BUILDING A PRODUCTIVE WORKFORCE: THE ROLE OF STRUCTURED MANAGEMENT PRACTICES

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Abstract

In an influential study, Bender et al. (2018) document consistent relationships between management practices, productivity, and workforce composition using administrative data from German firms matched to ratings of their practices from the World Management Survey. We replicate and extend their analysis using comparable data from Brazil. The main conclusions from their study are supported in ours, strengthening the view that more structured practices affect organizational performance through workforce selection across different institutional settings. However, we find more structured management practices are linked to greater wage inequality in Brazil, relative to greater wage compression in Germany, suggesting that some of the consequences of adopting structured practices are tied to the local context.

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We use the Brazilian employer-employee dataset (RAIS) data under an agreement with the *Ministério do Trabalho e Emprego* (MTE), Brazil's labor ministry, which collects and maintains RAIS. We thank Carlos Lessa at the Brazilian statistics agency (IBGE) for access to the Brazilian industrial survey data (PIA). We thank Katarzyna Bilicka, Nick Bloom, Erik Brynjolfsson, David Card, Bob Gibbons, Maria Guadalupe, Hilary Hoynes, Lisa Kahn, Pat Kline, Ekaterina Roshchina, Raffaella Sadun, Kathryn Shaw and John Van Reenen for helpful comments and suggestions. We also thank participants at the LERA Session at ASSA 2017, the Empirical Management Conference 2018, RES 2019, SOLE 2019, ESCoE productivity workshop, SIOE 2019 and EPED 2019 for useful discussions and comments. Schmutte gratefully acknowledges the financial support of the Bonbright Center for the Study of Regulation.

1 Introduction

Management practices drive many important firm- and market-level outcomes, particularly productivity (White et al. 1999; Bloom et al. 2012; McKenzie and Woodruff 2016) and the matching of workers to appropriate jobs (Shaw et al. 1998; Chen and Li 2017; Bidwell and Keller 2014). In an influential study, Bender et al. (2018) (hereafter Bender et al.) empirically document the connection between a firm's management practices and its ability to recruit and retain a high-quality workforce. Using data on German firms and workers, their key innovation was to link scores measuring firms' management quality from the World Management Survey (WMS) to measures of worker quality derived from administrative records. This allowed for a first look at the relationship between day-to-day management practices and worker sorting; a process that drives myriad important outcomes from firm productivity to wage inequality. They show that, in Germany, firms with higher management scores are more productive and also recruit and retain higher-quality workers. They also find that organizations with high management scores pay higher wages relative to other firms, but are more likely to compress pay differences between top and bottom earners.

In this paper, we ask whether the results obtained by Bender et al. also hold in Brazil, a large economy with a diverse labor force, though in a markedly different institutional environment. Our primary goal is to assess whether their findings for Germany reflect common relationships between management practices as measured in the WMS, workforce quality, and productivity. That they would is far from given. Firms in emerging economies like Brazil face a distinctly different institutional environment, and may operate differently than their counterparts in highly developed economies like Germany. It is also possible that the WMS is culturally biased in ways that affect its ability to consistently measure management (Waldman et al. 2012; Bloom et al. 2014). Replication and extension exercises such as this build a body of evidence around how systematic the relationship between management and various firm outcomes are across different settings.

We begin with an exact replication of Bender et al.'s main results, estimating the same models as they do using comparable Brazilian data. Our replication reveals a remarkable consistency across the two countries, and we also find some key differences that illustrate how local context could shape the relationship between management practices and firm behavior (Huselid 1995). For instance, like German firms, Brazilian firms with higher management scores pay higher average wages. Unlike in Germany, however, in Brazil higher management scores are associated with larger pay gaps between top and bottom earners. This discrepancy holds using different measures of pay dispersion, and cannot be explained by differences in worker quality. We discuss key features of the Brazilian labor market and institutional environment that might account for this result.

Moving beyond the direct replication, we exploit the occupational classification system in the Brazilian data to overcome Bender et al.'s inability to observe which workers are managers. Because they cannot identify the managers in the German data, Bender et al. proxy for manager quality by classifying all workers in the firm's top quality quartile as managers. Using this proxy, they show that firms with high management scores tend to have higher quality managers. We find the same result when we use their classification with the Brazilian data. However, when we use occupation codes to distinguish managers, the relationship between manager quality and management scores is severely attenuated and loses statistical significance. In Brazil, many top quartile workers are not employed in managerial occupations, so the result using Bender et al.'s definition should be interpreted less as an insight about the quality of managers and more about the quality of the firm's "best workers".

Finally, we extend the analysis to characterize the relationship between management practices and the recruiting and retention of managerial and non-managerial workers. First we show that in Brazil, as in Germany, firms with higher management scores hire workers with higher quality and tend to fire workers of lower quality first.[1] We then provide evidence of potential mechanisms at play for managers relative to non-managers. High-scoring firms are clearly more selective when hiring managers, but not obviously so when hiring non-managers. By contrast, firms with higher management scores are more selective when firing non-managers, but manager firings are entirely unrelated to manager quality. We also show that employment of higher quality managers is associated primarily

[1]Bender et al.'s empirical specification measures separations to unemployment, which cannot observe for Brazil. However, the Brazilian data include information, not available for Germany, that allows us to distinguish firings from quits. Our analysis is therefore similar and complementary, but does not constitute an exact replication in this case.

with operations management practices. Altogether, our results suggest that high-quality managers might be drawn to firms that are more productive or have high management scores, rather than the other way around.

We organize our paper to follow the same basic structure of Bender et al. For each of their main findings, we present an exact replication, then present relevant extensions, and discuss important similarities and differences. Where appropriate, we include their original results in tables and figures alongside our replication to aid the reader in making comparisons. We conclude with a discussion of the close similarity of the German and Brazilian findings, as well as the stark difference in the pay inequality results. As the replication is predicated on our ability to measure management practices, worker quality, and job flows in the same way that Bender et al. do, we begin with a description of our data and how they relate to the German data used in the original study.

2 Data and Institutional Setting

The primary goal of our replication exercise is to assess whether the relationship between management practices and workforce quality documented by Bender et al. for Germany also holds in Brazil. We use identical measures and methods such that the only difference between the two studies is the setting, with few exceptions. Our data on management practices come from the same source as the original study: the WMS. Like Bender et al., we derive our measures of workforce quality and worker flows from a high quality administrative dataset — in our setting, the *Relação Anual de Informações Sociais* (RAIS). To the extent possible, our data preparation follows Bender et al., with the only exception being the identification of employee exits to unemployment. Our data also provide additional information on managers and the causes of separation that we use in extensions that push beyond the direct replication.

2.1 Structured management practices: WMS

The WMS employs double-blind surveys to collect data on firms' management practices. Trained analysts interview the senior-most manager at a manufacturing plant using a structured but open-ended questionnaire, and score responses across eighteen practices covering two broad areas of management: operations and people. Within operations management, the practices measured span core operations (the adoption of lean manufacturing practices), monitoring (existence, tracking and monitoring of key performance indicators) and target-setting (how targets are devised and revised). Within people management, practices measured focus on those that facilitate identifying, developing and rewarding good performers.[2] The scores for each question range from 1 to 5 and, broadly, indicate the degree to which the firm has formal processes in place for that practice. The WMS focuses on day-to-day processes and does not capture every facet of management (Waldman et al. 2012). However, such measures are consistent across firms and have been causally associated with improved productivity and organizational performance in a variety of settings (Bloom et al. 2013; 2019).

The WMS sample is drawn from the population of manufacturing firms employing 50–5,000 workers. The Brazilian waves were completed in 2008 and 2013, with 763 firms surveyed: 227 in 2008 only, 228 in 2013 only, and 308 in both waves. Given the sampling restriction to firms with more than 50 employees, it is representative of firms that are larger and pay better than the average firm in Brazil, and our results should be interpreted with this sample selection in mind.[3] To summarize management practices for each firm-year, we follow Bender et al. and the preceding literature in constructing a double-standardized average quality measure.[4] Most of the analysis uses the overall management index averaging across all 18 questions, but we also build separate operations management and people management indexes by averaging over the respective subsets of questions under each topic.[5]

The standardized average management scores are useful analytically, but can be diffi-

[2]Online Appendix Tables D.4 and D.5 summarize the WMS questions in each practice measured. See Bloom and Van Reenen (2007); Bloom et al. (2014) or visit www.worldmanagementsurvey.org for more information on the survey.

[3]Online Appendix Tables D.6-D.10 compare the full population of RAIS firms to the firms in Orbis from which the WMS sampling frame is assembled.

[4]We standardize each of the 18 questions, average to build the index, and standardize again.

[5]Bloom et al. (2015) separate the questions in a similar fashion when studying schools. We standardize the final index relative to the sample, so each management index has mean of zero and standard deviation of one.

cult to interpret in a tangible sense. We therefore establish a binary classification based on the scoring methodology to distinguish firms that have adopted "more structured" management processes in the WMS topic areas from those that have not. As part of their training, WMS interviewers are instructed to assign a code of 3 or higher when, and only when, "the process described would still happen if they were not personally there — what is the structure of the *process*, not just what is the structure that the *manager* imposes?".[6] On this basis, we classify a firm's practices in WMS areas as "more structured" if its average score across all management topics covered in the WMS is equal to or above 3, and as "less structured" otherwise.[7]

The distinction between more and less structured practices yields insight into what is measured by the standardized management scores. Comparing the average score on each of the 18 indicators for Brazilian firms half a standard deviation above and below the mean overall management score, we find that firms scoring in the upper range on average also score higher across all the questions rather than having a concentrated advantage in a particular area. For Brazilian firms, a standard deviation difference near the mean compares a firm that is using "more structured" practices in many areas to one using them in nearly none of them.[8] Furthermore, it is not straightforward to compare results based on standardized scores between Brazil and Germany, since management scores in Germany are higher on average and less dispersed. These differences should be kept in mind when comparing our results with Bender et al..

2.2 Worker quality, occupation, and employment history: RAIS

RAIS is a collection of administrative records assembled by the Brazilian labor ministry (*Ministerio do Trabalho* — MTE) to administer social security programs. Each record captures the details of an employment relationship between a worker and an establishment

[6]Quote from the WMS analyst training manual. One of us developed these materials and used them to train hundreds of WMS interviewers. Materials available upon request.

[7]Note our classification of a firm's WMS practices as "less structured" does not imply that it has absolutely no structured management processes in place. It only implies that, *on average*, the practices the firm uses tend to be less structured and more informal, *as measured by the WMS*. Further, it naturally applies only to those areas of management covered by the WMS and should be interpreted as such.

[8]See Figure D.2 in the Online Appendix.

during an year. We use RAIS for three purposes: (1) construct a measure of worker quality; (2) distinguish managers from non-managers; and (3) identify when workers either quit or are fired.

We measure "worker quality" using the estimated worker effects from a decomposition of log wages into worker- and firm-specific components introduced by Abowd, Kramarz and Margolis (1999) (henceforth the AKM decomposition).[9] Using the RAIS waves (2003-2007) before the first WMS Brazil interview in 2008, we restrict the data to jobs employing workers between the ages of 20 and 60 in plants with more than four workers.[10] In any year, we associate each worker with the job where they were employed longest. These restrictions leave us with 176,452,785 unique worker-year observations covering 52,438,357 workers and 3,222,859 establishments.

We estimate the model

$$\ln y_{it} = \alpha + x_{it}\beta + \psi_{J(i,t)} + \theta_i + \varepsilon_{it}, \tag{1}$$

where the dependent variable, y_{it}, is the real log wage of worker i in year t.[11] The function $J(i,t)$ indicates the establishment where i was employed in t. The $\psi_{J(i,t)}$ are establishment effects that reflect employer-specific wage premia. The θ_i are worker effects that capture the value of portable skills and represent our measure of worker quality. The controls in x_{it} include a normalized cubic in age interacted with race and gender along with year effects.[12]

We measure the average quality of workers in WMS firms by the average of their $\hat{\theta}_i$s. As this occupation detail is not available in the German data, Bender et al. proxy manager quality with the average quality over the top quarter of workers as ranked by

[9]Bender et al. refer to the worker effects as "ability". We favor the term quality because the relationship between AKM worker effects and productive traits is theoretically unclear (Eeckhout and Kircher 2011). While no term is without contention, we use *quality* in the "better paid" sense, implicitly assuming that the private sector tends to pay better workers higher wages, and relying on the positive correlation between higher worker AKM fixed effects and firm productivity (Figure I).

[10]Online Appendix A.1 describes our preparation of RAIS and implementation of the AKM model.

[11]We convert nominal monthly average earnings to 2015 Reais, divide by weekly hours, and then by 4.17. In 2015, 1 USD = 2.66 BRL.

[12]Following Card et al. (2018), the age coefficient is not identified relative to worker effects without a normalization. We normalize the experience profile to be flat at 20 years of experience.

$\hat{\theta}_i$. Far fewer than a quarter of Brazilian workers are managers, making this measure unsuitable in our setting.[13] Based on this classification, average manager quality is 1.20, which is 15 times higher than that of non-managers. We find that the empirical relationship between management practices and manager quality are sensitive to the choice of manager classification.

Finally, RAIS records the date and reason for separation when a job ends.[14] Thus, we are able to examine a firm's hiring, retention and dismissal activity as a function of its management practices, for both managers and non-managers. While Bender et al. cannot distinguish types of separation, we cannot distinguish whether workers are unemployed or in some other labor market state. Hence, Bender et al. focus on job-to-job moves and transitions to unemployment, and our analysis of firing provides complementary evidence on how firms manage the quality of their workforce.

2.3 Matched RAIS-WMS samples

Following Bender et al., most of our analysis uses an employer-level dataset that augments the WMS observations from 2008 and 2013 with establishment-level summaries of worker characteristics from RAIS for the corresponding year. We use employer-level observations for all years between 2008 and 2013 for our analysis of employment flows.[15]

Table I reports statistics summarizing the primary employer-level sample. The WMS data closely matches the administrative data in RAIS for the variables recorded in both. Relative to Germany, Brazilian firms in WMS face fewer competitors, are more likely to be owned by their founder, and are eight years younger at the median. They are also smaller, but have similar shares of female and college-educated workers. The AKM coverage share of 0.79 is also comparable to the German data.

[13]The average manager share reported in the WMS is 4.83 percent. Using our occupation-based classification, the share of managers is 8.66 percent. See Table A.1 in the Online Appendix.

[14]The employer records the separation reason in RAIS, but the unemployment insurance system in Brazil could still induce some misreporting. We verify that this is not a concern by looking at the change in wages of workers who separate from their employer under a "fire", a "quit", or "other". Workers that were fired have substantially smaller increases in wage relative to those who quit, suggesting that misreporting is not a major problem. See Table D.11 in the Online Appendix.

