PICKING FROM THE TOP OR SHEDDING THE BOTTOM? PERSONNEL MANAGEMENT, WORKER QUALITY AND FIRM PRODUCTIVITY

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Abstract

It is well established that organizational practices matter for workforce composition and productivity, but the mechanisms behind these effects are less well understood. In this paper, we explore how structured personnel management practices relate to actual HR outcomes and productivity. We match structured management practices data from the World Management Survey to AKM estimates of worker and firm fixed effects and industrial survey data from ten years of Brazilian administrative data. We have four key findings: first, consistent with the literature, we find that worker and manager fixed effects, as well as structured management, are positively correlated with firm productivity. Second, we find evidence of positive recruitment: better managed firms hire a larger share of their new recruits — managers and production workers — from the top of the distribution of worker fixed effects. Third, we find suggestive evidence of better worker matching and retention from lower separation rates. Fourth, we decompose the variation of personnel management practices and find that promotion and retention practices show the strongest correlation with manager fixed effects.

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 participants at the LERA Session at ASSA 2017 and the Empirical Management Conference 2018 for useful discussions and comments.

1 Introduction

Workforce productivity is a key driver of competitiveness. Building a productive workforce, however, is a non-trivial organizational challenge fraught with information and agency problems. Hiring, retention and dismissal decisions are at the core of personnel management strategies, and good firms recognize the underlying matching problem that different skills are required at different levels in the organization. Understanding the relationship between personnel management practices, labor matching processes and productivity is essential for addressing larger questions related to productivity and pay differences, such as increasing inequality, the rise in managerial pay and of "superstar firms".

Given the information and agency challenges faced by managers who have discretion over personnel policy (Hoffman et al. 2018), the mechanisms behind how different organizational practices — or, management technology — help firms assemble a productive workforce is still an open question. Developing a full picture understanding of these relationships requires data on organizational hierarchy (distinguishing managerial and production layers), worker mobility (identifying new hires, internal promotions and separations), human capital (measuring experience and education) and internal managerial policies and processes (measuring management structures). We construct the ideal empirical setting by linking three unique datasets: the full roster of formal employment in Brazil (RAIS), the Brazilian annual industrial survey (PIA) and detailed management practices data from the World Management Survey (WMS).

We exploit our linked sample to characterize the importance of personnel management for workforce composition. We use the RAIS panel between 2003-2013 to estimate the Abowd-Kramarz-Margolis (henceforth AKM) decomposition of log wages into components associated with time-varying worker characteristics, a time-invariant firm effect and a time-invariant worker effect (Abowd et al. 1999). Our primary interest is in the worker-specific component of pay, which we treat as a measure of worker quality.

We first document the positive relationship between firm productivity and worker quality in Brazil: conditional on all other factor inputs and management practices, firms with higher revenues employ higher quality workers. This is in line with the findings in Bender et al. (2016) for Germany. Having established that there is indeed a relationship between our measure of worker quality and productivity, we focus on the role personnel management plays in building a productive workforce via hiring, retention, and dismissal practices. We show that firms with structured personnel management practices employ a greater share of high-quality workers than firm that lack structured practices. Furthermore, the incumbent managers in structured firms are twice as likely to be from the top quintile of the manager quality distribution and their advantage among incumbent production workers is almost as great. This advantage is consistently reinforced in hiring and firing. The median manager-level hire in a firm with structured management practices comes from the 60th percentile of the distribution of all hires; firms with unstructured practices get their median manager-level hire from the 48th percentile. The pattern is similar when considering production workers. Firms with structured management hire disproportionately high-quality production workers, while firms with unstructured management practices seem to hire almost at random. Firms with structured management are also much less likely to fire workers at all. When they do, they fire more selectively with respect to worker quality.

Finally, we find that managerial practices relating to personnel management are relatively more important in explaining variation in production worker quality, while practices relating to operations management are relatively more important for explaining variation in manager quality. For both managerial and production workers, however, the key personnel practice linked to worker quality is one that measures whether firms have policies that expressly make hiring high-quality workers a top priority for the firm, and reward senior managers accordingly.

Our paper bridges the literature in organizational economics studying how firms recruit and retain workers, with the literature in labor economics focused on the role of worker sorting across firms. The labor literature highlights the importance of worker-firm matching for understanding inequality (Card et al. 2013; Alvarez et al. 2018; Song et al. 2019), gender wage gaps (Card et al. 2016), compensating differentials (Lavetti and Schmutte 2018; Sorkin 2018), and productivity (Iranzo et al. 2008). While these studies generally abstract away from the process by which firms actually assemble their workforce, Hensvik and Rosenqvist (forthcoming) show that firms actively manage workgroups to retain high output. Further, there is evidence that turnover is costly: Jäger (2016) and Gallen (2018) show evidence that this is the case because it is difficult to replace incumbent workers with workers from the external labor market. This empirical work is consistent with the recent emphasis in organizational economics on understanding the value of recruiting and retention practices (Oyer and Schaefer 2011; Hoffman et al. 2018).

The empirical connection between overall management practices and firm productivity has been well-established (Bloom et al. 2012). However, while there is some evidence that better management is associated with more efficient use of energy inputs (Boyd and Curtis 2014), we have little evidence that structured personnel management practices have any effect on workforce quality.

Our paper is most closely related to Bandiera et al. (2015) and especially Bender et al. (2018). Both papers combine survey data on firm management practices with administrative data that can measure hiring and compensation outcomes. Bender et al. (2018) link WMS data for German firms to administrative earnings records to study how management practices and employee ability are related to productivity. However, they do not focus directly on personnel management, and are unable to directly distinguish managerial and non-managerial workers. Our work is also related to Friedrich (2017), who shows that more productive firms tend to hire managers internally and also select high-quality candidates in terms of their human capital and skill levels.

2 Empirical Setting

Our analysis relies on matching three unique Brazilian datasets for the first time: the full roster of formal employment records between 2003-2013 (RAIS), the Annual Industrial Survey (PIA) for the same period, and the manufacturing sector World Management Survey data for 2008 and 2013. We describe each in turn and provide basic summary statistics of the empirical setting.

2.1 Wages and employment history: RAIS data

We use the 2003-2013 waves of Brazil's *Relação Anual de Informações Sociais* (RAIS).RAIS matches all Brazilian formal-sector employees to their employers through a code assigned by the *Cadastro Nacional da Pessoa Jurídica* (CNPJ), which in turns allows a match to the industrial survey and the WMS. For every formal sector job, RAIS reports the employee's age, gender, race, education, monthly earnings, hours of work and occupation, along with the firm's industry and municipality.

For our wage decomposition, we construct a sample comprised of employees who are contracted to work at least 30 hours per week, have least one month of tenure and have complete set of covariates.[1] We exclude workers in sole-proprietorships, establishments with only one employee, and observations beyond the top and bottom 0.01 percent of the wage distribution. These restrictions result in an analysis sample with 353,141,951 unique worker-firm-year observations consisting of 96,499,697 unique workers and 4,433,492 unique establishments.

The wage variable for our decomposition is average monthly earnings, reported in 2003 Brazilian Reais, which we convert into an hourly measure.[2] For each worker, RAIS records the date of hire, as well as the month and year of separation, and whether the new hire's job is their first

[1]In particular, we require the information to identify a worker's race, gender, education, experience and tenure.

[2]The monthly earnings data can be thought of as measuring the contracted monthly wage, a common institutional arrangement in Brazil. We convert this to an hourly measure by dividing the monthly wage by contracted hours per week, and then by 4.17. When a worker is employed for 12 months, average monthly earnings is simply annual earnings divided by 12. When a worker is employed fewer than 12 months, the total earnings paid for the year are divided by the number of months worked; for partial months, the earnings are pro-rated to reflect what the worker would have earned for the entire month. All of these calculations are performed by the MTE and included in the raw RAIS data.

registered employment. This allows us to construct accurate measures of formal labor market experience.[3]

2.1.1 Wage Decomposition and Worker Quality

We define as the value of the skills a worker takes from job to job as "worker quality." To isolate the contribution of these skills to pay, we use the two-way fixed-effects framework introduced Abowd et al. (1999). This involves estimating a log-wage equation of the form

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

where y_{it} is the monthly wage of worker i at time t, x_{it} contains a cubic in labor-market experience interacted with race and gender and ε_{it} is a mean-zero error. The $\psi_{J(i,t)}$ are firm effects that reflect employer-specific wage premia paid by establishment $j = J(i,t)$, where $J(i,t)$ indicates worker i's job in year t. Our primary concern is with the θ_i, which, as the worker-specific component of pay, capture the value of portable skills.

