors clustered by manager in parentheses. The specifications are similar to the odd columns in Table 8, but restricts to employees who experience their first change (during our data period) in manager. * significant at 10%; ** significant at 5%; ***significant at 1%

Table C8: MOR and Employee Attrition: Heterogeneity by Occupation

Specification:	1st Stg	OLS	IV	Reduced Form
Panel A: Engineers				
MOR in other period	0.188***			-0.043
	(0.027)			(0.031)
MOR in current period		-0.076**	-0.231	
		(0.032)	(0.167)	
Mean dep. var.		1.109	1.109	1.109
F-stat on excl instrument			47.00	
Panel B: CS				
MOR in other period	0.106***			-0.057
	(0.032)			(0.040)
MOR in current period		-0.096**	-0.535	
		(0.041)	(0.371)	
Mean dep. var.		1.534	1.534	1.534
F-stat on excl instrument			10.80	
Panel C: Marketing				
MOR in other period	0.205***			-0.085**
	(0.039)			(0.039)
MOR in current period		-0.058	-0.413**	
		(0.038)	(0.206)	
Mean dep. var.		1.020	1.020	1.020
F-stat on excl instrument			27.36	
Panel D: Finance				
MOR in other period	0.190***			-0.070
	(0.040)			(0.080)
MOR in current period		-0.222***	-0.367	
		(0.076)	(0.415)	
Mean dep. var.		1.110	1.110	1.110
F-stat on excl instrument			22.98	

Notes: Each panel is similar to Panel A of Table 3. The difference is that we examine heterogeneity by worker occupation (job function). * significant at 10%; ** significant at 5%; *** significant at 1%

Table C9: MOR and Employee Attrition: Heterogeneity by Geography

Specification:	1st Stg	OLS	IV	Reduced Form
Panel A: Domestic				
MOR in other period	0.263***			-0.090***
	(0.020)			(0.025)
MOR in current period		-0.105***	-0.341***	
		(0.025)	(0.098)	
Mean dep. var.		1.451	1.451	1.451
F-stat on excl instrument			172.0	
Panel B: Foreign				
MOR in other period	0.166***			-0.094***
	(0.024)			(0.028)
MOR in current period		-0.080***	-0.562***	
		(0.027)	(0.182)	
Mean dep. var.		1.100	1.100	1.100
F-stat on excl instrument			46.79	
Panel C: Foreign, Poor Country				
MOR in other period	0.144***			-0.052
	(0.043)			(0.068)
MOR in current period		-0.077	-0.358	
		(0.058)	(0.493)	
Mean dep. var.		1.279	1.279	1.279
F-stat on excl instrument			11.25	
Panel D: Foreign, Rich Country				
MOR in other period	0.167***			-0.104***
	(0.029)			(0.029)
MOR in current period		-0.085***	-0.625***	
		(0.030)	(0.189)	
Mean dep. var.		1.026	1.026	1.026
F-stat on excl instrument			33.54	

Notes: Each panel is similar to Panel A of Table 3. The difference is that we examine heterogeneity by geography. * significant at 10%; ** significant at 5%; *** significant at 1%

Table C10: MOR and Employee Attrition: Heterogeneity by Hierarchy

Specification:	1st Stg	OLS	IV	Reduced Form
Panel A: Low Level in Hierarchy				
MOR in other period	0.214***			-0.077***
	(0.021)			(0.025)
MOR in current period		-0.113***	-0.358***	
		(0.025)	(0.122)	
Mean dep. var.		1.465	1.465	1.465
F-stat on excl instrument			103.4	
Panel B: Medium Level in Hierarchy				
MOR in other period	0.231***			-0.114***
	(0.019)			(0.026)
MOR in current period		-0.084***	-0.493***	
		(0.026)	(0.116)	
Mean dep. var.		0.991	0.991	0.991
F-stat on excl instrument			145.0	
Panel C: High Level in Hierarchy				
MOR in other period	0.239***			-0.141
	(0.038)			(0.087)
MOR in current period		0.069	-0.593	
		(0.073)	(0.379)	
Mean dep. var.		1.353	1.353	1.353
F-stat on excl instrument			39.85	

Notes: Each panel is similar to Panel A of Table 3. The difference is that we examine heterogeneity by heterogeneity in the firm hierarchy. * significant at 10%; ** significant at 5%; *** significant at 1%

Table C11: Manager Value-Added Estimates for Employee Attrition

Method:	OLS	Supervisor Fixed Effects	Supervisor Random Effects
R-squared	0.005	0.0141	
Mean term rate		0.0135	
SD boss effects		0.0133	0.0068

Notes: Columns 1-2 include a 3rd order polynomial in tenure, year of hire dummies, and current year dummies. Column 3 includes controls for work type (engineer, customer service, or other), year of hire, and current year. The fixed effect standard deviations are weighted by the number of observations per fixed effect. * significant at 10%; ** significant at 5%; *** significant at 1%

Table C12: What are Managers Rewarded For? Employees Survey Scores (MOR), Period 1 Only