[15]See Online Appendix A for further details.

3 Replication Results and Extensions

We organize our discussion of results around the three main conclusions in Bender et al., which link management practices to (1) worker quality and organizational productivity, (2) between- and within-firm pay differences, and (3) hiring and separation behavior. Most of their main findings carry over to Brazil. However, we find some key differences, most notably that firms in Brazil with higher management scores have greater pay inequality. Our extensions suggest high-quality managers are drawn to more productive firms and that more structured management practices may be more instrumental in finding and retaining high-quality non-managerial workers. Our conclusion offers a synthesis that reconciles our findings with those of Bender et al. in light of differences between Brazil and Germany.

3.1 Management practices, worker quality and productivity

As in Germany, Brazilian firms with higher management scores employ higher quality workers. Figure I replicates the non-parametric relationship between management scores and the average quality of workers, controlling for firm size. The figure shows that the relationship is positive and of very similar magnitude in both countries.[16] Table II takes a closer look at the relationship in Figure I, reporting results from regressions that project standardized management scores onto worker quality, controlling for a large set of firm characteristics. Panel A replicates the Bender et al. analysis, where "managers" are defined as those workers in the top quarter of the wage distribution. Panel B exploits the RAIS advantage of an occupation-based manager classification. We include corresponding Bender et al. estimates for the comparable table at the bottom of each of our tables for ease of comparison.[17]

[16] Figure D.4 in the Online Appendix replicates Figures 1 and 2 in Bender et al. describing the distribution of wages and worker quality. In Brazil, high-wage and high-quality workers are even more concentrated in firms with high management scores than in Germany.

[17] Each regression includes the same controls as Bender et al.: firm size, the share of female workers, ownership, number of competitors, industry, year effects, and a cubic in the AKM coverage share. Like them, we control for coverage share to address sample selection induced by estimating worker effects on the pre-2008 data. We also control for region, akin to their control for East Germany. Table D.12 in the Online Appendix shows that adding controls for the number of sites the firm operates does not alter the results.

Bender et al. argue that the relationship between management practices and worker quality mainly operates through the quality of managers. We find a similar pattern in Brazil when we exactly replicate their model and classify managers as they do.[18] Columns (1) and (2) show that higher worker quality and higher managerial quality (with their definition of manager), respectively, are associated with statistically and economically significant increases in management scores. Column (3) suggests that manager quality is the more significant correlate of management practices, though the confidence intervals overlap. Column (4) shows that the results persist even controlling for the share of workers with a college degree.[19]

However, the picture changes when we use occupation codes to distinguish managers and non-managers, as reported in Panel B. While the same qualitative findings appear in Columns (1) and (2), the estimated coefficients are attenuated. More notably, in Columns (3) and (4) we no longer find the strong, positive relationship between the management score and manager quality documented by Bender et al.. Instead, the estimated coefficients on manager quality are small and imprecise, and the management scores remain positively correlated to the average employee quality.

Our findings are sensitive to the definition of managers because the two measures capture very different groups of workers. Our occupation-based manager classification includes workers in managerial occupations, as well as production workers in supervisory positions. These workers are, indeed, primarily in the top quartile. However, there over ten times more production workers than managers and supervisors in these firms. As such, the majority of workers picked up in the top quality quartile (51 percent) are, in fact, non-supervisory production workers.[20] The Bender et al. measure captures the right-tail of

[18]The small quantitative differences between our results and Bender et al. may not be statistically or economically significant. The estimated confidence intervals overlap. Furthermore, the management scores and worker quality are standardized relative to each country, affecting the ability to compare across countries using only these two studies. See Section 2.1.

[19]Bender et al. also show that management scores are also linked to higher productivity. Further, the correlation between management and productivity seems to operate through worker quality; in particular, manager quality. Online Appendix B reports estimates from comparable models of log sales, controlling for capital, materials, as well as the management score and the average quality of managers and non-managers. Our findings for Brazil are very similar to those for Germany, despite the differences in economic conditions and institutions.

[20]Table A.1 in the Online Appendix shows how workers in five occupation groups are distributed across

worker quality in the firm. Consistent with Iranzo et al. (2008), a more dispersed right-tail is associated with higher management scores and greater productivity. Seemingly, however, the employment of higher quality managers is not associated with higher overall management scores in Brazil.

3.2 Management practices and firm-specific pay

The AKM decomposition also estimates a firm fixed effect that measures a firm-specific compensation premium. Bender et al. show that firms with more structured management practices essentially tend to pay their workers more. Figure II plots the conditional correlation between the AKM firm effect and the standardized management score, controlling for firm size. If anything, the positive correlation between management scores and *average* firm-specific pay is stronger in Brazil. However, when we look at within-firm pay distributions, there are meaningful differences between Brazil and Germany.

Table III reports the results from regressing measures of pay and worker-quality dispersion (90-10 differences and standard deviations) on the standardized management score. The results from Bender et al. are included at the bottom of the table for ease of comparison. They find that firms with higher management scores have lower within-firm inequality, and show management scores are only weakly related to the variance in worker quality. They interpret this to mean that structured management practices are associated with wage compression that equalizes pay across workers of different quality.

Our results for Brazil are more consistent with a story in which firms with higher management scores tend to employ higher quality workers and also pay them their market value. Columns (1) and (2) indicate that firms with higher management scores have greater 90-10 pay differences. These findings are mirrored in the worker-quality regressions given in Columns (5) and (6). The relationship between management scores and the coefficient of variation in log wages in Columns (3) and (4), and in worker quality in Columns (7) and (8), are also positive and of similar magnitudes.[21] Determining whether these contrasts

worker quality quartiles.

[21] Our presentation is nominally different than Bender et al.. The labels on their Table 8 suggest the dependent variable in columns (3) and (4) is the coefficient of variation in the natural logarithm of wages, and the natural logarithm of worker quality in columns (7) and (8). We report results using the standard

between Germany and Brazil reflect differences in management practices, pay norms, or regulatory practices is an interesting topic beyond the scope of our replication exercise. Still, we offer some speculative considerations in the discussion and conclusion section.

3.3 Management practices, hiring, retention, and firing

Bender et al. show that firms with higher management scores have higher quality workers and that higher quality workers are less likely to separate from those firms. We find similar patterns in the Brazilian data, and use our ability to differentiate managers from non-managers to show how management practices are associated with hiring and firing of managers relative to non-managers.

Hiring

To document the correlation between management practices and hiring, Bender et al. regress the share of new hires that have quality above different percentiles of the overall worker quality distribution onto the standardized management score.[22] We replicate their analysis in Table IV and find similar patterns: higher management scores are associated with higher quality inflows, particularly toward the top of the distribution. In Brazil, however, the association appears to be slightly less affected by controlling for firm size.[23]

In an extension, we examine the quality of newly hired managers and non-managers separately in firms with more and less structured management practices. Our distinct approach compares a worker's quality rank among all newly-hired workers in an occupation group with the rank they occupy among newly hired workers in that occupation group for both types of firms. Figure III provides binned scatter plots of residuals from rank-

deviation rather than the coefficient of variation because wages and worker quality are already measured in logarithmic units, so normalizing them by the mean is not necessary. Appendix C includes a complete discussion resolving apparent measurement differences, including alternative results using the coefficient of variation.

[22]These regressions include the same set of controls as Table II. Our analysis uses data from the WMS plants for all years between 2008-2013. For comparison, see their Table 6, which is fully replicated in Table D.13 in the Online Appendix.

[23]As described in Section 2, the analysis is based on a dataset measuring flows into and out of the sample firms. The analysis is based on 519,516 hires. The analysis in Table VI below is based on 248,003 fires.

rank regressions for both occupation groups. The circles represent firms that use more structured practices and triangles with firms that use less structured practices. Un-shaded elements indicate the baseline specification, while the shaded elements denote residuals from a controlled specification.[24]

If hiring were random with respect to management practices, the markers would simply fall on the 45-degree line. Instead, we see that firms with more structured practices hire workers from higher in the quality distribution, at every quality rank. This pattern is particularly pronounced for managers. For example, if we drew a horizontal line at the 50th percentile of the within-firm type, the baseline specification suggests that the median newly-hired manager in a firm with more structured management would be in the 61st percentile in the "overall market" distribution, but the median newly-hired manager in a firm with less structured management would only be in the 44th percentile — a 17-point gap. For non-managers, hiring is not nearly as selective. For the median newly-hired non-manager, the gap is only 2 points. These gaps are statistically significant, and in neither case are patterns explained by sorting on observable worker and firm characteristics.[25]

Retention

We next consider extensions that shed light on how management is related to worker selection. Table V presents regressions of the average quality of workers retained by the firm. Comparing the coefficients of z-management across Columns (1)-(3), we find that about two-thirds of the baseline correlation between management scores and worker quality is accounted for by worker and firm characteristics. This applies for both managers and non-managers. Hence, the link between management scores and worker quality arises in part because high-quality workers sort into firms with particular characteristics associated with more structured management practices. These findings suggest that the use of more structured management practices is associated with success in retaining workers with higher quality than observable characteristics would predict.

Ideally, we could determine whether more structured management practices actually

[24] In addition to year effects, the controlled specification includes employer size, employer age, number of competitors, ownership type, region, gender, race, education, and two-digit industry effects.

[25] See Tables D.14 and D.15 in the Online Appendix for the regressions underlying the figures.

enable firms to identify higher quality workers more effectively. This is not possible with our data because we cannot rule out sorting on unobserved worker or firm characteristics. However, if more structured management practices primarily drive the *selection* of higher quality workers, we would also observe that the process operates through people management. Columns (4)-(6) decompose the overall management index into operations and people indices. When we introduce these indices individually, we find operations predicts both manager and production-worker quality, with a stronger relationship for managers, while people management scores only predict production-worker quality. When we include the indices together, operations practices emerge as the key for manager quality. For non-managers, the data are not able to distinguish the relative importance of operations management relative to people management.

This result is intuitive: most of the people management processes measured in the WMS relate to the selection, monitoring and retention of non-managerial production workers. However, the story is not as simple when considering managerial occupations. These more structured people management practices are not directly related to selection and retention of managers, but rather *enacted* by them. The results suggest that it is variation in the structured nature of the operations management that may seem more attractive to better managers, rather than variation in structures of people management.

Firing

The ability to dismiss under-performing workers is an important tool for building a productive workforce. Bender et al. show that high management scores predict a declining gap between the quality of workers leaving to unemployment and those remaining with the firm, which leads them to infer that firms with higher scores more judiciously manage their separations.[26] Because RAIS includes the reason for separation, we can isolate dismissals from quits and examine firing decisions directly.[27] However, unlike with the German data, when workers do not immediately appear in another job in RAIS after separating from

[26]See their Table 7.

[27]We define a separation as a firing if it was recorded as an “employer-initiated termination without just cause.” We can also include as fires jobs reported to end due to “employer-initiated terminations with just cause,” but these constitute an extremely small number of terminations. The reason for separation is reported by the employer.

their employer, we do not know whether they were unemployed or exited the formal labor force.[28]

Table VI replicates the specification from Bender et al., but where the dependent variable is the difference between the average ability of fired and incumbent workers. We find firms with higher management scores are less likely to fire higher quality workers, consistent with the Bender et al. analysis. Although the relationship is attenuated somewhat when we include our basic firm controls and fired-worker characteristics, the coefficient estimate on the management score remains statistically and economically significant.

Figure IV presents binned scatter plots of firing rates for managers and production workers by worker quality, distinguishing between firms with more and less structured management.[29] For managers, there is no discernible relationship between the use of more structured management practices and firing behavior. However, for non-managers, firms with more structured practices have lower firing rates throughout the worker-quality distribution. This could be evidence of better matching earlier in the employee's job cycle. Finally, for a given firing rate, firms with more structured practices dismiss workers of lower average quality, suggesting that such firms indeed fire more selectively.

4 Discussion and Conclusions

A primary conclusion of our analysis is that the management practices measured by the WMS are consistently associated with observed outcomes and behavior vis-à-vis productivity, compensation, hiring and recruiting. While the connection between WMS management scores and productivity has been documented in many countries (Bloom and Van Reenen 2011; Bloom et al. 2012), their relationships with worker quality and workforce management have not. Our paper thus helps to clarify how management practices do, and do not, extend across countries. It also helps address some concerns that the WMS is culturally biased (Waldman et al. 2012; Bloom et al. 2014).

[28]Given the size of the informal sector in Brazil, this is an important distinction that we cannot address with only the RAIS data.

[29]The firing rate and worker-quality measures are adjusted for worker and firm characteristics. See Online Appendix Tables D.16 and D.17.

The similarities in the relationship between management scores, firm and worker quality and productivity are remarkable. Despite substantial differences in the economies and labor markets of the two countries, our results suggest that these simple set of practices are consistently correlated with a set of good firm outcomes related to their labor force. Further replications across different settings would help strengthen the understanding of where there are "natural laws of management" that extend beyond the more straightforward productivity sphere.

However, it would be a mistake to blindly extrapolate to other settings. First, this is because the results in the original study and in this one do not document causal effects of management or worker quality, but conditional relationships. Second, the documented relationships are not always the same. In particular, we find the WMS management score has a different association with pay inequality in Brazil than it does in Germany. The reasons why are undoubtedly complex and merit a full investigation. Ex-ante, it is not clear how more structured management practices should be related to internal pay dispersion. On one hand, firms with more structured practices may be more likely to use performance-based pay, which could contribute to greater pay dispersion (Huffman and Bognanno 2017; Lemieux et al. 2009). On the other hand, some firms might adopt more structured personnel practices that compress pay to maintain morale in the presence of fairness norms. Unpacking these patterns is a fruitful area of future work.

Notably, earnings inequality declined in Brazil over the period of our sample, while it was increasing in Germany. The decline in Brazil was largely associated with a decline in differences in pay across firms (Alvarez et al. 2018) and increases in the minimum wage and other pay-compressing institutions (Engbom and Moser 2018). Perhaps in Brazil, firms with more structured management practices are more adept at avoiding wage-compressing institutions. Along these lines, Brazilian firms are legally constrained against outsourcing their lowest-paid jobs in a way that German firms are not. Hence, wage compression in German firms with higher management scores may reflect their ability outsource low-paid jobs (Goldschmidt and Schmieder 2017).[30] In summary, certain

[30]Song et al. (2019) show increased inequality in the U.S. is associated with greater segregation of high-quality workers into higher-paying firms, consistent with U.S. firms likely contracting out their lowest-paying jobs.

aspects of management practice are inescapably contingent on the local context (Huselid 1995) and are by design not fully reflected in the WMS management scores.