Under strict exogeneity of ε_{it} with respect to x_{it}, θ_i and $\psi_{J(i,t)}$, least squares will produce unbiased estimates of worker and firm effects.[4] We carry out the decomposition of wages on our panel of workers and establishments from the 2003–2013 waves of RAIS. Similar to other settings — for example, Germany (Card et al. 2013), Portugal (Card et al. 2016) and the US (Abowd et al. 2015) — we find the AKM model provides a thorough description of the sources of wage variation, with an R^2 above .90. Worker quality ($\hat{\theta}_i$) accounts for just under half of the total variation in log wages. By contrast, the firm-specific component of pay ($\hat{\psi}_j$), explains 18.5 percent.[5]

We compute firm-level worker-quality measures by averaging the estimated θ_i across worker occupation. Roughly 5 percent of the employees in Brazilian WMS firms hold managerial positions and the remaining 95 percent fill production jobs. This is reassuringly consistent with the survey measure in the WMS, where the average share of managers in a firm is reported to be 4.88 percent. Average worker quality measures for managers in these firms is almost twenty times that of production workers. However, manager quality is also more variable, with a standard deviation of 0.389 compared with 0.305 for production workers.[6]

[3]For workers whose first employment occurs after 2003, experience is the sum of all months in which the RAIS report that worker in at least one active employment relationship. For workers whose first employment occurs prior to 2003, we approximate experience as the greater of potential experience (age-years of schooling-6) or tenure in the first observed job. Appendix A provides details of the sample construction and summary statistics for the wage decomposition variables.

[4]However, as explained in Abowd et al. (1999), this assumption rules out endogenous mobility.

[5]Table C.5 and C.6 reports the canonical AKM variance decomposition and correlation tables.

[6]For more detail, Figure C.6 compares the full distribution of the quality of managers and production workers.

2.2 Structured management practices: World Management Survey data

2.2.1 Measuring management: the WMS survey methodology

First described in Bloom and Van Reenen (2007), the World Management Survey project employs double-blind surveys to collect data on firms' use of operations management and people management practices. The WMS focuses on medium- and large-sized firms, selecting a random sample of firms with employment of 50–5,000 workers. To measure the level of structured management in a firm, the WMS uses an interview-based evaluation tool where trained analysts interview the senior-most manager at the plant and subsequently score the responses on a set of 18 basic management practices. The scores range from 1 to 5: a score of 1 indicates no structured practices at all, 2 indicates some informal practices are in place, 3 indicates formal practices in place but with weaknesses, 4 indicates solid formal practices and 5 represents stable best practices. A high score implies that a firm has adopted a series of *structured* management practices, which have been causally associated with improvements in productivity (Bloom et al. 2013).[7]

Previous work with the WMS data has focused on using the standardized average of the 18 management practices scores, and we follow this convention in our regression analyses that focus on the continuous measure of structured management.[8] We use the average management practices score (all 18 topics), as well as a sub-index for only the "people management" questions (6 topics) and one for the "non-people management" questions (12 topics). In our figures, we depart from the data-driven approach to determining cut-offs and use a methodology-driven approach that focuses on the implicit meaning of the management scores when they were being awarded to firms during the data collection. In the WMS scoring guide, a score of 3 and above implies that there are at least some formal structures in place, while a score of 2 and below implies that while there may be a process in place, it is entirely informal and it would not be carried out if the individual manager who led it was not present. We use this conceptual divide to classify our sample into firms that have "structured management" (meaning *formal processes*) and "unstructured management" (meaning *informal processes*). We choose this nomenclature to avoid confusing informal processes with the informal sector, which is a large and important part of the Brazilian economy.

[7]See Bloom et al. (2014) for a survey.

[8]Specifically, we standardize each of the 18 questions, average across each index (overall management, operations and people management) and standardize again. We also follow the more recent convention (Bloom et al. (2015)) of grouping the 12 operations questions — formally lean operations, monitoring and target setting questions — and the 6 people management questions into two separate indices, rather than using four separate indices.

2.2.2 Summary statistics: matched Brazilian WMS sample

There are 763 unique firms in the Brazilian sample of the WMS: 227 surveyed in 2008 only, 228 surveyed in 2013 only, and 308 surveyed in 2008 and 2013. Out of the 763 firms, 745 have valid CNPJ identifiers and 690 can be matched to our RAIS sample for at least one year. This yields 955 observations in total, between 2008 and 2013.

The firms in our sample are established, large firms. The average firm is 35 years years old and has 583 employees. The median firm is four years younger and about half as large. Most firms are exposed to some degree of competition, with three-quarters reporting five competitors or more. Over 60 percent of firms are first or second generation family firms, and a fifth of firms are multinational corporations.[9]

Relative to the other 35 countries in the WMS database, Brazilian firms rank in the lower-middle range of adoption of management structures. The average overall management score is 2.67 with a standard deviation of approximately 0.6, implying Brazilian firms have some structured practices in place for a set of practices, but most are idiosyncratic to a particular manager rather than standard operating procedure for the entire firm.

When considering the two large groupings of the WMS index, those practices relating to people management and those relating to operations and monitoring-type practices, we see slightly diverging patterns. The operations average score is the average of the 12 operations-based questions, including adoption of lean manufacturing processes, monitoring of key performance indicators and target-setting. Brazilian firms score on average 2.78 on this set of practices, with a standard deviation of 0.74. This suggests firms have formal processes with regular follow-up, but that for many firms such practices are not a part of the culture of the organization and communication between managers and workers is limited. Further, Brazilian firms appear to focus more on the short-term targets and mainly address relatively narrow operational or financial indicators, without consistently communicating to workers how their efforts translate into hitting the targets.

The people management score, in contrast, is the average of the 6 people management questions, including how to evaluate employees and deal with poor and good performers. The average score is 2.52, with a standard deviation of 0.58. This suggests that the typical Brazilian firm has a basic performance review of its employees, but the review does not help the manager clearly identify the best and worst performers. Consequently, performance pay is does not make sharp distinctions and promotions tend to be based on tenure. Well-defined processes for discharging poor performers and recruiting and retaining productive workers are uncommon.

[9] Table C.2 provides the full descriptive statistics for the matched RAIS-WMS firms.

2.3 Firm production and performance: PIA data

The performance data comes from Annual Industrial Survey (*Pesquisa Industrial Anual - PIA*) from the Brazilian statistics agency (*Instituto Brasileiro de Geografia e Estatistica - IBGE*). PIA includes information on the conventional factor inputs that allow for a production function estimation, including a measure of sales, value added, employment and materials expenditure. While the survey does not include a direct measure of capital stock, one is estimated by the Brazilian economic research institute, *Instituto de Pesquisa Econômica Avançada* (IPEA), and made available to researchers at the microdata access room at IBGE.

3 Results

3.1 More productive firms hire higher quality workers

To document the relationship between productivity and worker quality we match input and output data from PIA to our WMS manufacturing firms and estimate production functions for log sales, including the overall management practices score and our measures of worker quality across occupations. In addition to factor inputs (capital, labor and materials), we control for industry sub-sector and family or founder ownership. Table I reports the results.

We first present baseline specifications excluding the factor inputs in Columns (1) and (2). In line with Bender et al. (2016), higher management scores — that is, structured management processes — strongly predict sales, and, conditional on management practices, so does overall worker quality. Adding the factor inputs in Column (3) reduces the estimated coefficient of overall worker quality to .076, and the management score coefficient to a similar-magnitude 0.088, though both are still significant at the 1% level.

Next, we disaggregate overall worker quality into our separate measures for managerial and production layers in Columns (4) through (6).[10] Worker quality at both levels matters for productivity, but the variation loads to a much greater degree on the manager fixed effects relative to the worker fixed effects: the manager quality coefficient estimate of .078 is more than twice that of production workers. The results in Column (5) show that the results are robust to controlling for the share of workers with a college degree, an often-used proxy for worker quality. In Column (6) we include the AKM firm quality fixed effect, which renders the relationship between average production worker quality and sales is no longer significant. The structured management measure and the AKM manager quality measures, however, are still significant — though the coefficients

[10]Disaggregating causes us to lose about 14 percent of the sample because of missing data on worker type.

decrease slightly. These results are consistent with previous findings that mangers within an organization are primarily responsible for value generation, and it also suggests that much of the important variation in production worker quality is happening within firms, rather than between firms.

3.2 Firms with structured management hire the top and shed the bottom

We have established that worker quality — especially manager quality — is important for productivity. Next, we examine the hiring, retention and firing activity of the firms in our sample, distinguishing those with structured personnel management practices from those with unstructured practices. The personnel management score reflects a firm's processes for managing talent, evaluating performance, dealing with low performers, retaining and promoting high performers, and sustaining a distinctive employee value proposition.