Dep var:	Subjective performance (normalized)	Promoted (x100)	Log Salary (x100)	Comp ratio	Change in span of control	Key individual (x100)	Attrition (x100)	Holding power	Change in holding power
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: OLS									
MOR in current period	0.0672***	0.0700	-0.0348	0.258	0.298***	0.673*	-0.174***	0.0154**	0.0229**
	(0.0111)	(0.0590)	(0.176)	(0.255)	(0.0525)	(0.375)	(0.0423)	(0.00765)	(0.0113)
Panel B: IV									
MOR in current period	0.183***	0.927***	0.219	1.049	0.264	3.282*	-0.00479	0.0183	0.0807
	(0.0520)	(0.284)	(0.916)	(1.190)	(0.251)	(1.966)	(0.0406)	(0.0420)	(0.0697)
Panel C: Red. Form									
MOR in other period	0.0486***	0.264***	0.0299	0.262	0.0752	0.850	-0.00168	0.00416	0.0202
	(0.0137)	(0.0755)	(0.250)	(0.324)	(0.0714)	(0.527)	(0.0110)	(0.0109)	(0.0178)

Notes: Standard errors clustered by manager in parentheses. The controls are the same as Table 3, except that locations with less than 10 employee-months are lumped into a separate location category. "Subjective performance" is an employee's subjective performance on a 1-5 scale. "Employee Engagement" is normalized employee engagement. In columns 7-8, the outcome is whether an employee receives a promotion, with coefficients multiplied by 100 for readability. * significant at 10%; ** significant at 5%; *** significant at 1%

Table C13: What are Managers Rewarded For? Employees Survey Scores vs. Subjective Performance Score vs. Value-Added, Period 1 Only

Dep var:	Subjective performance (normalized)	Promoted (x100)	Log Salary (x100)	Comp ratio	Change in span of control	Key individual (x100)	Attrition (x100)	Holding power	Change in holding power
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: OLS									
MOR in current period	0.0664***	-0.0812	-0.125	0.199	0.300***	0.245	-0.145***	0.0137*	0.0114
	(0.0111)	(0.0608)	(0.183)	(0.262)	(0.0544)	(0.391)	(0.0437)	(0.00778)	(0.0112)
Subj performance		2.328***	0.501***	0.246	-0.0584	6.855***	-0.338***	0.0768***	0.172***
		(0.0864)	(0.181)	(0.248)	(0.0576)	(0.405)	(0.0559)	(0.00778)	(0.0138)
Manager FE in retention	0.0175	0.0112	-0.337	0.577*	0.0850	0.754*	-0.621***	-0.0144	0.00986
	(0.0123)	(0.0691)	(0.239)	(0.310)	(0.0634)	(0.455)	(0.0688)	(0.00917)	(0.0126)
Panel B: IV									
MOR in current period	0.184***	0.591**	0.0671	0.653	0.324	2.308	0.0195	0.0116	0.0549
	(0.0525)	(0.295)	(0.971)	(1.246)	(0.275)	(2.068)	(0.0134)	(0.0440)	(0.0712)
Subj performance		2.386***	0.489**	0.246	-0.0614	6.699***	0.0143*	0.0851***	0.164***
		(0.0960)	(0.210)	(0.281)	(0.0653)	(0.468)	(0.00751)	(0.00897)	(0.0158)
Manager FE in retention	-0.00586	-0.0338	-0.525**	0.709*	0.0856	0.522	-0.0317*	-0.00196	0.0128
	(0.0141)	(0.0837)	(0.268)	(0.365)	(0.0642)	(0.548)	(0.0169)	(0.00979)	(0.0159)
Panel C: Red. Form									
MOR in other period	0.0486***	0.171**	-0.0102	0.149	0.0892	0.565	0.00517	0.00277	0.0135
	(0.0138)	(0.0776)	(0.258)	(0.331)	(0.0761)	(0.543)	(0.00353)	(0.0113)	(0.0179)
Subj performance		2.423***	0.505***	0.294	-0.0419	6.883***	0.0156*	0.0857***	0.168***
		(0.0930)	(0.193)	(0.263)	(0.0581)	(0.439)	(0.00824)	(0.00771)	(0.0151)
Manager FE in retention	-0.00140	-0.000856	-0.530**	0.698*	0.0928	0.581	-0.0309*	-0.00232	0.0150
	(0.0138)	(0.0816)	(0.263)	(0.360)	(0.0637)	(0.537)	(0.0166)	(0.00951)	(0.0154)

Notes: Standard errors clustered by manager in parentheses. The controls are the same as Table 3, except that locations with less than 10 employee-months are lumped into a separate location category. "Subjective performance" is an employee's subjective performance on a 1-5 scale. "Employee Engagement" is normalized employee engagement. In columns 7-8, the outcome is whether an employee receives a promotion, with coefficients multiplied by 100 for readability. * significant at 10%; ** significant at 5%; *** significant at 1%

Appendix References

Baker, George P., Michael Gibbs, and Bengt Holmstrom, "The Wage Policy of a Firm," *Quarterly Journal of Economics*, 1994, *109* (4), pp. 921–955.