Pushing beyond the replication exercise, we offer a more nuanced understanding of how more structured management is associated with recruitment and retention. For the managerial workforce, firms with more structured management practices are more selective on the front end, when hiring. In contrast, for non-managers they are more selective on the back end, when firing. We also find that the quality of managers is associated more strongly with operations management than with people management. Taken together, these results are consistent with a model where firms with more structured operations management attract, or recruit, higher quality managers, who then are able to better identify and retain high quality production workers. Altogether, given the large informal economy and lower average productivity of Brazilian firms, management may play an even more important role in matching workers to more productive firms in Brazil than in Germany.

In replicating Bender et al., we have maintained their focus on static measures of compensation and worker quality, and on the movements of workers in and out of firms. Of course, human resource management deals more generally with the use of promotions and raises to attract and motivate workers (Bidwell and Keller 2014). A comprehensive examination of the connection between more structured management practices and the dynamic elements of internal labor markets will demand much more of the data but also promises great insights. We are actively pursuing these topics in ongoing research.

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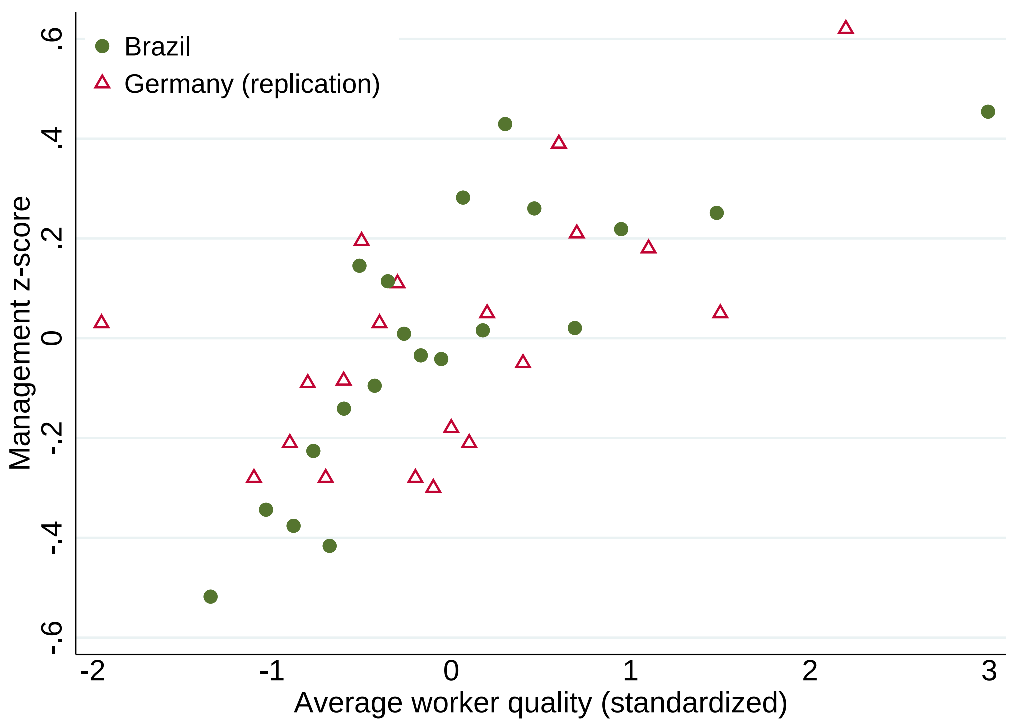
Tables and Figures

Table I: Descriptive Statistics

	Mean	Median	Min	Max	SD	N
Number of competitors						
No competitors	0.01	0.0	0.0	1.0	(0.08)	964
Fewer than five competitors	0.23	0.0	0.0	1.0	(0.42)	964
Five or more competitors	0.76	1.0	0.0	1.0	(0.43)	964
Ownership						
Family owned	0.26	0.0	0.0	1.0	(0.44)	964
Founder owned	0.36	0.0	0.0	1.0	(0.48)	964
Manager owned	0.02	0.0	0.0	1.0	(0.15)	964
Nonfamily private owned	0.29	0.0	0.0	1.0	(0.45)	964
Institutionally owned	0.07	0.0	0.0	1.0	(0.25)	964
Government ownership	0.00	0.0	0.0	1.0	(0.06)	964
Other WMS variables						
Firm age (years)	36.87	34.0	1.0	316.0	(24.97)	964
Management score (standardized)	0.00	-0.0	-2.6	3.1	(1.00)	964
% of female employees (WMS)	29.85	25.2	0.0	100.0	(23.65)	475
% of employees with college degree (WMS)	13.08	10.2	0.0	100.0	(13.24)	964
% of managers	4.83	3.5	0.0	30.0	(4.19)	960
RAIS variables						
Number of workers	287.10	184.0	1.0	5072.0	(373.85)	964
Median hourly wage	12.09	9.0	3.4	200.1	(11.91)	964
% of female employees (RAIS)	29.13	23.8	0.0	100.0	(21.43)	964
% of employees with college degree (RAIS)	15.52	9.1	0.0	100.0	(19.01)	964
Share of managers in total workforce	8.66	6.0	0.0	100.0	(10.82)	964
RAIS/AKM variables						
AKM coverage (% empl with worker effects)	0.79	0.8	0.2	1.0	(0.16)	964
Average employee quality (AKM worker effects)	0.00	-0.2	-1.8	6.7	(1.00)	964
Average managerial quality (occupation-based)	0.00	-0.1	-2.2	3.7	(1.00)	964
Average managerial quality (top quartile)	-0.00	-0.2	-2.2	3.9	(1.00)	964
Firm wage premium (AKM employer effect)	0.00	-0.0	-2.3	7.4	(1.00)	964

Notes: Descriptive statistics from the firm-year data used for estimation. The data includes one observation for each WMS firm in each year it was surveyed and can be matched to RAIS. This table is comparable in format to Table 1 in Bender et al., for Germany. The WMS only asked Brazilian firms about percent of female employees in 2013, which explains the reduced number of observations.

Figure I: Correlation between management score and worker quality



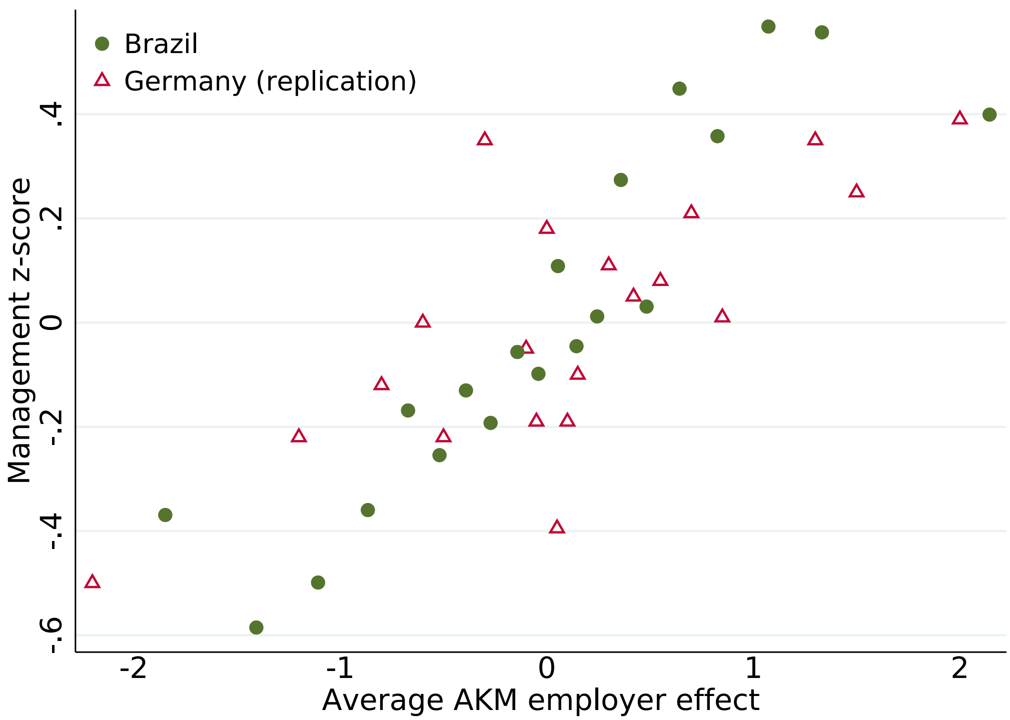
Notes: Binned scatter plot of management scores and average worker quality for Brazil and Germany. The points for Germany are taken from Bender et al. (2018). Both variables are adjusted for firm size.

Table II: Correlation between management practices and worker quality

Panel A: Quartile of quality-based managers *(replication of Bender et al. method/definitions)*	(1)	(2)	(3)	(4)
	Dependent variable: z-management			
Mean employee quality	0.131***		-0.062	-0.080
	(0.036)		(0.073)	(0.069)
Mean managerial quality (top quartile worker effects)		0.177***	0.232**	0.212**
		(0.036)	(0.074)	(0.070)
ln(number of employees)	0.362***	0.353***	0.353***	0.341***
	(0.031)	(0.031)	(0.031)	(0.030)
% of employees with college degree				1.331***
				(0.277)
Panel B: Occupation-based managers *(extension with our definitions)*	(1)	(2)	(3)	(4)
	Dependent variable: z-management			
Mean employee quality	0.119***		0.097*	0.069
	(0.035)		(0.039)	(0.038)
Mean managerial quality (occupation-based)		0.093**	0.049	0.040
		(0.035)	(0.039)	(0.038)
ln(number of employees)	0.365***	0.361***	0.359***	0.347***
	(0.031)	(0.032)	(0.032)	(0.031)
% of employees with college degree				1.368***
				(0.280)
Observations	964	964	964	964
Firms	696	696	696	696
Bender et al estimates for their Table 2 (for comparison, coefficients only)				
Mean employee quality	*0.216****		*0.29*	*-0.093*
Mean managerial quality (top quartile worker effects)		*0.294****	*0.277****	*0.258****
ln(number of employees)	*0.237****	*0.261****	*0.264****	*0.263****
% of employees with college degree				*1.022****

Notes: Robust standard errors clustered at firm level in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Estimates from linear regression models on matched WMS-RAIS firm-year data. The dependent variable is the standardized WMS overall management score. All specifications include year fixed effects, region indicators, log(employment), firm age, ownership status, the share of female employees, the number of competitors, 2-digit industry fixed effects, and a cubic in the AKM coverage share. Panel A measures average manager quality using the Bender et al. proxy for classifying managers (top quartile of worker quality), while Panel B measures average manager quality using the RAIS occupation codes. All worker quality measures are standardized relative to the estimation sample.

Figure II: Correlation between management score and employer wage premium



Notes: Binned scatter plot of management scores and average Abowd et al. (1999) (AKM) firm (employer) effects for Brazil and Germany. The points for Germany are taken from Bender et al. (2018), and represented in red triangles. The points for Brazil are estimated using RAIS data from 2003-2007, and are represented by green circles. Both variables are adjusted for firm size.

Table III: Within-firm heterogeneity in wages and worker quality

	90-10 Log Wages		Standard Deviation in Log Wages		90-10 Quality		Standard Deviation in Quality	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
z-management	0.143***	0.096***	0.053***	0.030***	0.175***	0.106***	0.071***	0.036**
	(0.016)	(0.016)	(0.006)	(0.006)	(0.025)	(0.024)	(0.011)	(0.009)
General Controls		✓		✓		✓		✓
Observations	964	964	964	964	964	964	964	964
Firms	696	696	696	696	696	696	696	696
	Bender et al estimates for their Table 8 (for comparison, coefficients only)							
Management score	*-0.037**	*-0.030**	*-0.097****	*-0.030***	*0.027**	*0.015*	*0.035***	*0.023*

Notes: Robust standard errors clustered at firm level in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Estimates from regressions of pay and worker-quality dispersion (90-10 differences and standard deviations) on the standardized management score. All specifications include year fixed effects. Fully controlled specifications include region indicators, log of employment, firm age, ownership status, the share of female workers, the number of competitors, 2-digit industry controls, and a cubic in the AKM coverage share. The management score is standardized relative to the estimation sample.

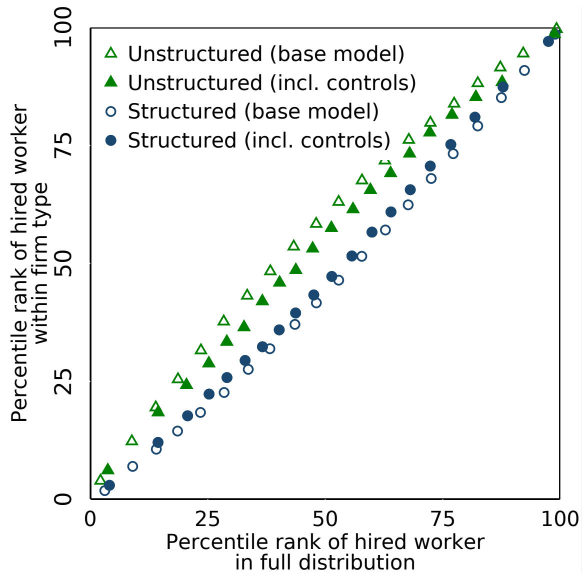
Table IV: Inflows to WMS firms

	Share of hired workers at or above quantiles of the quality distribution				
	10%	25%	50%	75%	90%
	(1)	(2)	(3)	(4)	(5)
	A. Not Including Size Control				
z-management	0.001	0.006*	0.012**	0.014**	0.012***
	(0.001)	(0.003)	(0.004)	(0.004)	(0.004)
	B. Including Size Control				
z-management	0.002	0.005	0.011*	0.011*	0.009*
	(0.002)	(0.003)	(0.004)	(0.005)	(0.004)
Observations	3857	3857	3857	3857	3857
Firms	706	706	706	706	706
Bender et al estimates for their Table 6 (for comparison, coefficients only)					
	A. Not Including Size Control				
Management score	*0.003*	*0.003*	*0.006*	*0.016***	*0.019****
	B. Including Size Control				
Management score	*0.003*	*0.004*	*0.005*	*0.007*	*0.010**

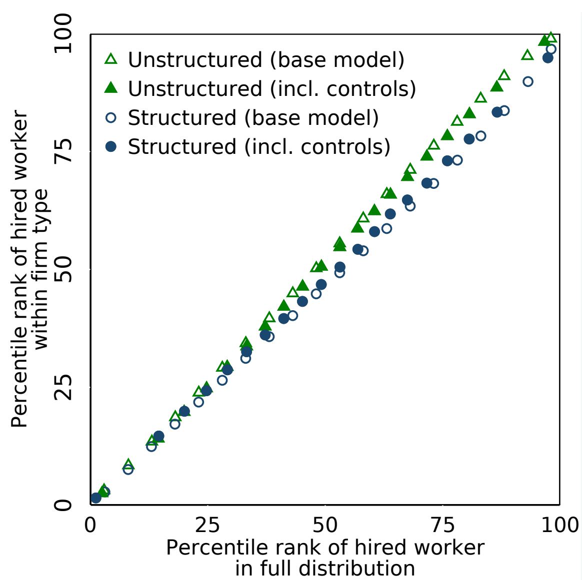
Notes: Robust standard errors clustered at firm level in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Estimates from regressions of the share of newly hired workers with quality at or above the labeled percentile on management scores. All specifications include year fixed effects, region indicators, firm age, ownership status, the share of female workers, the number of competitors, 2-digit industry effects, a cubic in the AKM coverage share, and the share of employees with a college degree. Panel B additionally controls for the number of employees. The management score is standardized relative to the estimation sample. Table D.13 reports the full set of coefficient estimates.