3.2.1 Hiring practices

Figure 1 plots the ranked distributions of managers (panel A) and production workers (panel B), depicting the positive hiring outcomes in firms with structured management relative to firms with unstructured management practices. If the pool of all hires was fixed, but those hires were randomly allocated between structured and unstructured firms (proportional to their respective shares of hiring activity), both curves would sit on the 45 degree line. In reality, we see that the curve for firms with structured management practices in place falls to the right of the 45-degree line, while firms with unstructured management practices fall slightly to the left of the 45-degree line.

For example, the median manager working in a firm with unstructured management practices is in the 46th percentile of the overall manager quality distribution. In contrast, the median manager working in a firm with structured management practices was hired from the 58th percentile of the overall manager quality distribution. For production workers, the pattern is even starker. The median production worker hired into an unstructured management practices firm is in the 49th percentile of the overall occupation's distribution — effectively a random draw. The median production worker in a firm with structured management, however, is drawn from the 56th percentile of the overall distribution.

3.2.2 Retention practices

After hiring from the top of the distribution, firms need to ensure they can keep their high quality employees in the firm. We observe the "stayers" in our data by classifying job-year observations that do not start or end in that year as a "retained" employee. Further, we rank workers based on the distribution of estimated worker effects ($\hat{\theta}_i$) by year, and categorize them into "high-quality" and "low-quality" workers if $\hat{\theta}_i$ is above the 80th or below the 20th percentile, respectively. Figure 2 shows the ten-year pattern of the shares of employees in each rank of quality, as well as type of firms (structured or unstructured management practices). Firms with structured management practices consistently capture almost twice the share of managers and production workers from the top of the distribution of worker quality. The slight movement in the pattern for production workers after 2007 can be partly explained by the loss in overall employment share by unstructured firms over time; from 2003 to 2013, the employment share of firms with unstructured management fell by about 7 percentage points, effectively all of which was picked up by firms with structured management.[11] As employees at the bottom of the quality distribution are more likely to suffer a job separation, some of these employees are being hired by the expanding structured management firms.

3.2.3 Selective dismissal practices

Previous work with employer-employee matched datasets use transitions in and out of jobs, but do not record the reason for job separations. This is problematic as workers who quit are inherently different from those who are fired. Our data is unique in that it includes the reason for separation, allowing us to identify jobs that ended due to firing.[12] Figure 3 presents binned scatter plots of firing rates for managers and production workers by worker quality, distinguishing between firms with structured and unstructured practices.[13] Two features of the data stand out: first, firms with structured personnel management practices have lower firing rates throughout the worker-quality distribution. This could be evidence of better matching earlier in the employee's job cycle. Second, for a given firing rate, a structured-practices firm sheds workers of lower quality than firms with unstructured practices, suggesting that firm without structured practices firms make more mistakes in firing. The slopes of the graphs further suggest that the mistakes may more pronounced in the upper part of the quality distribution.

[11] Figure C.7 in the Appendix depicts the pattern.

[12] Specifically, 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.

[13] Specifically, we plot the residuals from regressions of a firing indicator and the worker effects ($\hat{\theta}_i$s) on a set of dummies for sex, race, year, and completed education. Each bin represents two percent of the observations and the figure plots the bin-specific means.

3.3 Organizational mechanisms driving better labor market matches

The patterns depicted in Figures 1, 2 and 3 provide new evidence that structured personnel practices are important for building a stable, high-quality workforce. We quantify and characterize this relationship in Table II, documenting the relationship between worker quality and structured management practices. We go beyond previous work and decompose the average structured management measure into its components, and focus on occupation-specific worker quality for managers and production workers separately. All specifications include firm and industry controls.

First, consider the results for production workers. Column (1) suggests that one standard deviation higher structured personnel management practices are associated with 0.1 standard deviation higher production worker quality. Column (2) suggests a similar relationship between the operations management index and production worker quality. When we include both indices in Column (3), it is clear that the people management index explains most of the conditional variation in production worker quality; in fact, the coefficient is very similar in magnitude to the unconditional correlation. Column (4) disaggregates the people management index into its six components identified in the WMS, and find that the component that absorbs most of the variation is the measure of how much the firm's practices "instill a talent mindset". The topic measures whether firms make hiring high-quality workers a top priority and whether there are structures in place to reward senior managers according to the talent pool they build.

Turning our focus to the managers, Columns (5)-(8) repeat the specifications in the first four columns. As in the case of production workers, both personnel and operations management practices are unconditionally correlated with higher worker quality, although the unconditional operations index is larger for managers. When we include both indices, we find the opposite relationship relative to production workers. For managers, the operations management index absorbs most of the variation and is significant at the 1% level, while the conditional relationship of the people management index with manager quality is a fairly tight zero. The relationship between the operations management index is robust to decomposing the people management index, though the same "talent mindset" variable is also marginally significant for manager quality, as for production worker quality.

The relationships we uncovered are new, though intuitive. They suggest that structured people management practices are important for building a stock of high quality production workers — this makes sense, as many of the managerial structures the index encompasses are primarily aimed at the level of the production worker. The reverse relationship when considering managerial quality suggests that structured operations practices possibly facilitate matches with better managerial talent, as better managers prefer working in environments where there are structured operations practices in place (though of course, we cannot rule out reverse causality).

4 Conclusion

We use a unique set of datasets to explore how organizational structures in a firm relate to the ability of their managers to build a good workforce. While there is evidence that managers do not always make the best decisions on personnel policy, we show the most comprehensive evidence to date that managers in firms that adopt structured management practices make better decisions relative to their counterparts in firms with unstructured management practices.

For almost 700 firms in Brazil, our dataset includes a decade of job transitions (including wage and occupation information for all formal employees over the period), production and value added data from industrial survey records, and the most detailed data on structured management practices available from the World Management Survey. We use a standard AKM wage decomposition to estimate a firm-specific and a worker-specific effect. The firm-specific effect measures the wage premium that a particular firm offers as a worker moves between firms. Using detailed occupation codes, we separately estimated worker effects for production workers and managers, essentially measuring the value of the worker's portable skills as they move from one job to another.

Based on the scoring methodology of the World Management Survey, we classified firms into using structured management practices or unstructured management practices. While this measure is coarser than the usual standardized measures used in previous work, it is a more intuitive way to think about the differences between their internal organizational practices in this context.

We find that, consistent with previous work, more productive firms are associated with better quality managers and production workers, as well as more structured management practices. With our data, we shed new light on the mechanisms behind the patterns that have been consistently observed across countries. Our results suggest that the advantage of firms that have adopted structured management practices comes from being able to (a) hire more often from the top of the distribution of production worker and manager quality, (b) retain a larger share of high quality workers over time, and (c) make fewer mistakes in selecting workers to dismiss relative to firms with unstructured management practices.

More specifically, we find that more structured personnel practices are particularly important in explaining variation of the quality of production workers in the firm, while it is structured operations practices that are important when explaining the variation in manager quality. This is an intuitive result that highlights the importance of understanding the heterogeneity of the matching problem across different levels of the organization. This is the first step in an exciting research agenda, as it opens the possibility of learning more about the transmission of practices across firms via job-to-job transitions, patterns of gender and race discrimination within and across firms, as well as the highly unequal distribution of pay between levels of the organizations.

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Tables and Figures

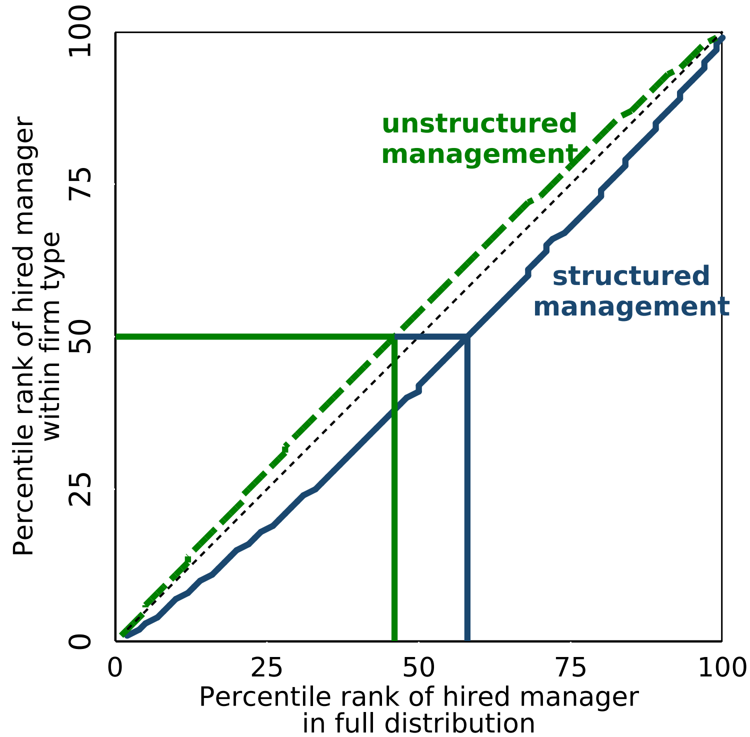
Table I: Production Function Estimates: WMS-RAIS-PIA Matched Data

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-firm quality						0.098***
						(0.02)
Firm characteristics						
Share workers with college degree					0.05	0.05
					(0.10)	(0.10)
Factor inputs			Y	Y	Y	Y
Industry	Y	Y	Y	Y	Y	Y
Ownership	Y	Y	Y	Y	Y	Y
# 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

Notes: Results from OLS regressions of log sales onto the variables described. In addition to the reported variables, the estimated models also include: industry dummies, and the log of capital, raw materials, and the number of employees. The data are prepared by merging the WMS, RAIS, and PIA samples for years 2008 and 2013.