Figure III: Hiring rank-rank regression

(a) Managers



(b) Non-managers



Notes: Binned scatter plots of residuals from regressions of worker ranks in the distribution of all newly-hired workers, and their ranks in the distribution of all newly-hired workers into the same type of firm, on year dummies (base specification) and, additionally, employer size, employer age, number of competitors, ownership type, region, gender, race, education, and two-digit industry effects (controlled specification). Panel (a) plots the average residual quality rank of managers hired in firms with more structured management (blue circles), and managers hired in firms with less structured management (green triangles) across 50 equal-sized bins of residual overall quality rank across the entire distribution of hired managers. Panel (b) plots the average residual quality rank of production workers hired in firms with more structured management (blue circles), and production workers hired in firms with less structured management (green triangles) across 50 equal-sized bins of residual overall quality rank across the entire distribution of hired production workers. The model specifications are identical to those reported in Table D.14 and D.15.

Table V: Predicting quality of stayers

	Panel A: Avg. manager quality					
	(1)	(2)	(3)	(4)	(5)	(6)
z-management	0.299***	0.149***	0.114***			
	(0.032)	(0.032)	(0.033)			
z-operations				0.103***		0.106***
				(0.030)		(0.034)
z-people					0.040	-0.008
					(0.031)	(0.034)
	Panel B: Avg. non-manager quality					
	(1)	(2)	(3)	(4)	(5)	(6)
z-management	0.249***	0.134***	0.087***			
	(0.037)	(0.033)	(0.033)			
z-operations				0.067**		0.044
				(0.032)		(0.037)
z-people					0.071**	0.051
					(0.030)	(0.034)
Year controls	✓	✓	✓	✓	✓	✓
Full controls		✓	✓	✓	✓	✓
College share			✓	✓	✓	✓
# Observations	964	964	964	964	964	964
# Firms	696	696	696	696	696	696

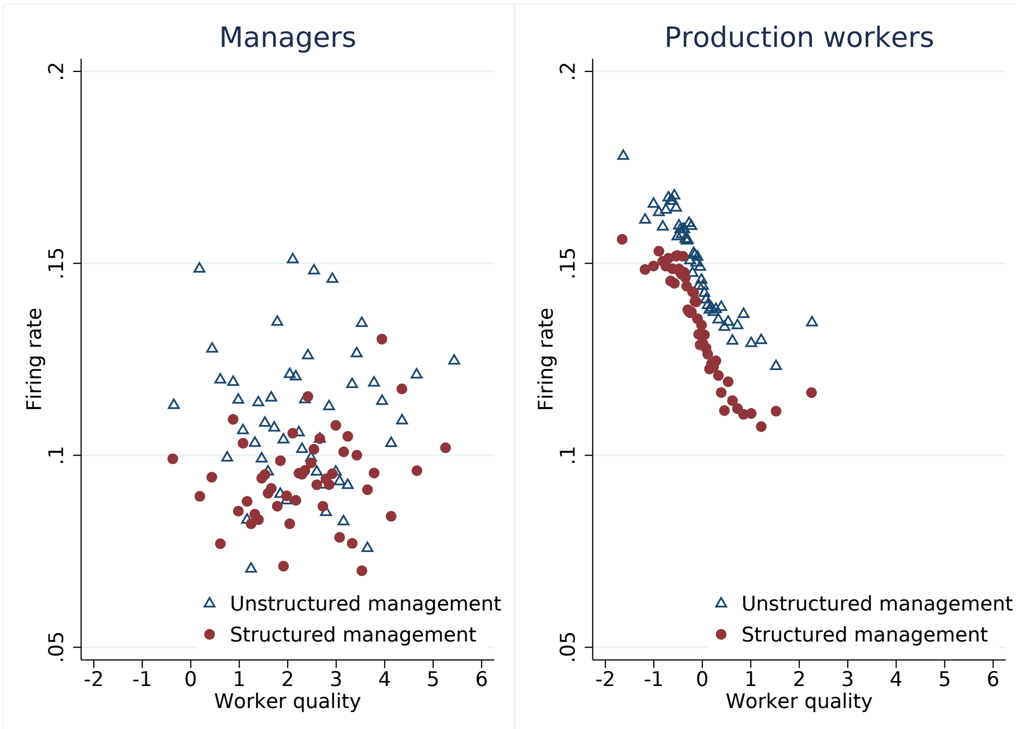
Notes: Robust standard errors clustered at firm level in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Estimates from regressions of average retained-worker quality on the management score. Panel A reports the estimates for managers and Panel B for non-managers. The full set controls includes region indicators, log of employment, firm age, ownership status, the share of female workers, the number of competitors, 2-digit industry controls, and a cubic in the AKM coverage share. All worker quality measures are standardized relative to the estimation sample.

Table VI: Fires from WMS firms

	Avg. quality of fired - Avg. quality of incumbents			
	(1)	(2)	(3)	(4)
z-management	-0.062***	-0.041***	-0.039***	-0.036***
	(0.010)	(0.010)	(0.010)	(0.009)
Average age of fired workers			0.007***	0.010***
			(0.002)	(0.002)
% college of fired workers				-0.983
				(0.542)
Controls		✓	✓	✓
Observations	3856	3856	3856	3856
Firms	704	704	704	704
Bender et al estimates for their Table 7 (for comparison, coefficients only)				
Management score	*-0.091**	*-0.115***	*-0.106**	*-0.133**
Average age of outflows			*0.048****	*0.041****
% of college of outflows				*4.887****

Notes: Robust standard errors clustered at firm level in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Estimates from regressions of the difference in average quality of fired workers and the average quality of incumbent workers. Controls include year effects, region indicators, firm age, ownership status, the share of female workers, the number of competitors, 2-digit industry effects, a cubic in the AKM coverage share, and the share of employees with a college degree. The management score is standardized relative to the estimation sample.

Figure IV: Firing rates for managers and production workers by worker quality



Notes: Binned scatter plots of firing rates for managers and production workers by worker quality, adjusted for year, tenure, race, gender, education, firm size, firm age, ownership status, the number of competitors, and 2-digit industry controls. Plots show the average residual firing rate in 50 equal-sized bins of worker quality.

ONLINE APPENDIX

"Building a productive workforce: the role of structured management practices,"

Christopher Cornwell, Ian M. Schmutte, Daniela Scur

November 2020

A Details of Data and Data Preparation

A.1 Preparation of RAIS Data and Estimation of the AKM Model

We prepare the data from RAIS in three steps. First, we extract and clean the data for the years 2003–2013. Second, we estimate the AKM model on the data from 2003–2007. Finally, we merge the estimated AKM worker and employer effects back the the RAIS data for the years of our main analysis: 2008–2013.

We otherwise impose minimal restrictions on the data for 2008–2013, which we use in our analysis. To compute the real hourly wage (in 2015 Brazilian Reais), we divide real monthly earnings by the number of contracted hours per month. To approximate the number of hours a worker is contracted to work each month, we multiply contracted hours per week, which is reported in RAIS, by $\frac{30}{7}$. Average monthly earnings are reported in nominal reais, which we convert to constant 2015 reais using the OECD's Consumer Price Index for Brazil (Organization for Economic Co-operation and Development 2019).

Before estimating the AKM model on the 2003–2007 data, we retain only observations for contract-years where: both the worker and employer IDs are valid; the record is not for a non-employer business; average monthly earnings are positive; the employed worker is between 20 and 60 years of age. For each worker, we restrict the data to one job per year: the one they worked the longest over the year, using earnings to break ties. Finally, we drop observations with data missing on race, gender, age, or education.

To estimate the AKM model, we follow the now standard approach as outlined by Abowd et al. (2002) and the implementation details from Card et al. (2013) in preparing the estimates used in Bender et al. (2018). Specifically, our time-varying observables consist of a cubic in age interacted with race and gender, along with a full set of unrestricted year effects. To ensure the worker effects are separately identified relative to the year effects and linear term in age, we normalize the age profile to flatten out at age 30 (Card et al. 2018). We find the parameter vector that solves the least squares normal equations using the pre-conditional conjugate gradient algorithm (`pcg` in MATLAB) and then separately identify the firm and worker effects within each connected components of the realized mobility network following Abowd et al. (2002).

Our primary interest is in the worker effects, θ_i, which capture the value of portable skills and represent our measure of worker quality. Under strict exogeneity of ε_{it} with respect to x_{it}, θ_i and ψ_j, least squares will produce unbiased estimates of the worker and establishment effects. Similar to Germany (Card et al. 2013), Portugal (Card et al. 2016) and the US (Song et al. 2019), the AKM model provides a reasonable description of cross-sectional variation in log wages for Brazil.[31]

After our sampling restrictions, we fit the AKM model on 176,452,785 worker-year observations that follow 52,438,357 across 3,222,859 establishments. There are 612,801 connected components, or groups, within which worker and firm effects are separately identified. As is common, well over 95 percent of all observations are within this connected component, and 100 percent of the WMS firms that we are able to match to RAIS. After fitting the AKM model, we merge the estimated worker and establishment effects to all years of the unrestricted RAIS panel. We then use the data from 2008–2013 to construct both employer-level summaries and worker-level microdata for the subsequent analysis. In this full panel, we construct several additional key variables. We use data on the date the worker separates from their job and the reason why to create a variable indicating whether a worker quit or was fired during the year. We also create a variable indicating whether a worker was hired in the current year. The RAIS data explicitly record the date of hire, so we do not have to infer when a worker was hired based on their first appearance in the firm.

We also construct indicator variables to distinguish managers from non-managers using information in reported occupation codes. In RAIS, occupations are classified according to the 2002 vintage *Classificação Brasileiro de Ocupações* (CBO) (*Classificação Brasileiro de Ocupações: Downloads - 5.1.0* 2020). We classify as managers all workers in jobs where the first digit of the CBO code is "1" or where the third digit is "0". The former captures all high-level managers and directors, while the latter captures workers who supervise others in the same broad (2-digit) occupation group. Bender et al. (2018) cannot distinguish managers directly, and instead classify as managers all workers whose estimated AKM worker effect is in the top 25 percent within their firm. We also construct an indicator variable for this alternative proxy of managerial status. Table A.1 reports a summary of the share of workers within occupations and quartiles of quality. In the Brazilian data, the classification of managers in Bender et al. does a good job in capturing the majority of managers (86%) and supervisors (67%). However, because the production workers vastly outnumber managers and supervisors, the top quartile of quality is made up of mostly production workers (51%) and technical workers (28%), with only 21% of the classification accounting for managers and production supervisors.

[31] See Alvarez et al. (2018) for evidence supporting the the AKM modeling assumptions in RAIS.

Table A.1: Quartile of wages and occupations

(a) Panel A: Share of total workers within each occupation

Occupation type	**Quartile of quality**				**Total %**	**Total count**
	1	**2**	**3**	**4**		
Managers	1.3%	3.5%	9.2%	86.0%	100%	3,481
Production workers	29.9%	28.1%	25.6%	16.4%	100%	90,133
Supervisor (production)	5.9%	8.2%	18.5%	67.5%	100%	4,787
Supervisor (technical)	23.1%	23.6%	30.2%	23.1%	100%	182
Technical/professional	11.6%	18.0%	27.2%	43.3%	100%	18,795
Total %	-	-	-	-	-	
Total count	29,521	29,278	29,413	29,166		**117,378**

(b) Panel B: Share of total workers within each quartile

Occupation type	**Quartile of quality**				**Total %**	**Total count**
	1	**2**	**3**	**4**		
Managers	0%	0%	1%	10%	-	3,481
Production workers	92%	87%	79%	51%	-	90,133
Supervisor (production)	1%	1%	3%	11%	-	4,787
Supervisor (technical)	0%	0%	0%	0%	-	182
Technical/professional	7%	12%	18%	28%	-	18,795
Total %	100%	100%	100%	100%	-	
Total count	29,521	29,278	29,413	29,166		**117,378**

Notes: Data from WMS-RAIS matched dataset for 2008 only. Occupation types are classified using the Brazilian Occupational Classification (CBO), and quartiles of quality are classified based on the top quartile of worker quality estimated using an AKM model on the RAIS data from 2003 to 2007. Panel (A) has the share of workers within each occupation across each quartile of quality, with each row adding up to 100%. Panel (B) has the share of workers within each quartile of quality across each occupation, with each column adding up to 100%.

A.2 Analysis Samples

We construct our main plant-level analysis samples to replicate Bender et al. (2018), treating the full WMS as a repeated cross-section, and merging plant-level summaries from the RAIS data for each plant-year observation. In Brazil, the WMS was conducted in two waves: one in 2008 and another in 2013. The WMS data for Brazil cover 1,145 firm-year observations: 585 from 2008 and 560 from 2013. In 2013, 331 are re-interviews of firms originally surveyed in 2008. There are 814 distinct firms. Of these, 69 firms do not have a valid identifier, so 745 firms are at risk to be matched to RAIS. We are able to match RAIS summaries to 966 observations. We standardize the management scores and summaries of average worker quality relative to the matched sample.

Bender et al. (2018) prepare the data used for analysis of worker flows in a slightly different way. They use construct a single cross-section of firms that ever appear in WMS. They then construct and match summaries of the characteristics of workers who join or leave the WMS firms over a range of years. To replicate their analysis, we prepare the data similarly. We construct a cross-section of WMS firms. For firms that appear in both 2008 and 2013, we retain the information from 2008. We then match these firms to summaries of the RAIS data for each year between 2008–2013. We are able to match 706 of the 745 WMS firms with valid identifiers to data and a total of 3,857 plant-year observations. This represents the maximum number of firms in each piece of analysis, though sometimes the firm count drops slightly as a result of missing observations for key variables in a particular model. We also use the microdata version of the flow data in our extensions looking at hiring, firing, and retention differences between firms with and without structured management practices. Specifically, using the same cross-section information on the 745 WMS firms, we match the microdata records for each contract in each year between 2008 and 2013. There are approximately 1.2 million contract-year observations with AKM information in the flow microdata.

B Productivity estimates

We match firm revenue, employment and materials expenditures from the Brazilian annual industrial survey, *Pesquisa Industrial Anual* (PIA) to our WMS-RAIS matched sample of firms. While the survey does not produce a direct measure of capital stock, one is estimated by the flagship Brazilian economic research institute, *Instituto de Pesquisa Economica Avancada* (IPEA) and made available to eligible researchers. We accessed PIA through an agreement with the Brazilian statistics agency, *Instituto Brasileiro de Geografia e Estatistica* (IBGE), in Rio de Janeiro. For this analysis, we use the definition of worker quality based on occupation codes, and not simply the top quartile of workers as in Bender et al..

We favor this classification because, as discussed in the paper, the top quartile definition in Brazil picks up primarily production workers and not managers or supervisors.

Columns (1) and (2) exclude factor inputs and replicate the finding from Germany that firms with higher overall management scores have larger revenues. Moving from Column (1) to Column (2), we see that part, but not all, of the relationship between management score and revenues is mediated through average worker quality. Adding the factor inputs in Column (3) reduces the estimated management-score coefficient by almost 50%, similar to Bender et al.[32]

In Columns (4)-(6), we use our occupation-based definition to distinguish manager and non-manager quality. Column (4) indicates that both matter for productivity, but variation loads to a much greater degree on manager quality: the manager quality coefficient estimate of .078 is more than twice that of non-managers. Column (5) shows the results are robust to controlling for the share of workers with a college degree, another proxy for worker quality. When we add the AKM firm effect in Column (6), the estimated coefficient of production-worker quality is no longer statistically significant. However, the management score and manager quality still predict sales, albeit with slightly smaller magnitudes. These results are consistent with the conclusion of Bender et al. that not all of the relationship between management practices and productivity can be explained by differences across firms in worker quality. They also suggest that higher wages may be one tool firms use to attract better production workers and motivate them to work harder.

We also replicate the productivity-related figures in Bender et al. in Figure B.1. Panel (a) replicates the relationship between productivity and the management score, where we see a consistent positive (and effectively linear) relationship. Panel (b) replicates the relationship between productivity and the average worker fixed effect from the AKM model. Here there is a difference in the shape of the relationship, where in Brazil it is more consistently positive across the support of the distribution whereas in Germany it is relatively flat in the lower end of the employee quality distribution, and positive in the upper half of the distribution. Panel (c) replicates the relationship between productivity and the average firm fixed effect from the AKM model. We again see a consistent positive relationship. In Panel (d) we replicate the relationship between management score and the firm fixed effect, and see a consistent positive relationship albeit slightly noisier.

[32]The decision to include the management score as a linear term may appear to be a strong assumption given evidence elsewhere showing non-linear relationships between performance and strategic management (Chadwick 2007). The assumption of linearity is supported by Figure B.1, which shows the non-parametric relationship between the WMS management score and productivity.

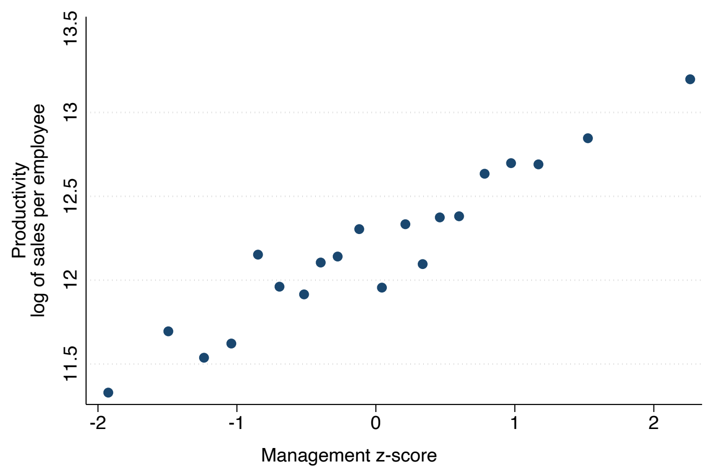
Table B.2: Productivity, management practices, and worker quality

Dependent variable: ln(sales)	(1)	(2)	(3)	(4)	(5)	(6)
Management score						
z-management	0.213***	0.168***	0.088***	0.065***	0.064***	0.059***
	(0.039)	(0.039)	(0.02)	(0.01)	(0.01)	(0.01)
AKM quality measures						
z-worker quality		0.247***	0.076***			
		(0.039)	(0.02)			
z-production worker quality				0.031**	0.028*	0.010
				(0.02)	(0.02)	(0.02)
z-manager quality				0.078***	0.076***	0.053***
				(0.02)	(0.02)	(0.02)
z-AKM firm effect						0.098***
						(0.02)
Firm characteristics						
Share workers with college degree					0.05	0.05
					(0.10)	(0.10)
Factor inputs			✓	✓	✓	✓
Industry	✓	✓	✓	✓	✓	✓
Ownership	✓	✓	✓	✓	✓	✓
# Observations	775	775	773	663	663	663
# Firms	679	679	679	594	594	594
R^2	0.753	0.796	0.96	0.97	0.97	0.97
Bender et al estimates for their Table 3 (for comparison, coefficients only)						
Management score	*0.264****	*0.199****		*0.35****	*0.33**	*0.029*
Employee quality		*0.821****		*0.110**	*0.083*	*0.058*
Managerial quality				*0.082**	*0.082**	*0.082**
ln(firm effect - wages)						*0.039**
% employees with college degree					*0.192*	*0.282*

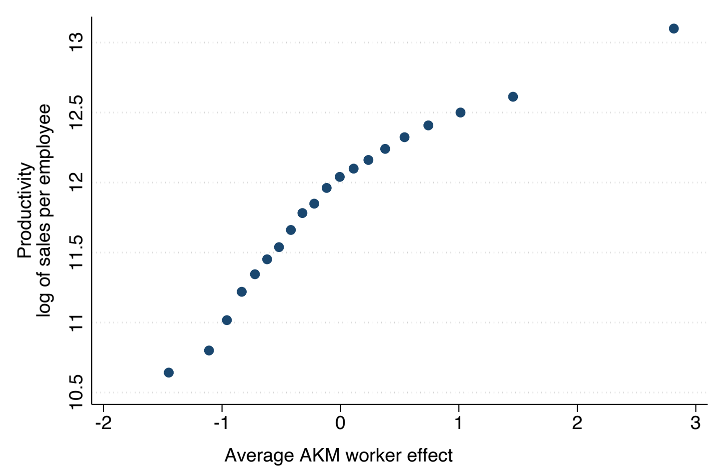
Notes: Robust standard errors clustered at firm level in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Estimates from regressions of ln(sales) on WMS management score, AKM quality measures, and firm characteristics. Factor inputs include log of capital, raw materials, and log of number of employees.

Figure B.1: Replication of Bender et al. (2018) figures associated with production function estimation

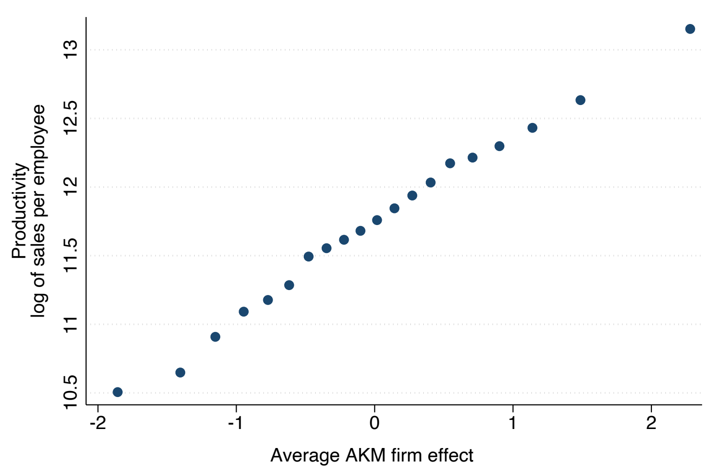
(a) Bender et al. (2018) Figure 5 replication



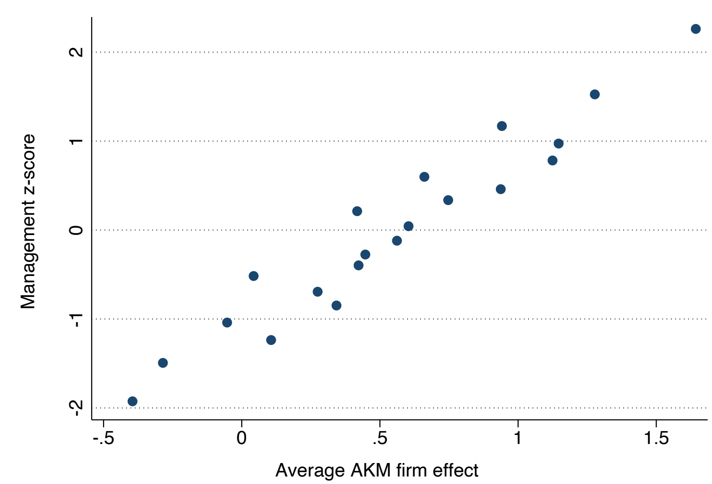
(b) Bender et al. (2018) Figure 6 replication



(c) Bender et al. (2018) Figure 7(a) replication



(d) Bender et al. (2018) Figure 7(b) replication



Notes: Firm data from the Brazilian Annual Industrial Survey (PIA). Management data from the World Management Survey (WMS). Worker data from the Brazilian roster of formal employment, (RAIS). Productivity is measured as the log of sales per employee. Management is measured as the standardized average score of the WMS questions. AKM effects are the two-way fixed effects estimated using the Abowd et al. method. Panels (a) to (c) show average productivity within vingtiles of management in (a), vingtiles of AKM worker effect in (b), and vingtiles of AKM firm effect. Panel (d) shows the average management z-score relative to vingtiles of the AKM firm effect. Variables were residualized by regressing the underlying variable on log employment.

C Clarification of variable definitions

The Bender et al. code archive does not include the processing code that generated the dependent variables used in their Tables 7 and 8. It also does not include the code used to produce Table 8. We believe, based on statements in the text and the context, that our dependent variables are equivalent to the variables they used for these models. However, the variable labels in their Tables 7 and 8 in Bender et al. are unclear, and in some cases we believe them to be unintentionally inaccurate. The lack of clarity has primarily to do with how they communicate about what they call worker “ability”, and we call worker quality. In both papers, these terms refer to the estimated worker effects from the AKM decomposition. The worker effects are measured in logarithmic units by construction, leading to some confusion in the table labeling.

For example in their Table 7 ("Outflows to Unemployment"), the dependent variable is labeled as "ln(Average Ability of Outflows) - ln(Average Ability of Incumbents)". Taken at face value, this labeling suggests that they (1) compute the average worker effect of outflows, and then take its logarithm; (2) compute the average worker effects of incumbents, and take its logarithm, then (3) take the difference. Constructing the dependent variable that way does not make sense, though, because worker effects are already in logarithmic units. The authors are clearly aware of this: in the text, they state that “the dependent variable in all models is the average value of the person effect for leavers who move to unemployment, normalized by differencing from the mean person effect at the firm among all employees in the previous year”. The code archive provided by *Journal of Labor Economics* does not include the code that generated that variable, but their naming conventions elsewhere suggest it is a measure of the standardized person effect of outflows to unemployment, presumably net of the standardized person effect of retained workers based on the text. The dependent variable in our corresponding Table VI is defined, as we state in the text, as “the difference between the average ability of fired and retained workers”. That is, in exactly the same way as in their paper.

In building our replication of their Table 8 (our Table III), the code archive does not describe how their table was estimated nor how the dependent variables were constructed. The text does not provide any clarification. The dependent variables in our Table III are:

- The difference between the log wages of the 90th percentile worker and the 10th percentile worker (Columns 1 and 2).
- The standard deviation of log wages within the firm-year (Columns 3 and 4).
- The difference between the estimated person effects of the 90th percentile worker and the 10th percentile worker (Columns 5 and 6).

- The standard deviation of estimated person effects within the firm-year (Columns 7 and 8).

These definitions are based on the text and the nature of the exercise. Bender et al. state that they "take the 90-10 difference in ln(wages) at each firm in our sample as the dependent variable" for columns 1 and 2. Because the AKM model is additive in log wages, the worker effects (called "quality" or "ability" in our paper and theirs) are already measured in logarithmic units. Hence, we conclude that the dependent variable in columns (5) and (6) of their table is the 90-10 difference in worker ability / person effects, without any redundant logarithmic transformation. As we state in footnote 4 from the previous submission. One apparent discrepancy is that their labeling suggests they report results for the coefficient of variation in the natural logarithm of wages and the natural logarithm of worker quality. We use the standard deviation because wages and worker quality are already measured in logarithmic units, so re-scaling by the mean is not necessary. Additionally, note that using the standard deviation is consistent with other work by some of the authors (Card et al. 2013; Song et al. 2019). For completeness, Table C.3 shows results using the coefficient of variation rather than the standard deviation of log wages and worker quality.