Figure 1: Quality distribution of newly hired managers and production workers

(a) Managers



(b) Production workers

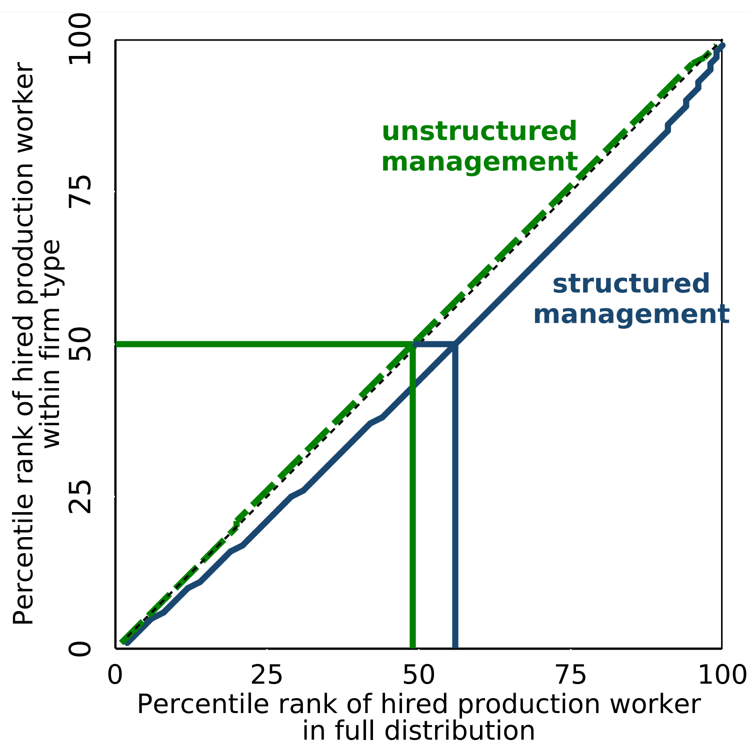
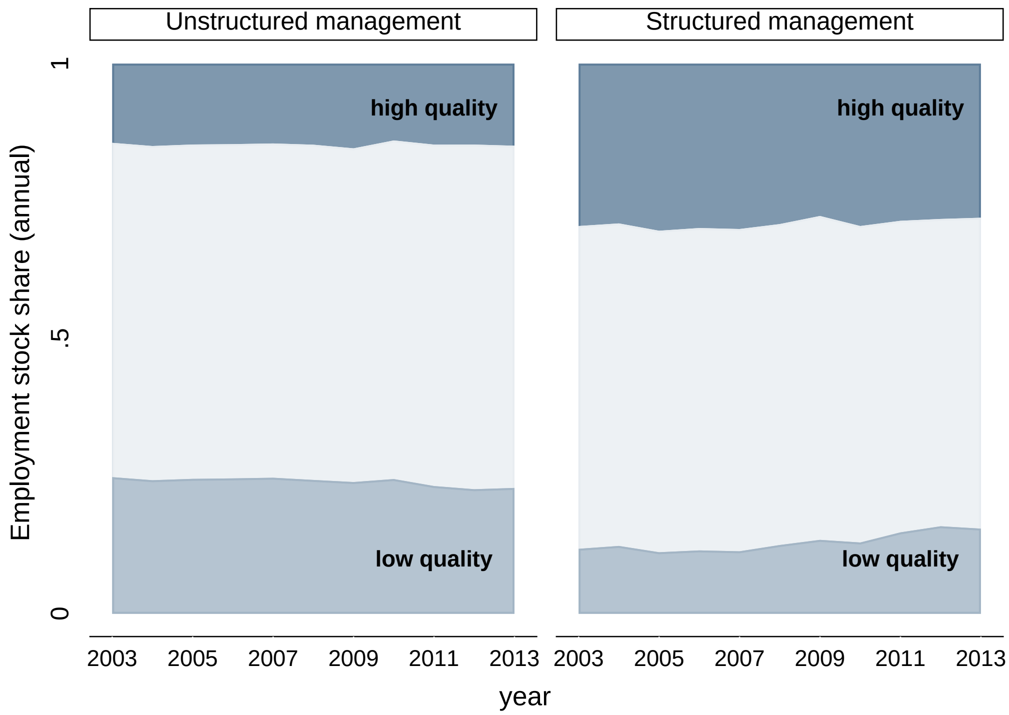
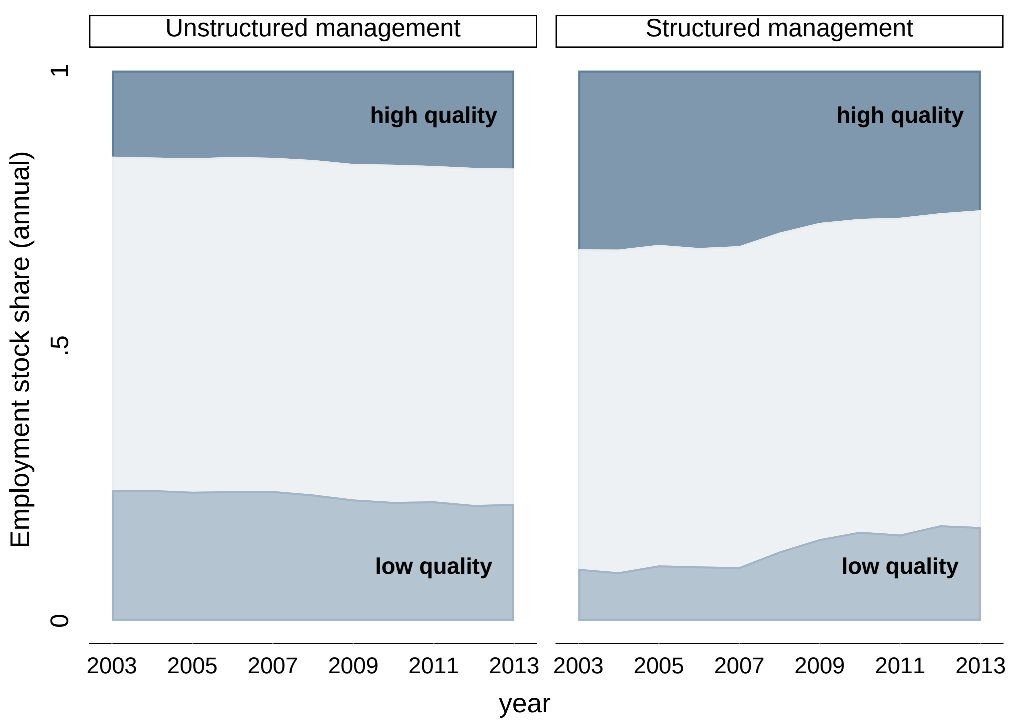


Figure 2: Quality distribution of managers and production workers in continuing jobs

(a) Managers



(b) Production workers



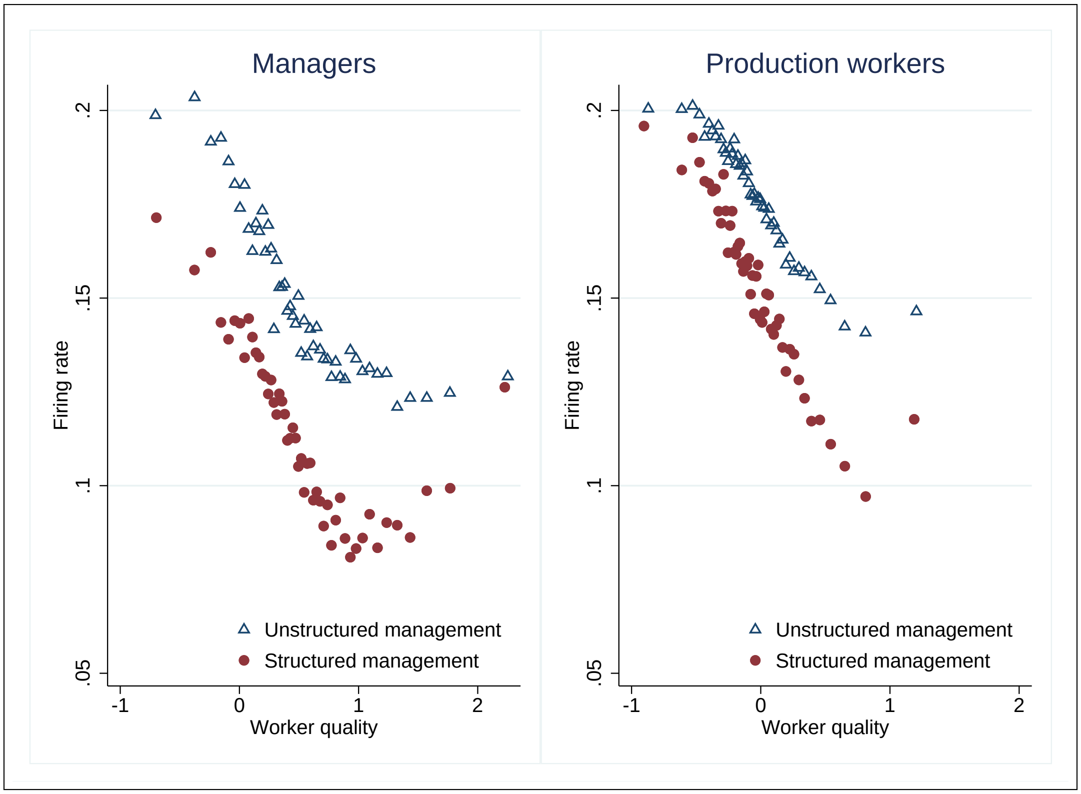


Figure 3: Firing rates for managers and production workers by worker quality

Table II: Relationship between Worker and Management Quality

Dependent variable:	z-(production worker quality)				z-(manager quality)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Management indices								
z-people	0.100***		0.098**		0.086***		0.007	
	(0.036)		(0.042)		(0.030)		(0.035)	
z-operations		0.074**	0.004	-0.007		0.143***	0.137***	0.130***
		(0.037)	(0.043)	(0.042)		(0.033)	(0.040)	(0.040)
Individual practices								
z-talent mindset				0.091**				0.059*
				(0.036)				(0.031)
z-performance culture				0.016				0.008
				(0.033)				(0.032)
z-talent capacity				-0.027				-0.018
				(0.033)				(0.032)
z-talent development				0.032				-0.013
				(0.041)				(0.035)
z-value proposition				0.016				-0.015
				(0.036)				(0.037)
z-retaining talent				0.017				-0.009
				(0.038)				(0.033)
Firm controls	Y	Y	Y	Y	Y	Y	Y	Y
Industry controls	Y	Y	Y	Y	Y	Y	Y	Y
# Observations	955	955	955	955	955	955	955	955
# Firms	690	690	690	690	690	690	690	690
R^2	0.273	0.269	0.273	0.277	0.353	0.360	0.360	0.362

Notes: Results of linear regressions projecting plant-level averages of worker quality (estimated AKM worker effects) onto measures of management. In columns (1)–(4), the dependent variable is the average quality of production workers. In columns (5)–(8), the dependent variable is the average quality of managers. All models control for the log of employment, the year of observation (either 2008 or 2013), two-digit industry codes, the share of unionized workers, firm age, and whether the firm is multinational. In columns (1)–(3) and (5)–(7), the regressors of interest are the standardized measures of operations management and people management. In columns (4) and (8), the regressors of interest are the six subcomponents of the people-management measure. These measure the extent of structured management practices with respect to: (i) instilling a talent mindset; (ii) building a high-performance culture; (iii) making room for talent; (iv) developing talent; (v) creating a distinctive employee value proposition; (vi) retaining talent. For details of these different measures, see Bloom and Van Reenen (2007) and Bloom et al. (2014).

Appendix for Cornwell, Schmutte, and Scur "Picking from the top or shedding the bottom? Personnel management, worker quality and firm productivity," January 21, 2019

A Data Sources

A.1 The *Relação Anual de Informações Sociais* (RAIS)

We use matched employer-employee data from Brazil's *Relação Anual de Informações Sociais* (RAIS) for the period 2003-2013. The RAIS is an administrative census of all jobs in Brazil covered by a formal contract. Each year, the Brazilian Ministry of Labor and Employment (MTE) collects data from each establishment on every employment contract that was active during the calendar year. For businesses, reporting the data under RAIS is mandated by the constitution. Hence, compliance with reporting requirements is extremely high, as employers who fail to complete the survey face mandatory fines and also risk litigation from employees, to whom the company must make mandatory leave-loading and social security payments.

For each job, in each year, the employer reports characteristics of the worker, the job, and the establishment. Worker characteristics include gender, race, age, and educational attainment.[14] Job characteristics relevant to this study include the monthly wage, weekly contracted hours, occupation, and the cause of job separations (which we use to distinguish voluntary and involuntary separations.) Establishment characteristics include the establishment's industry, location, and number of employees.

A.2 Distinguishing Managers and Production Workers in RAIS

In RAIS, We are able to distinguish workers holding managerial positions from production workers. Each contract-year observation includes a variable that reports the 5-digit occupation code according to the Brazilian classification system, the *Classificação Brasileira de Ocupações* (CBO).[15] Under the CBO, occupations with the first digit '1' correspond to "Membros superiores do poder público, dirigentes de organizações de interesse público e de empresas e gerentes" (Leaders of public agencies, and directors and managers of organizations and businesses). We therefore classify as managerial all jobs with first digit of CBO code equal to 1.

[14] Because individual characteristics are reported by the employer, they can change as workers move from job to job. **?** provide evidence that discrepancies in employers' reports of worker characteristics are associated with other unobserved determinants of earnings, so we leave these variables in as reported.

[15] Detailed information on the CBO classification system is available via http://www.mtecbo.gov.br.

We find that many of the establishments in RAIS do not have any workers in occupations classified as managerial according to the rule above. Hence, we expand our classification of managers in two ways. First, we use the third digit of the occupation code, which indicates hierarchical level. Specifically, a third digit of '0' in the CBO code indicates the position is supervisory over the jobs in the corresponding two-digit group. For example, occupations classified with leading digits "52" are "vendors of commerical services." Occupations with leading digits "520" are "supervisors of vendors of commercial services." We classify all such supervisory occupations as managerial.

Second, in the WMS data, we know the survey respondent is a manager or director. While the WMS does not record the CBO occupation of the respondent, ... [TO FINISH]

A.3 Formal Employment in Brazil

In Brazil a worker is formally employed if he or she has a registered identification number with one of two social security programs: the *Programa de Integração Social* (PIS), or Social Integration Program, or the *Programa de Formação do Patrimônio do Servidor Público* (PASEP), or Civil Servants Equity Formation Program, depending on whether the worker is employed in the private sector or the public sector. PIS/PASEP numbers are consistent across workers and follow a worker for life. For firms, formal employment means that the employer contributes the *Abono Salarial* along with other social security payments to a bank account administered by either *Caixa Econômica Federal* if registered with PIS, or *Banco do Brasil* for PASEP workers. Formal employers must also have employment contracts for all employees. The most common contract type is the *Consolidação das Leis de Trabalho* (CLT), or Labor Law Consolidation. Other formal employment relationships include internships, independent contracting, directorships and government contracts, but we do not consider these types of contract in this paper. The number of formal contracts grew steadily in Brazil during our sample period, from nearly 42 million jobs in 2003 to over 72 million jobs in 2010. Unemployment decreased from eleven percent to five percent, and real wages grew over the period as well. Our sample therefore covers a period of growth and tightening labor-market conditions.

A.4 Preparation of the RAIS Analysis Data

We base our analysis on an extract of the full RAIS data with several restrictions. For workers with multiple jobs in a given year, we focus on the job with the highest total earnings in that year, based on the reported number of months worked and the average monthly earnings. We also restrict attention to jobs with at least 30 hours contracted hours per week. Using this unbalanced panel of workers, we drop all observations in plants with fewer than five workers, and observations with missing data on tenure or earnings. Finally, we drop all observations where the job is reported to be some form of government contract.

Table C.1 provides basic descriptive statistics summarizing our main analysis file assembled from the raw RAIS data.