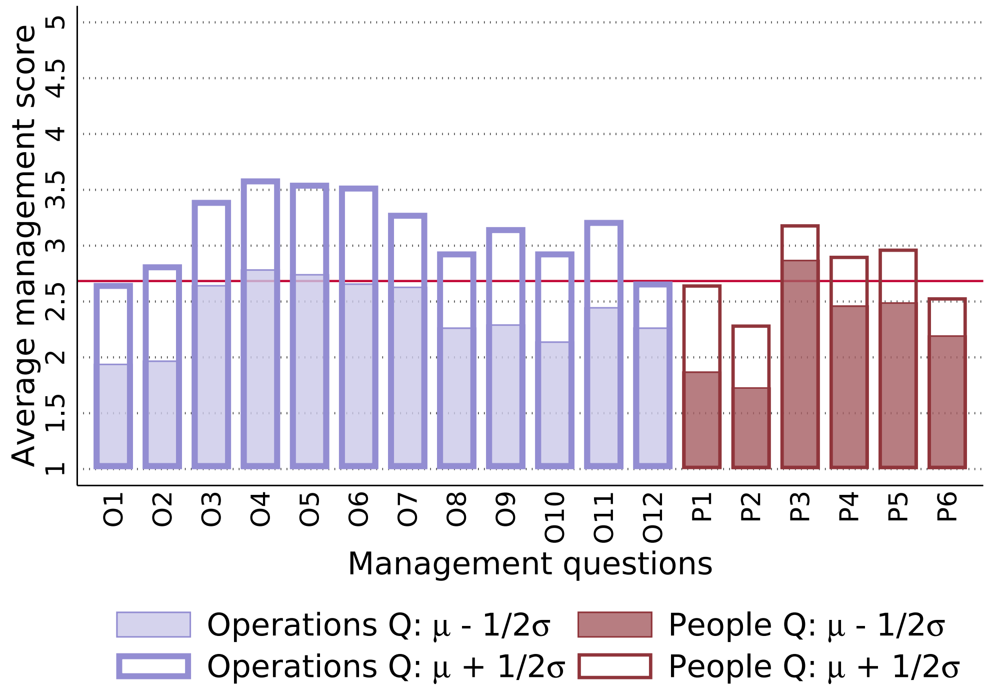
Table C.3: Within-firm heterogeneity in wages and worker quality, using coeff. of variation

	90-10 Log Wages		Coefficient of Variation in Log Wages		90-10 Quality		Coefficient of Variation in Quality	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
z-management	0.143***	0.096***	0.008***	0.004	0.175***	0.106***	3.647	5.428
	(0.016)	(0.016)	(0.002)	(0.002)	(0.025)	(0.024)	(4.332)	(6.079)
General Controls		✓		✓		✓		✓
Observations	964	964	964	964	964	964	964	964
Firms	696	696	696	696	696	696	696	696

Notes: Robust standard errors clustered at firm level in parentheses. * p<0.05, ** p<0.01, *** p<0.001. This table is identical to Table C.3 in the main text, except here we report models of the coefficient of variation in log wages and in worker quality for consistency with the presented results in Bender et al. (2018). Estimates from linear regression models on matched WMS-RAIS firm-year data. All models control for year effects. Where indicated, models also include the set of general controls: region indicators, total employment, firm age, ownership status, the female share in employment, the number of competitors, 2-digit industry controls, and a cubic in the AKM coverage share. The management score is standardized relative to the estimation sample.

D Supplementary tables and figures

Figure D.2: Scores on individual management questions for firms above and below the overall average



Notes: Data from the World Management Survey, averaging 1,145 observations for 814 Brazilian firms. Each shaded bar plots the average score for firms half a standard deviation below the mean, and each line bar plots the average score for firms half a standard deviation above the mean for that management topic. The overall average management score, which is indicated by the horizontal red line, is 2.6 for Brazilian firms.

Table D.4: World Management Survey Questions: Operations management

Q	Question topic	Explanation of scoring
O1	Adoption of modern practices (Lean operations sub-index)	What aspects of manufacturing have been formally introduced, including just-in-time delivery from suppliers, automation, flexible manpower, support systems, attitudes, and behavior?
O2	Rationale for adoption (Lean operations sub-index)	Were modern manufacturing techniques adopted just because others were using them, or are they linked to meeting business objectives like reducing costs and improving quality?
O3	Process problem documentation (Monitoring sub-index)	Are process improvements made only when problems arise, or are they actively sought out for continuous improvement as part of normal business processes?
O4	Performance tracking (Monitoring sub-index)	Is tracking ad hoc and incomplete, or is performance continually tracked and communicated to all staff?
O5	Performance review (Monitoring sub-index)	Is performance reviewed infrequently and only on a success/failure scale, or is performance reviewed continually with an expectation of continuous improvement?
O6	Performance dialogue (Monitoring sub-index)	In review/performance conversations, to what extent are the purpose, data, agenda, and follow-up steps (like coaching) clear to all parties?
O7	Consequence management (Monitoring sub-index)	To what extent does failure to achieve agreed objectives carry consequences, which can include retraining or reassignment to other jobs?
O8	Target balance (Target setting sub-index)	Are the goals exclusively financial, or is there a balance of financial and non-financial targets?
O9	Target interconnection (Target setting sub-index)	Are goals based on accounting value, or are they based on shareholder value in a way that works through business units and ultimately is connected to individual performance expectations?
O10	Target time horizon (Target setting sub-index)	Does top management focus mainly on the short term, or does it visualize short-term targets as a "staircase" toward the main focus on long-term goals?
O11	Target stretching (Target setting sub-index)	Are goals too easy to achieve, especially for some "protected/special" areas of the firm, or are goals demanding but attainable for all parts of the firm?
O12	Performance clarity (Target setting sub-index)	Are performance measures ill-defined, poorly understood, and private, or are they well-defined, clearly communicated, and made public?

Notes: Table contents from Bloom et al. (2014). The Q column refers to the question numbers as we have defined the indices in this paper (operations and people management), and matches the summary statistics in Figure D.2. The question topic column includes the topic title and, in parentheses, the WMS sub-index topic. The main difference between our categorization and the WMS is that we

Table D.5: World Management Survey Questions: People management

Q	Question topic	Explanation of scoring
P1	Managing human capital (People management sub-index, survey Q13)	To what extent are senior managers evaluated and held accountable for attracting, retaining, and developing talent throughout the organization?
P2	Rewarding high performance (People management sub-index, survey Q14)	To what extent are people in the firm rewarded equally irrespective of performance level, or is performance clearly related to accountability and rewards?
P3	Fixing poor performers (People management sub-index, survey Q15)	Are poor performers rarely removed, or are they retrained and/or moved into different roles or out of the company as soon as the weakness is identified?
P4	Promoting high performers (People management sub-index, survey Q16)	Are people promoted mainly on the basis of tenure, or does the firm actively identify, develop, and promote its top performers?
P5	Attracting human capital (People management sub-index, survey Q17)	Do competitors offer stronger reasons for talented people to join their companies, or does a firm provide a wide range of reasons to encourage talented people to join?
P6	Retaining human capital (People management sub-index, survey Q18)	Does the firm do relatively little to retain top talent, or does it do whatever it takes to retain top talent when they look likely to leave?

Notes: Table contents from Bloom et al. (2014). The Q column refers to the question numbers as we have defined the indices in this paper (operations and people management), and matches the summary statistics in Figure D.2. The question topic column includes the topic title and, in parentheses, the WMS sub-index topic. The main difference between our categorization and the WMS is that we bundle the operations sub-practices into one, so we can effectively compare people and non-people practices. The last column includes a more detailed explanation of the types of follow-up questions that are asked of the manager to garner the information required for scoring.

Table D.6: Frame frequencies: RAIS, Orbis, and WMS

Count of firms that...	2008	2013
Appear in RAIS but not in Orbis	3021141	3758345
Appear in RAIS and Orbis but not in WMS frame	18025	14663
Appear in RAIS and WMS frame, but were not surveyed	754	444
Appear in RAIS and WMS survey sample	492	491
Appear in WMS survey sample but not RAIS	93	69
Total	3040505	3774012

Notes: This table reports the number of firms in different cuts of the data.
Row 1 reports the number of firms that appear in RAIS in 2008 or 2013 that do not appear in the Orbis universe.
Row 2 reports the number of firms that appear in RAIS and Orbis universe that do not appear in the WMS sampling frame.
Row 3 reports the number of firms that appear in RAIS and in the WMS sampling frame that are not surveyed.
Row 4 reports the number of firms that are surveyed for WMS and match to RAIS.
Row 5 reports the number of firms surveyed for WMS that do not match to RAIS.

Table D.7: Sampling and frame restrictions (RAIS): 2008

	RAIS w/o Orbis	Orbis w/o Frame	Frame w/o WMS	WMS with RAIS
General RAIS				
End of year emp. (RAIS)	12.07	100.5	296.6	270.1
share of male employees (RAIS)	0.579	0.673	0.692	0.725
Avg. worker age (RAIS)	33.66	32.71	33.67	33.44
Monthly earnings (2015 BRL)	1138.9	1616.3	2392.1	2665.6
Share white	0.668	0.696	0.686	0.689
Size class				
Zero	0.111	0.0155	0.0106	0.0102
less than 5	0.570	0.0388	0.0411	0.0142
5 to 9	0.159	0.0223	0.0186	0.00610
10 to 19	0.0868	0.0400	0.0265	0.0183
20 to 49	0.0472	0.352	0.0650	0.0630
50 to 99	0.0131	0.327	0.147	0.120
100 to 249	0.00767	0.140	0.377	0.429
250 to 499	0.00294	0.0391	0.172	0.226
500 to 999	0.00147	0.0161	0.0849	0.0752
Region				
North	0.0375	0.0352	0.0398	0.0467
Northeast	0.142	0.0920	0.0716	0.0813
Southeast	0.509	0.560	0.622	0.573
South	0.219	0.274	0.240	0.266
Central-West	0.0913	0.0385	0.0265	0.0325

Notes: This table reports the summaries of RAIS variables for firms in different data samples, as defined in Table D.6.
Column 1 includes firms that appear in RAIS in 2008 or 2013 that do not appear in the Orbis universe.
Column 2 includes firms that appear in RAIS and Orbis universe that do not appear in the WMS sampling frame.
Column 3 includes firms that appear in RAIS and in the WMS sampling frame that are not surveyed.
Column 4 includes firms that are surveyed for WMS and match to RAIS.

Table D.8: Sampling and frame restrictions (WMS): 2008

	WMS w/RAIS	WMS w/o RAIS
General WMS		
Management score	2.706	2.612
# employees (plant)	316.7	267.9
Firm age (years)	35.72	35.76
% of managers	4.515	4.570
Ownership		
Family owned	0.234	0.204
Founder owned	0.370	0.430
Manager owned	0.0183	0.0108
Nonfamily private owned	0.134	0.118
Institutionally owned	0.201	0.183
Government ownership	0.0427	0.0538

Notes: This table reports the summaries of WMS variables for firms that are, and are not matched to RAIS.
Column 1 includes firms that are surveyed for WMS and match to RAIS.
Column 2 includes firms surveyed for WMS that do not match to RAIS.

Table D.9: Sampling and frame restrictions (RAIS): 2013

	RAIS w/o Orbis	+ Orbis w/o Frame	+Frame w/o WMS	+ WMS
General RAIS				
End of year emp. (RAIS)	12.11	118.9	271.6	304.5
share of male employees (RAIS)	0.556	0.654	0.653	0.698
Avg. worker age (RAIS)	34.53	35.15	35.60	34.53
Monthly earnings (2015 BRL)	1367.8	1950.9	2683.5	3001.6
Share white	0.604	0.646	0.646	0.643
Size class				
Zero	0.106	0.0241	0.0293	0.0163
less than 5	0.564	0.0659	0.0653	0.0285
5 to 9	0.164	0.0376	0.0248	0.0143
10 to 19	0.0886	0.0681	0.0631	0.0265
20 to 49	0.0498	0.261	0.133	0.0570
50 to 99	0.0140	0.275	0.176	0.145
100 to 249	0.00792	0.173	0.245	0.312
250 to 499	0.00286	0.0574	0.133	0.240
500 to 999	0.00143	0.0237	0.0833	0.110
Region				
North	0.0415	0.0358	0.0428	0.0367
Northeast	0.155	0.0926	0.0811	0.0896
Southeast	0.493	0.565	0.606	0.578
South	0.216	0.269	0.232	0.269
Central-West	0.0955	0.0374	0.0383	0.0265

Notes: This table reports the summaries of RAIS variables for firms in different data samples, as defined in Table D.6.
Column 1 includes firms that appear in RAIS in 2013 that do not appear in the Orbis universe.
Column 2 includes firms that appear in RAIS and Orbis universe that do not appear in the WMS sampling frame.
Column 3 includes firms that appear in RAIS and in the WMS sampling frame that are not surveyed.
Column 4 includes firms that are surveyed for WMS and match to RAIS.

Table D.10: Sampling and frame restrictions (WMS): 2013

	WMS	WMS - RAIS
General WMS		
Management score	2.685	2.597
FIRM: employees (plant)	329.6	269.1
Firm age (years)	37.95	38.69
% of managers	5.088	6.319
Ownership		
Family owned	0.297	0.203
Founder owned	0.348	0.507
Manager owned	0.0102	0.0145
Nonfamily private owned	0.143	0.0725
Institutionally owned	0.185	0.203
Government ownership	0.0163	0

Notes: This table reports the summaries of WMS variables for firms that are, and are not matched to RAIS.
Column 1 includes firms that are surveyed for WMS and match to RAIS.
Column 2 includes firms surveyed for WMS that do not match to RAIS.

Table D.11: Cause of separation and next-job statistics

Type of separation	**Mean**	**SD**	**Min**	**Max**	**N**
Fires					
change in log wage	0.031	0.471	-4.827	4.770	549852
months in unemployment	8.400	3.968	0	20	400562
Quits					
change in log wage	0.162	0.446	-3.966	4.801	139927
months in unemployment	7.634	4.361	0	20	74130
Other					
change in log wage	0.117	0.373	-4.413	4.282	407051
months in unemployment	4.522	3.147	0	20	305388

Notes: This table reports an analysis of a five percent random sample of all male workers age 23 to 50 observed in RAIS between 2008 and 2013. Each entry corresponds to a pair of adjacent years for which the RAIS report that the job in the initial year ended for any reason. We restrict the sample to include only observations where we observe a change in the employer identifier acros adjacent years. For each observation, we record the change in the hourly wage between the initial year dominant job and the next year dominant job and the number of months between the reported end date of the initial job and the reported start date of the new job. Duration of unemployment measured in months.