B Additional Details of the Firm-level Data

We show the distribution of the skill of managers and of production workers, as measured by the AKM worker effect, in Figure C.6. Managers clearly have much higher average skill, but also higher variance. The distribution of managerial skill is also highly skewed. The skill distribution for production workers is approximately log-normal. The distribution of manager skill has a very fat right-tail, indicating the presence of many highly-paid managers. Moreover, the distribution shows some evidence of being bi-modal.

C Appendix Tables and Figures

Table C.1: Summary of RAIS 2003–2013

Variable	Mean Std.	Dev.
Log Wage	1.65	0.69
Log Monthly Earn.	6.87	0.67
White	0.59	0.49
Male	0.64	0.48
Age	33.24	10.59
age $\leq$ 30	0.48	0.50
age $\geq$ 50	0.09	0.28
Work Hours	43.12	2.58
Hours $\geq$ 35	0.98	0.13

Notes: Summary statistics of the RAIS data used to estimate the AKM decomposition. The data are a worker-year panel constructed from the raw RAIS job-year files. We assign workers to the job with highest reported earnings over the year. We also drop all worker-year observations where the number of reported jobs is greater than 2. We drop jobs with fewer than 30 contracted hours per week, jobs in the public sector, jobs in plants with fewer than 5 workers, and jobs with missing data on tenure or earnings. The final number of observations is $N = 353,141,951$.

Table C.2

	Mean	Median	Min	Max	SD	N
Firm characteristics						
Number of employees (WMS)	600.78	300.0	40.0	5000.0	(816.49)	961
Number of production sites, total (WMS)	3.79	1.0	0.0	91.0	(9.40)	961
Number of production sites, abroad (WMS)	2.28	0.0	0.0	100.0	(11.05)	961
Firm age (WMS)	36.42	33.0	1.0	316.0	(25.55)	961
Firm has no competitors (WMS)	0.01	0.0	0.0	1.0	(0.08)	961
Firm has less than 5 competitors (WMS)	0.23	0.0	0.0	1.0	(0.42)	961
Firm has 5 or more competitors (WMS)	0.76	1.0	0.0	1.0	(0.43)	961
Firm is family owned (WMS)	0.26	0.0	0.0	1.0	(0.44)	961
Firm is founder owned (WMS)	0.36	0.0	0.0	1.0	(0.48)	961
Firm is institutionally owned (WMS)	0.05	0.0	0.0	1.0	(0.22)	961
Firm is non-family privately owned (WMS)	0.16	0.0	0.0	1.0	(0.36)	961
Firm is owned by dispersed shareholders (WMS)	0.14	0.0	0.0	1.0	(0.34)	961
Other ownership (WMS)	0.04	0.0	0.0	1.0	(0.19)	961
Firm is a multinational (WMS)	0.21	0.0	0.0	1.0	(0.41)	961
Firm is a domestic multinational (WMS)	0.01	0.0	0.0	1.0	(0.11)	961
Hierarchy: layers between CEO and shopfloor (WMS)	3.33	3.0	1.0	8.0	(1.15)	961
Span of control: number of direct reports (WMS)	7.09	6.0	1.0	30.0	(5.01)	961
Management scores						
Overall management score, raw (WMS)	2.70	2.7	1.1	4.7	(0.65)	961
Operations management score, raw (WMS)	2.44	2.5	1.0	5.0	(1.02)	961
Monitoring management score, raw (WMS)	3.08	3.2	1.0	5.0	(0.81)	961
Target management score, raw (WMS)	2.63	2.6	1.0	5.0	(0.78)	961
People management score, raw (WMS)	2.52	2.5	1.0	4.7	(0.58)	961
Worker characteristics						
Share of female managers (WMS)	0.18	0.1	0.0	1.0	(0.19)	480
Share of female non-managers (WMS)	0.30	0.3	0.0	1.0	(0.24)	480
Share of female workers, total (WMS)	0.30	0.3	0.0	1.0	(0.24)	480
Share of female workers, total (RAIS)	0.29	0.2	0.0	1.0	(0.22)	961
Age of workers (RAIS)	33.05	32.7	21.0	53.0	(3.75)	961
Weekly hours worked (RAIS)	43.51	44.0	30.0	44.0	(1.29)	961
Weekly hours worked (WMS)	43.80	44.0	35.0	65.0	(2.47)	961
Weekly hours worked, managers (WMS)	48.68	45.0	35.0	80.0	(7.06)	961
Weekly hours worked, non-managers (WMS)	43.63	44.0	35.0	65.0	(2.45)	961
Employee tenure, weeks (RAIS)	43.98	39.8	2.9	213.7	(22.12)	961
Hourly wage, BRL Reais (RAIS)	11.24	8.3	2.5	159.7	(10.61)	961
Monthly earnings, BRL Reais (RAIS)	2079.36	1530.3	463.4	30120.6	(1931.22)	961
Worker education						
Share of managers with university degree (WMS)	0.73	0.9	0.0	1.0	(0.33)	961
Share of non-managers with university degree (WMS)	0.10	0.1	0.0	1.0	(0.13)	961
Share of employees with university degree (WMS)	0.13	0.1	0.0	1.0	(0.13)	961
Share of employees with university degree (RAIS)	0.13	0.1	0.0	1.0	(0.18)	961
Share of employees with high school degree (RAIS)	0.55	0.6	0.0	1.0	(0.21)	961

Notes: Summaries of the matched WMS-RAIS panel. The dataset is a firm-year panel with one observation for each WMS firm in each year it was surveyed and can be matched to RAIS. There are 694 unique firms. Of these, 267 were surveyed in both years, 213 were surveyed only in 2008, and 214 were surveyed only in 2013. The data also include firm-level summaries of RAIS variables. Note that the WMS only asked Brazilian firms about gender composition in 2013, which explains the discrepancies in the number of observations for those variables.

Table C.3: Composition of Establishments in RAIS-WMS Data: 2003–2013

Year	(1) Share Active	(2) Management Score	(3) Plant Effect
2003	0.88	$-.011$	.155
2004	0.91	$-.025$	.151
2005	0.94	$-.033$	.157
2006	0.95	$-.017$	.160
2007	0.95	$-.010$	.160
2008	0.95	$-.011$	.150
2009	0.93	$-.006$	.151
2010	0.92	$-.003$	.152
2011	0.94	0.004	.154
2012	0.93	0.022	.167
2013	0.91	0.027	.169

Notes: Table entries are summaries of characteristics of 728 establishments from WMS that can be matched to at least one year of RAIS between 2003–2013. Column (1) reports the share of these 728 establishments observed in a given year. Columns (2) reports the average standardized management score, which is centered on zero with standard deviation 1. Column (3) reports the average estmated establishment effect across firms observed in a given year.

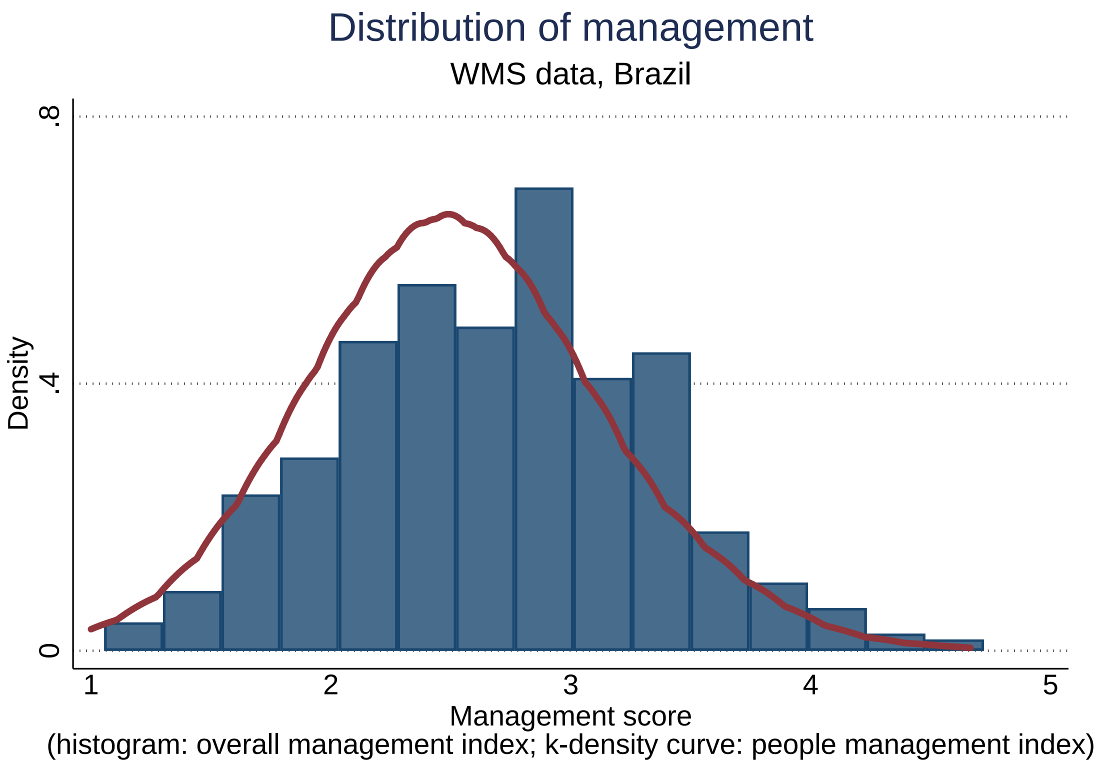


Figure C.1: Distribution of overall management score (histogram) and people management score (kernel density) for Brazilian plants surveyed in 2008 or 2013.