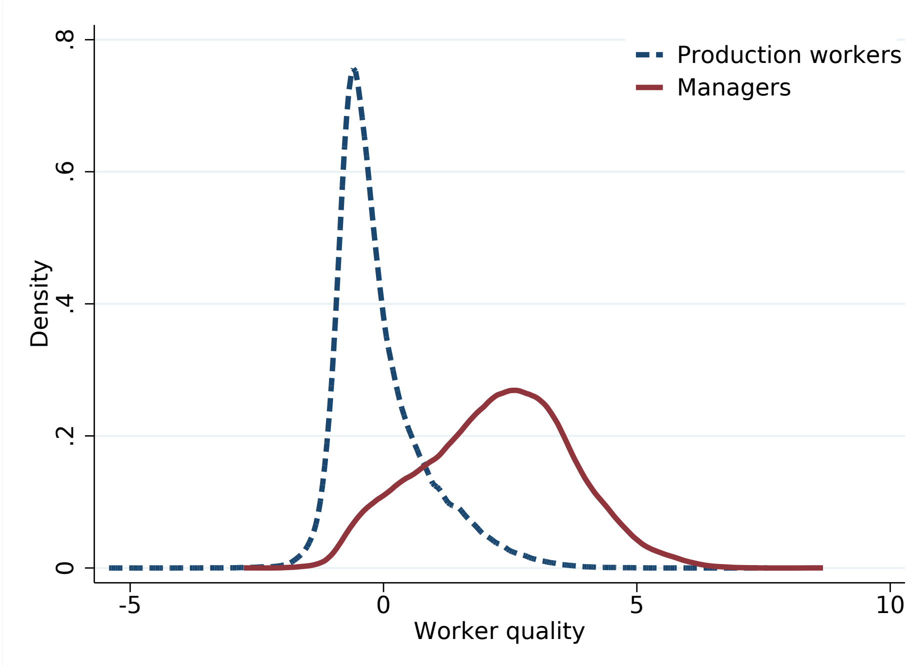
Table D.12: Correlation between management practices and worker quality: Alternative specifications

	Overall mgmt. z-score		People mgmt. z-score	
	(1)	(2)	(3)	(4)
Mean employee quality	-0.074		0.003	
	(0.076)		(0.073)	
Mean manager quality (BBCVW measure)	0.207**		0.109	
	(0.073)		(0.077)	
Mean non-manager quality (occ.-based)		0.073		0.098*
		(0.038)		(0.041)
Mean manager quality (occ.-based)		0.041		-0.018
		(0.038)		(0.041)
Ln of firm employment (WMS)	0.301***	0.302***	0.238***	0.243***
	(0.033)	(0.034)	(0.037)	(0.038)
% all workers with degree	1.421***	1.464***	1.422***	1.461***
	(0.274)	(0.276)	(0.267)	(0.267)
Observations	964	964	964	964
Firms	696	696	696	696

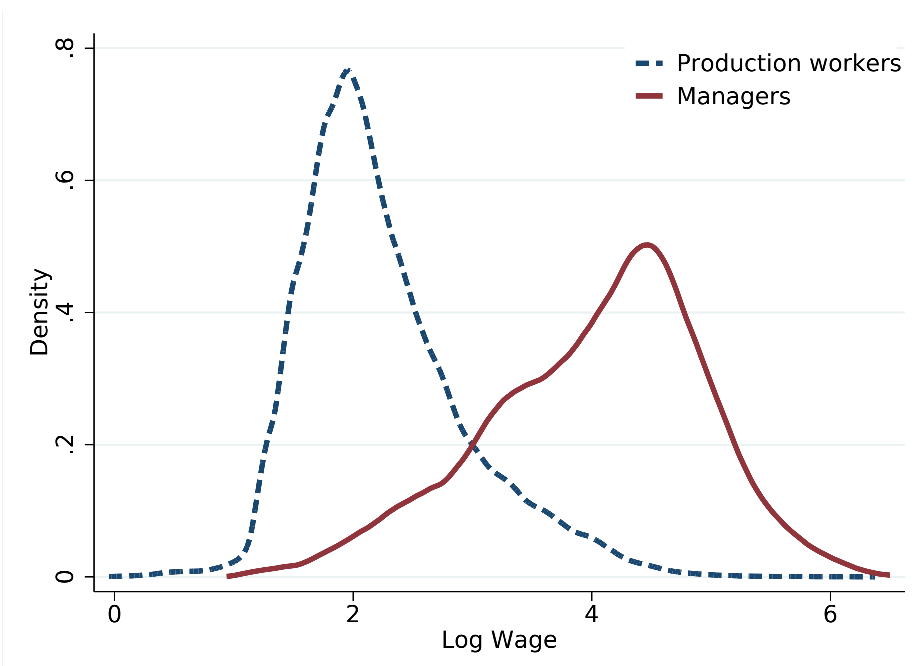
Notes: Robust standard errors clustered at firm level in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Estimates from linear regression models on matched WMS-RAIS firm-year data. The dependent variable in columns (1) and (2) is the standardized WMS overall management score, and in columns (3) and (4) is the standardized people management score. In addition to the variables listed, all models also include year effects, region indicators, total employment, firm age, ownership status, the female share in employment, the number of competitors, 2-digit industry controls, and a cubic in the AKM coverage share. These models also control for the number of sites operated by the firm. Columns (1) and (2) All worker quality measures are standardized relative to the estimation sample.

Figure D.3: Distribution of worker quality and wages

(a) Estimated worker fixed effects (AKM)



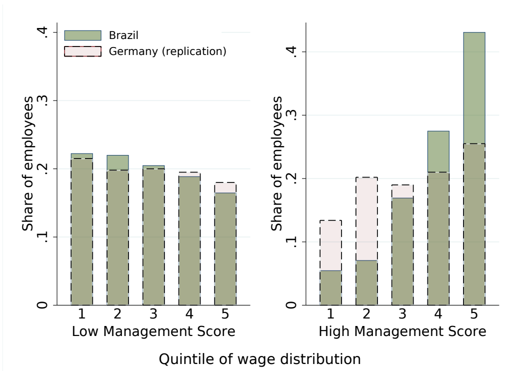
(b) Log of wages



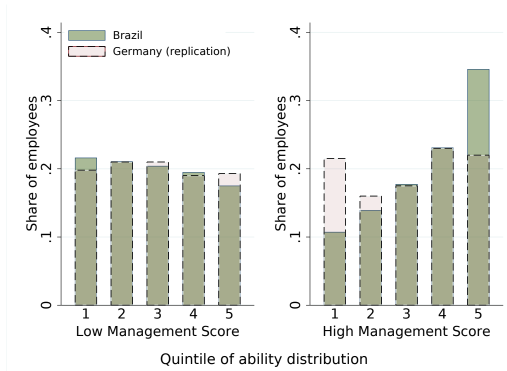
Notes: Panel A plots the distribution of Abowd et al. (1999) worker fixed effects estimated using data from RAIS from 2003 to 2008. Panel B plots the distribution of log of wages for the same set of workers.

Figure D.4: Fraction of workers in different wage and ability quintiles

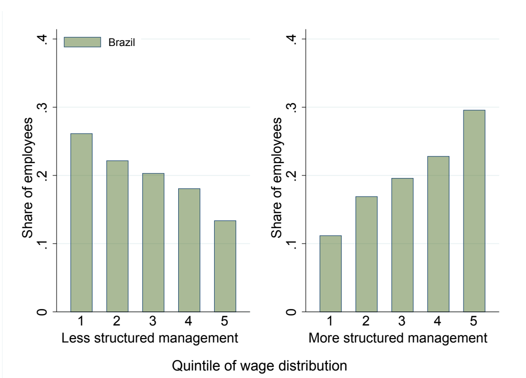
(a) Replication with Brazilian data



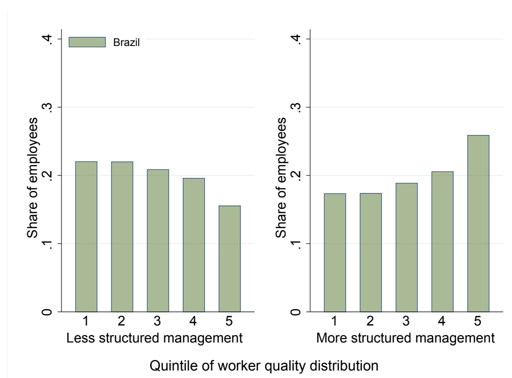
(b) Replication with Brazilian data



(c) Extension: different threshold definition



(d) Extension: different threshold definition



Notes: Each bar plots the average share of employees within each quintile of the wage distribution (panels a and c) and ability distribution (panel b and d) for firms with low/high management score. In panels a and b, low/high management scores correspond to firms below/above the 90th percentile of the country score distribution. In panels c and d, low/high scores follow our more/less structured management practices classification. The definition for “more structured management” is whether a firm scores equal or above a score of 3 in the WMS 1 to 5 classification. “Less structured management” is defined as a firm that scores between 1 and 3 in that classification. Please see the Data section for further details on the rationale behind this definition.

Table D.13: Inflows to WMS firms

	Share of hired workers at or above quantiles of the quality distribution				
	10%	25%	50%	75%	90%
	(1)	(2)	(3)	(4)	(5)
	A. Not Including Size Control				
z-management	0.001	0.006*	0.012**	0.014**	0.012***
	(0.001)	(0.003)	(0.004)	(0.004)	(0.004)
% college	0.000*	0.001**	0.001*	0.001*	0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	B. Including Size Control				
z-management	0.002	0.005	0.011*	0.011*	0.009*
	(0.002)	(0.003)	(0.004)	(0.005)	(0.004)
% college	0.000*	0.001**	0.001*	0.001*	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln(employment)	-0.002	0.001	0.004	0.007	0.008*
	(0.002)	(0.003)	(0.004)	(0.005)	(0.004)
Observations	3857	3857	3857	3857	3857
Firms	706	706	706	706	706
Bender et al estimates for their Table 6 (for comparison, coefficients only)					
	A. Not Including Size Control				
Management score	*0.003*	*0.003*	*0.006*	*0.016***	*0.019****
Management score	*0.003*	*0.004*	*0.005*	*0.007*	*0.010**

Notes: Robust standard errors clustered at firm level in parentheses. * p<0.05, ** p<0.01, *** p<0.001. This table reports additional parameter estimates from models reported in Table D.13 in the main text. The dependent variable in each column is the share of newly hired workers with quality at or above the labeled percentile. The set of full controls includes year effects, region indicators, firm age, ownership status, the female share in employment, the number of competitors, 2-digit industry effects, a cubic in the AKM coverage share, and the share of employees with a college degree. Panel A omits the control for number of employees. The management score is standardized relative to the estimation sample.

Table D.14: Hiring rank-rank regressions: Managers

	Dependent variable: Worker rank in the distribution of new manager hires					
	(1)	(2)	(3)	(4)	(5)	(6)
More structured mgmt = 1			-1.111***			-1.221***
			(0.089)			(0.215)
Rank	1.411***	0.749***	1.411***	1.409***	0.750***	1.410***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)
Rank Squared	-0.004***	0.003***	-0.004***	-0.004***	0.003***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
More structured mgmt = 1			-0.662***			-0.660***
× Rank			(0.004)			(0.004)
More structured mgmt = 1			0.007***			0.007***
× Rank Squared			(0.000)			(0.000)
Year controls	✓	✓	✓	✓	✓	✓
Firm & Worker controls				✓	✓	✓
N	1735	2758	4493	1735	2758	4493
Firms	330	209	539	330	209	539
Sample:	**Less**	**More**	**All**	**Less**	**More**	**All**
(firm type)	**Structured**	**Structured**		**Structured**	**Structured**	

Notes: Robust standard errors clustered at firm level in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Analysis of worker-year RAIS data for 2008–2013 matched to WMS firm characteristics. The sample is restricted to newly-hired workers. The dependent variable is a worker's rank in the distribution of newly-hired workers, conditional on being employed in either a firm that does, or does not use structured management practices. Where indicated, these models also control for employer size, employer age, number of competitors, ownership type, region, gender, race, education, and two-digit industry effects.

Table D.15: Hiring rank-rank regressions: Non-managers

	Dependent variable: Worker rank in the distribution of new non-manager hires					
	(1)	(2)	(3)	(4)	(5)	(6)
More structured mgmt = 1			1.925***			1.559***
			(0.148)			(0.286)
Rank	1.089***	0.840***	1.089***	1.088***	0.843***	1.088***
	(0.004)	(0.007)	(0.004)	(0.003)	(0.006)	(0.003)
Rank Sq.	-0.001***	0.001***	-0.001***	-0.001***	0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
More structured mgmt = 1			-0.250***			-0.246***
× Rank			(0.008)			(0.007)
More structured mgmt = 1			0.002***			0.002***
× Rank Squared			(0.000)			(0.000)
Year controls	✓	✓	✓	✓	✓	✓
Firm & Worker controls				✓	✓	✓
N	114923	74653	189576	114923	74653	189576
Firms	469	242	711	469	242	711
Sample:	**Less**	**More**	**All**	**Less**	**More**	**All**
(firm type)	**Structured**	**Structured**		**Structured**	**Structured**	

Notes: Robust standard errors clustered at firm level in parentheses. * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Analysis of worker-year RAIS data for 2008–2013 matched to WMS firm characteristics. The sample is restricted to newly-hired workers. The dependent variable is a worker's rank in the distribution of newly-hired workers, conditional on being employed in either a firm that does, or does not use structured management practices. Where indicated, these models also control for employer size, employer age, number of competitors, ownership type, region, gender, race, education, and two-digit industry effects.

Table D.16: Firing and management practices: Managers

	(1) Fired = 1	(2) Fired = 1	(3) Fired = 1	(4) Fired = 1	(5) Fired = 1	(6) Fired = 1
More structured mgmt = 1			-0.050**			0.469**
			(0.019)			(0.148)
Manager quality	-0.017**	-0.018*	-0.017**	-0.013*	-0.005	-0.013*
	(0.006)	(0.007)	(0.006)	(0.005)	(0.005)	(0.005)
Manager quality squared	0.002	0.003**	0.002	0.003**	0.002	0.003*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
More structured mgmt = 1			-0.002			0.008
× Manager quality			(0.009)			(0.008)
More structured mgmt = 1			0.001			-0.001
× Manager quality squared			(0.002)			(0.002)
Year controls	✓	✓	✓	✓	✓	✓
Firm & Worker controls				✓	✓	✓
N	15883	22354	38237	15883	22354	38237
Firms	438	239	677	438	239	677
Sample:	**Less**	**More**	**All**	**Less**	**More**	**All**
(firm type)	**Structured**	**Structured**		**Structured**	**Structured**	

Notes: Robust standard errors clustered at firm level in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Estimates of linear regression models in worker-year RAIS data for 2008–2013 matched to WMS firm characteristics. The dependent variable is an indicator for whether the worker was fired. Where indicated, these models also control for job tenure, employer size, employer age, number of competitors, ownership type, region, gender, race, education, and two-digit industry effects.

Table D.17: Firing and management practices: Non-managers

	(1) Fired = 1	(2) Fired = 1	(3) Fired = 1	(4) Fired = 1	(5) Fired = 1	(6) Fired = 1
More structured mgmt = 1			-0.009			0.085
			(0.012)			(0.065)
Non-manager quality	-0.030***	-0.044***	-0.030***	-0.020***	-0.027***	-0.020***
	(0.004)	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)
Non-manager quality squared	0.004*	0.009***	0.004*	0.004***	0.008***	0.004***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
More structured mgmt = 1			-0.013*			-0.008*
× Non-manager quality			(0.005)			(0.003)
More structured mgmt = 1			0.006**			0.004**
× Non-manager quality squared			(0.002)			(0.001)
Year controls	✓	✓	✓	✓	✓	✓
Firm & Worker controls				✓	✓	✓
N	710460	500770	1211230	710460	500770	1211230
Firms	478	244	722	478	244	722
Sample:	**Less**	**More**	**All**	**Less**	**More**	**All**
(firm type)	**Structured**	**Structured**		**Structured**	**Structured**	

Notes: Robust standard errors clustered at firm level in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Estimates of linear regression models in worker-year RAIS data for 2008–2013 matched to WMS firm characteristics. The dependent variable is an indicator for whether the worker was fired. Where indicated, these models also control for job tenure, employer size, employer age, number of competitors, ownership type, region, gender, race, education, and two-digit industry effects.

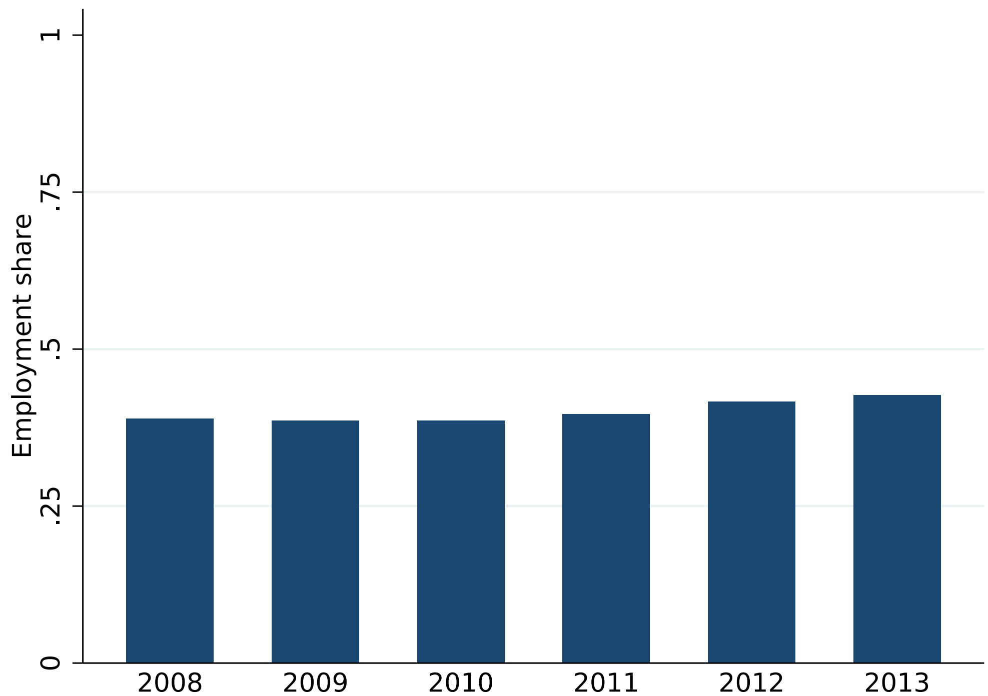
E Additional descriptive statistics and model specifications

Table E.1: Correlation among components of the management score

	overall	people	operations
overall	1.00		
people	0.86	1.00	
operations	0.74	0.53	1.00

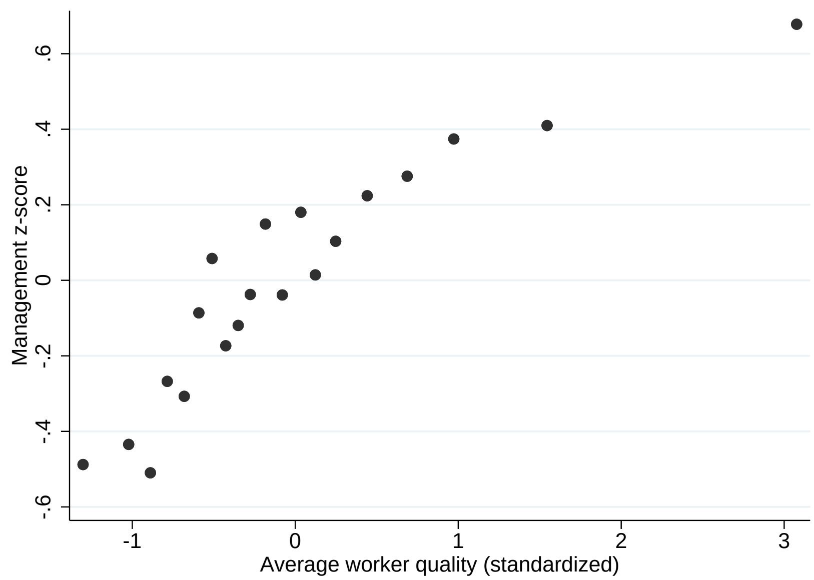
Notes: This table reports the correlations among different management scores across all plant-year observations from the WMS for Brazil. The overall management score is the simple average of the 18 individual management practices scored by the WMS. The people score is the simple average on the six practices covering people management. The operations score is the simple average of the 12 management practices not associated with people management.

Figure E.1: Share of employment in structured management firms



Notes: Each bar reports the share of employment in the sample that is captured by firms classified as having structured management practices, relative to the firms classified as having unstructured management practices. The share of employment only includes firms in the WMS sample for each year, and it is simply the sum of employees who work in firms that have structured management relative to the entire set of employees captured in the firms within the WMS sample.

Figure E.2: Correlation between management score and worker quality: No controls



Notes: This graph is a binned scatterplot of the raw correlation between the overall management score index and average worker quality (AKM worker fixed effect) for Brazil. This graph does not include any controls.

Table E.2: Correlation between management practices and worker quality: Distinguish non-managers using quality quartiles

	Management z-score			
	(1)	(2)	(3)	(4)
Average employee quality (AKM worker effects)	0.131***			
	(0.036)			
Average managerial quality (top quartile worker effects)		0.177***	0.215***	0.188***
		(0.036)	(0.052)	(0.050)
Mean non-manager quality (bottom quartiles)			-0.050	-0.061
			(0.050)	(0.048)
Log of firm employment (WMS)	0.362***	0.353***	0.352***	0.341***
	(0.031)	(0.031)	(0.031)	(0.030)
% of employees with college degree (WMS)				1.331***
				(0.277)
Observations	964	964	964	964
Firms	696	696	696	696

Notes: Robust standard errors clustered at firm level in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Estimates from linear regression models on matched WMS-RAIS firm-year data. The dependent variable is the standardized WMS overall management score. In addition to the variables listed, all models also include year effects, region indicators, total employment, firm age, ownership status, the share of female workers, the number of competitors, 2-digit industry controls, and a cubic in the AKM coverage share. Here, we report models that include mean non-manager quality, measured as the average quality of the bottom 75 percent of workers in the firm. All worker quality measures are standardized relative to the estimation sample.

Table E.3: Correlation between management practices and worker quality: Distinguish non-managers using quality quartiles

	Management z-score	
	(1)	(2)
Average employee quality (AKM worker effects)	0.113**	0.081
	(0.043)	(0.041)
Average managerial quality (occupation-based)	0.034	0.028
	(0.042)	(0.040)
Log of firm employment (WMS)	0.358***	0.346***
	(0.032)	(0.031)
% employees with college degree (WMS)		1.359***
		(0.280)
Observations	964	964
Firms	696	696

Notes: Robust standard errors clustered at firm level in parentheses. * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Estimates from linear regression models on matched WMS-RAIS firm-year data. The dependent variable is the standardized WMS overall management score. In addition to the variables listed, all models also include year effects, region indicators, total employment, firm age, ownership status, the female share in employment, the number of competitors, 2-digit industry controls, and a cubic in the AKM coverage share. Here, we report models that include the average quality of all workers and the average quality of managers, where managers are identified from occupation codes. All worker quality measures are standardized relative to the estimation sample.

Table E.4: Within-firm heterogeneity in wages and worker quality: Added controls

	90-10 log wage	Standard deviation of log wage	90-10 Abilty	Standard deviation of ability
	(1)	(2)	(3)	(4)
z-management	0.094***	0.029***	0.101***	0.034***
	(0.017)	(0.006)	(0.024)	(0.009)
General Controls	✓	✓	✓	✓
Observations	964	964	964	964
Firms	696	696	696	696

Notes: Robust standard errors clustered at firm level in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Estimates from linear regression models on matched WMS-RAIS firm-year data. All models control for year effects. Where indicated, models also include the set of general controls: region indicators, total employment, firm age, ownership status, the female share in employment, the number of competitors, 2-digit industry controls, and a cubic in the AKM coverage share. Relative to the main text, these models also include controls for the firm's number of sites. The management score is standardized relative to the estimation sample.

Table E.5: Within-firm heterogeneity in wages and worker quality: Relationship to people management

	90-10 log wage	Standard deviation of log wage	90-10 Abilty	Standard deviation of ability
	(1)	(2)	(3)	(4)
z-people	0.060***	0.016**	0.069**	0.020*
	(0.015)	(0.005)	(0.022)	(0.008)
General Controls	✓	✓	✓	✓
Observations	964	964	964	964
Firms	696	696	696	696

Notes: Robust standard errors clustered at firm level in parentheses. * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Estimates from linear regression models on matched WMS-RAIS firm-year data. All models control for year effects. Where indicated, models also include the set of general controls: region indicators, total employment, firm age, ownership status, the female share in employment, the number of competitors, 2-digit industry controls, and a cubic in the AKM coverage share. Relative to the main text, the key regressor is the standardized people management score rather than the overall management score. The management score is standardized relative to the estimation sample.

Table E.6: Firing logit model: Base specification

	Managers		Non-managers	
	(1) Fired = 1	(2) Fired = 1	(3) Fired = 1	(4) Fired = 1
Quality	-0.016**	-0.017**	-0.031***	-0.041***
	(0.005)	(0.006)	(0.004)	(0.003)
Qual. Sq.	0.002	0.003**	0.002	0.007***
	(0.001)	(0.001)	(0.002)	(0.001)
Year controls	✓	✓	✓	✓
N	15883	22354	710460	500770
Firms	438	239	478	244
Sample:	**Less Structured**	**More Structured**	**Less Structured**	**More Structured**

Notes: * p<0.05, ** p<0.01, *** p<0.001. Estimates of logit models in worker-year RAIS data for 2008–2013 matched to WMS firm characteristics. The dependent variable is an indicator for whether the worker was fired. The sample indicates whether firms were classified as having more or less structured management. The table reports marginal effects evaluated at the sample mean, along with standard errors in parentheses computed using the delta method.

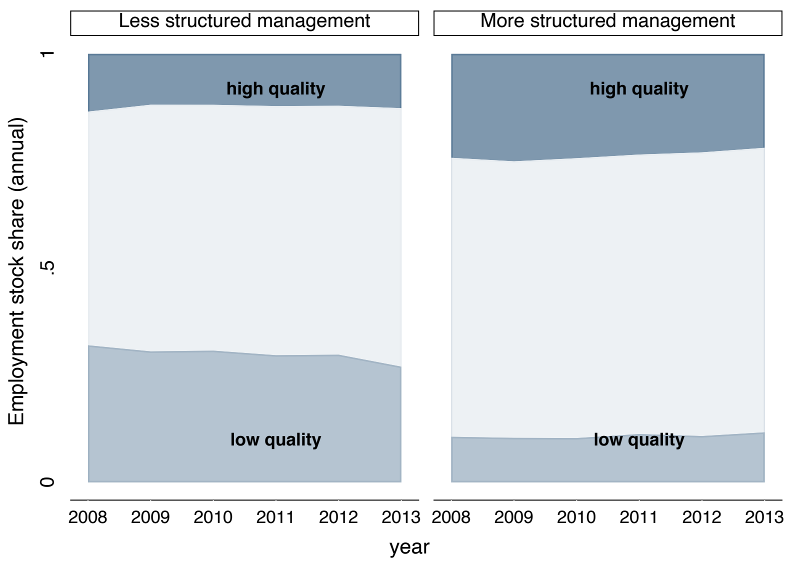
Table E.7: Predicting quality of stayers: Added controls

	Panel A: Avg. manager quality			
	(1)	(2)	(3)	(4)
z-management	0.108***			
	(0.033)			
z-operations		0.098***		0.103***
		(0.030)		(0.034)
z-people			0.034	-0.011
			(0.031)	(0.034)
	Panel B: Avg. non-manager quality			
	(1)	(2)	(3)	(4)
z-management	0.088***			
	(0.034)			
z-operations		0.067**		0.044
		(0.031)		(0.036)
z-people			0.071**	0.051
			(0.030)	(0.035)
Year controls	✓	✓	✓	✓
Full controls	✓	✓	✓	✓
College share	✓	✓	✓	✓
# Observations	964	964	964	964
# Firms	696	696	696	696

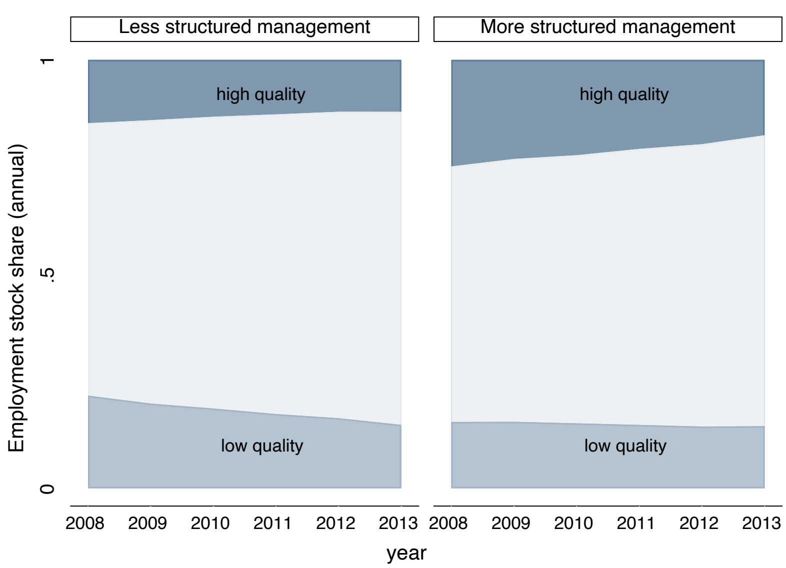
Notes: Robust standard errors clustered at firm level in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Estimates from linear regression models on matched WMS-RAIS firm-year data. The dependent variable is the standardized WMS overall management score. In Panel A, the dependent variable is average quality of workers in managerial occupations. In Panel B, the dependent variable is average quality of workers in all other occupations. The set of full controls includes region indicators, total employment, firm age, ownership status, the female share in employment, the number of competitors, 2-digit industry controls, and a cubic in the AKM coverage share. Relative to the main text, these models also include controls for the firm's number of sites. All worker quality measures are standardized relative to the estimation sample.

Figure E.3: Share of retained employees over time

(a) Managers



(b) Non-managers



Notes: The graphs depict the share of retained managers (Panel A) and Non-managers (Panel B) in firms across years, within quartile of worker quality and firm type. Retained workers are those that did not change place of employment, and were not hired neither fired within that year. Worker quality is defined by the Abowd et al. (1999) fixed effects. High quality workers are defined as those within the top quartile of worker quality, and low quality workers are defined as those within the bottom quartile of worker quality. Less structured management refers to firms with a score below 3 on the WMS. More structured management refers to firms that score a 3 or above on the WMS.

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