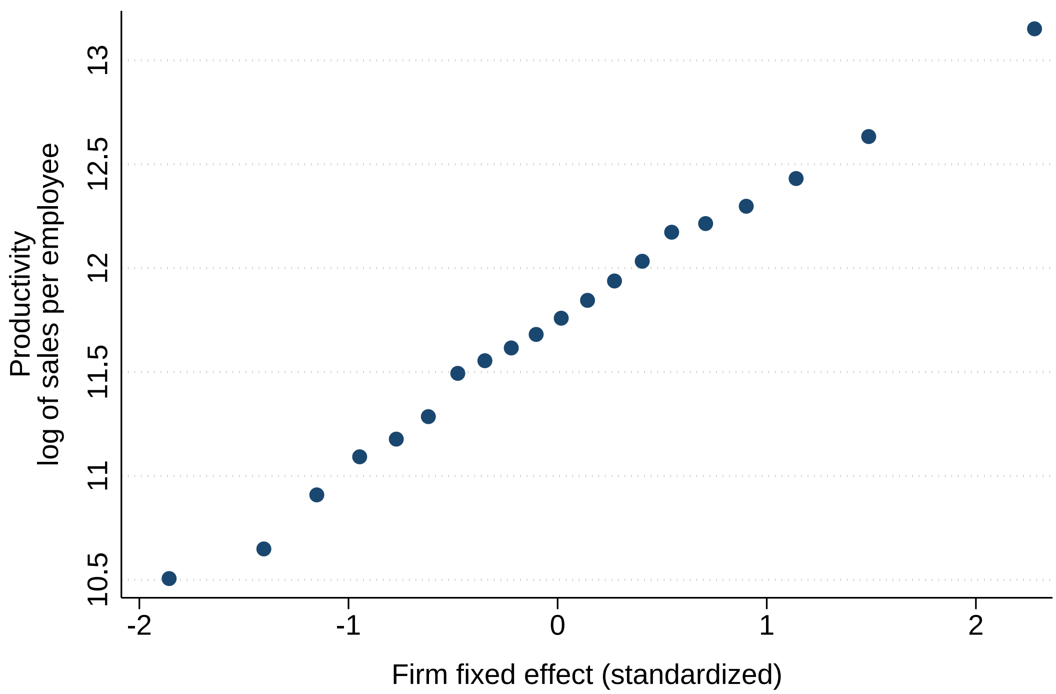
Table C.4: Descriptive Statistics: WMS-RAIS-PIA Matched Data

	Mean	25th p	Median	75th p	Std. Dev.	Num. Obs.
Multinational status	0.21	0	0	0	0.41	685
Avg share of union members	51.34	10	50	95	39.02	684
Firm age	35.5	18	31	46	25.61	685
Avg number of reported competitors	7.37	4	10	10	3.11	685
Share of female workers	30.64	13.34	28.2	45.6	22	675
Share of family firms (Orbis)	0.44	0	0	1	0.5	19595
Share of private firma (WMS)	0.19	0	0	0	0.39	685
Share of institutional firms (WMS)	0.07	0	0	0	0.26	685
Share of founder firms (WMS)	0.36	0	0	1	0.48	685
Share of family firms (WMS)	0.25	0	0	1	0.43	685
Share workers with college degree	0.07	0	0.02	0.07	0.13	19788
Avg share of high school educated workers	0.41	0.2	0.39	0.58	0.26	19788
Avg share of white workers	0.71	0.56	0.82	0.95	0.3	19788
Log of wage mean (RAIS)	1.74	1.39	1.69	2.01	0.5	19788
Separation mean (RAIS)	0.28	0.18	0.26	0.36	0.16	19788
# employees	260.49	60	91	180	1065.05	20056
Log employees	4.76	4.14	4.54	5.23	1.05	19263
Log capital	13.4	12.6	15.02	16.61	5.47	19537
Log materials	15.49	14.04	15.73	16.99	2.32	19272

Notes: Summaries of variables in the WMS-RAIS-PIA matched data. The variables are from PIA, except where noted. Variables from WMS are only available for WMS firms, as reflected in the number of observations.

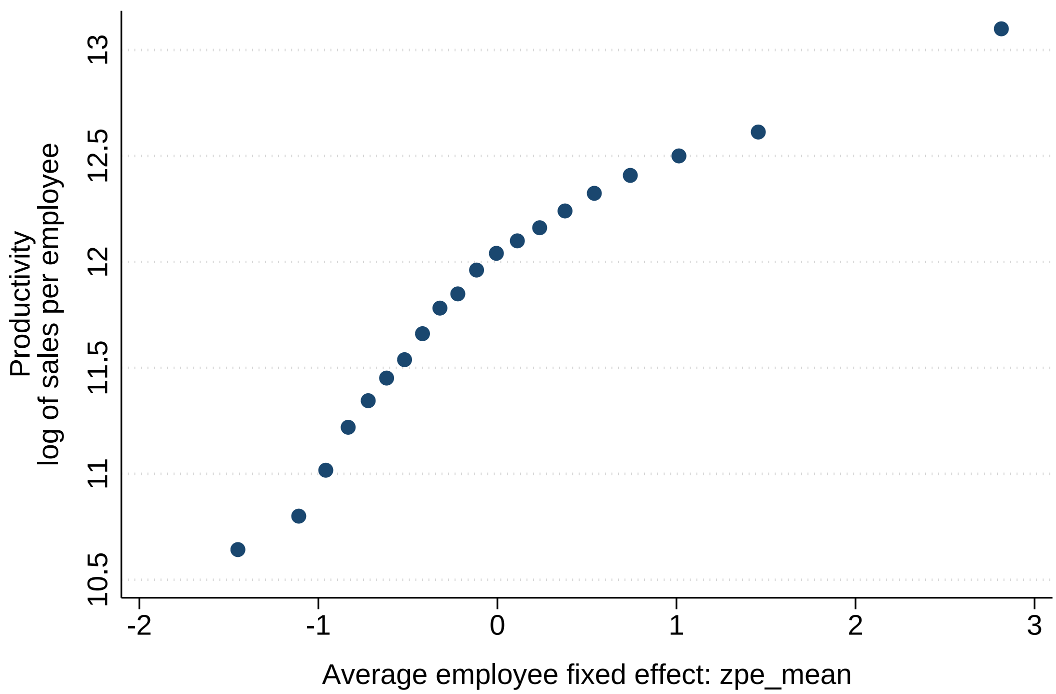
Note: productivity data from PIA, worker data from RAIS, management data from WMS. Raw data.
N=6666. Both variables residualized by regressing the underlying variable on log employment.

Figure C.2: Relationship between sales and WMS management score



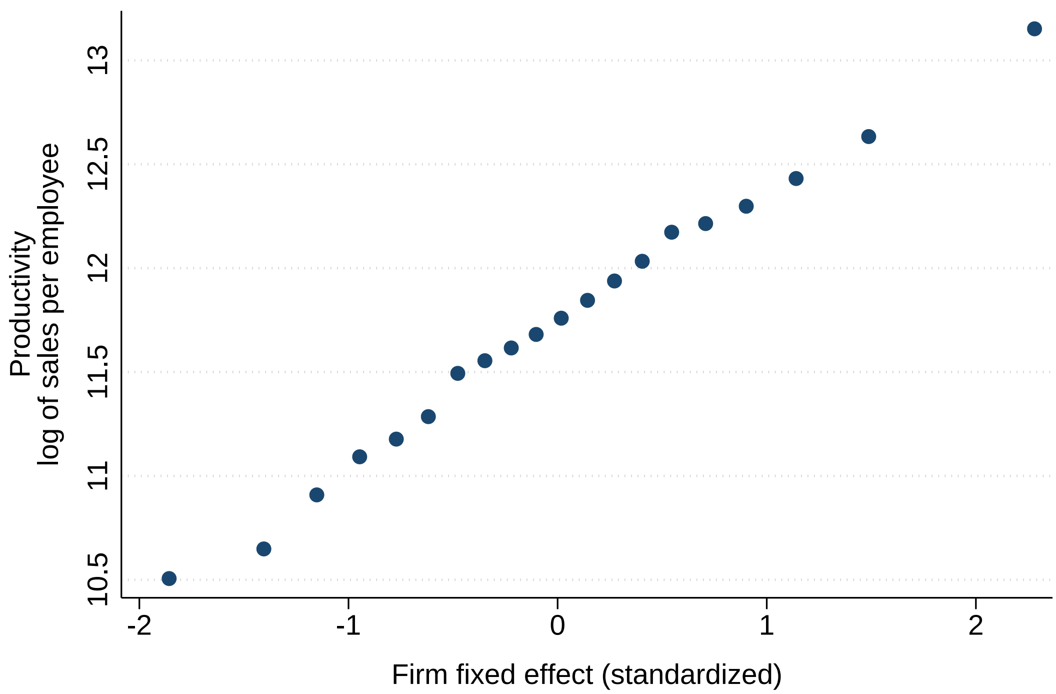
Note: productivity data from PIA, worker data from RAIS, management data from WMS. N=191510.
This graph was made by collapsing by vingtiles of FE.

Figure C.3: Relationship between sales and estimated AKM firm effect



Note: productivity data from PIA, worker data from RAIS, management data from WMS. Raw data.
N=191510. Both variables residualized by regressing the underlying variable on log employment.

Figure C.4: Relationship between sales and average estimated AKM worker effect



Note: productivity data from PIA, worker data from RAIS, management data from WMS. N=191510.
This graph was made by collapsing by vingtiles of FE.

Figure C.5: Relationship between sales and estimated AKM firm effect

Table C.5: Decomposition of Variance in Log Wages: RAIS 2003-2013

	Variance Component	Share of Total
Log Wage Var.	0.472	100.0%
Variance Components:		
var(Worker Effect θ)	0.235	49.8%
var(Estab. Effect ψ)	0.088	18.5%
$\text{var}(X\beta)$	0.046	9.7%
var(Residual)	0.044	9.2%
$2 \times \text{cov}(\theta, \psi)$	0.095	20.2%
$2 \times \text{cov}(X\beta, \theta)$	-0.034	-7.3%
$2 \times \text{cov}(X\beta, \psi)$	-0.001	-0.0%

Notes: Share of variance in log wages explained by components estimated from the AKM model described in Equation (1).

Table C.6: Correlation among log wage components from AKM model: RAIS 2003–2013

				Component Correlations				
Component	Label	Mean	Std. Dev.	Y	$X\hat{\beta}$	$\hat{\theta}$	$\hat{\psi}$	$\hat{\varepsilon}$
Y	Log wage	1.649	0.687	1.000				
$X\hat{\beta}$	Time varying characteristics†	0.137	0.215	0.192	1.000			
$\hat{\theta}$	Worker effect	0.000	0.485	0.797	$-.166$	1.000		
$\hat{\psi}$	Firm effect	0.000	0.296	0.663	$-.009$	0.332	1.000	
$\hat{\varepsilon}$	Sample residual	0.000	0.209	0.304	0.000	0.000	0.000	1.000

Notes: Observation-weighted correlations among the variance components of log wages estimated from the AKM model described in Equation (1)

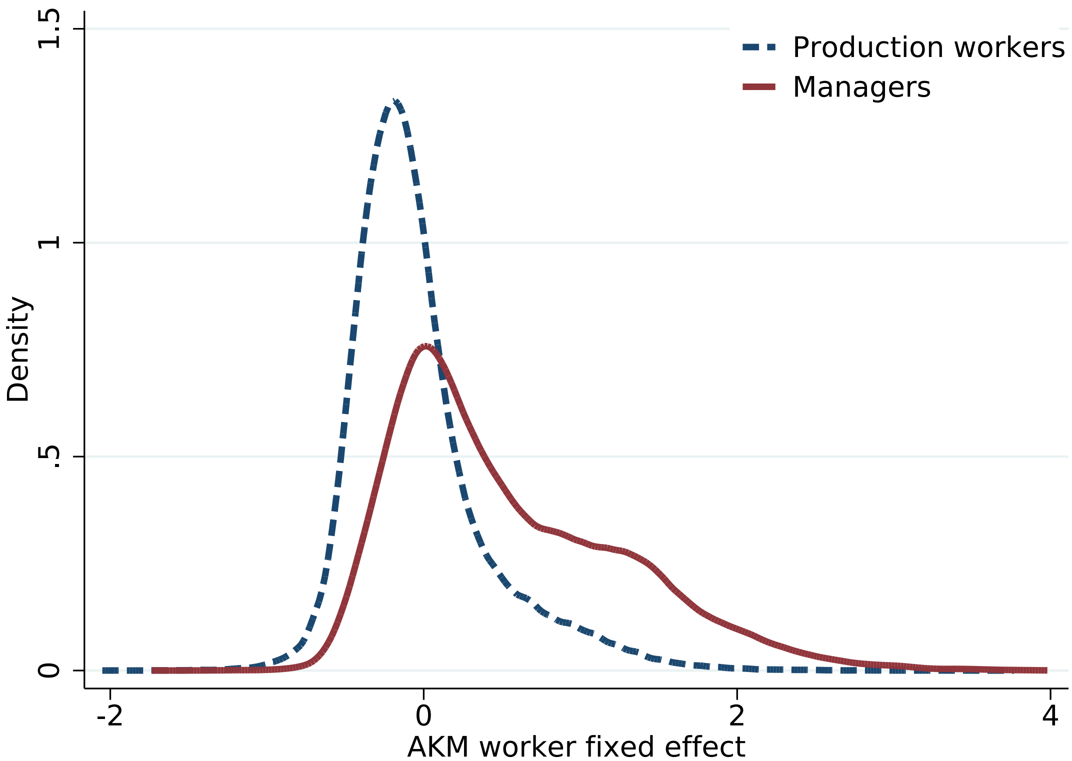


Figure C.6: Distribution of AKM Worker Fixed Effect for Managers and Nonmanagers

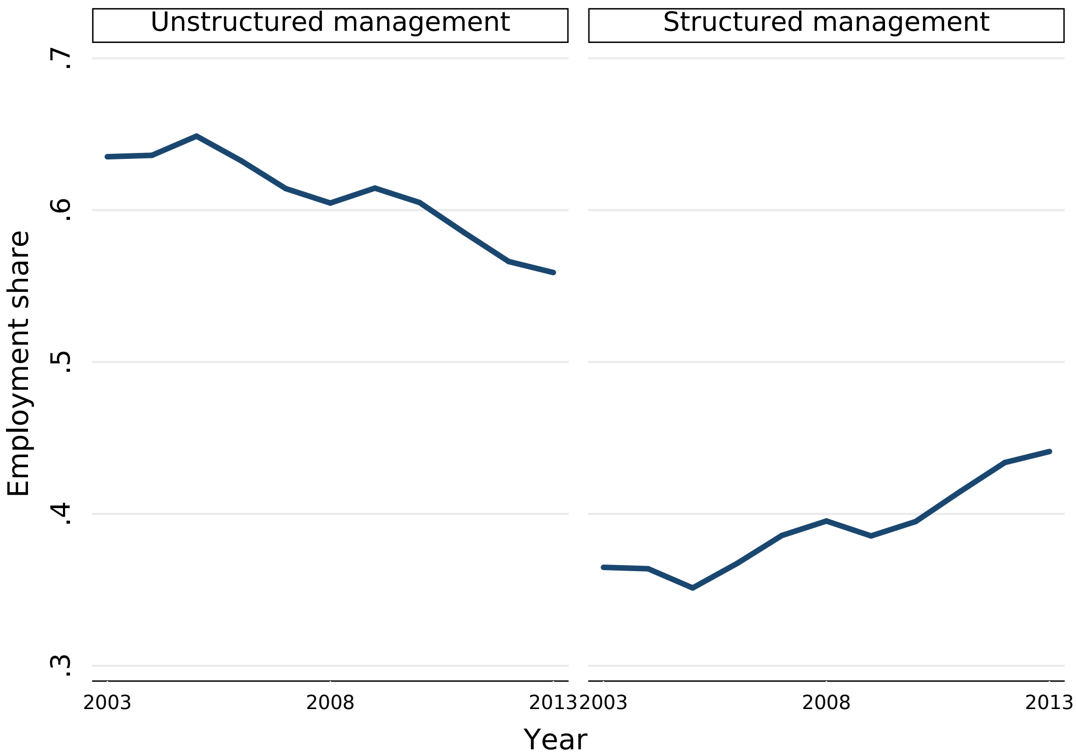


Figure C.7: Employment shares in structured and unstructured firms