ISSN 2042-2695

CENTRE *for* ECONOMIC PERFORMANCE

CEP Discussion Paper No 1644

August 2019

Building a Productive Workforce: The Role of Structured Management Practices

Christopher Cornwell
Ian M. Schmutte
Daniela Scur

THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

E·S·R·C ECONOMIC & SOCIAL RESEARCH COUNCIL

Abstract
Firms' hiring and firing decisions affect the entire labor market. Managers often make these decisions, yet the effects of management on labor allocation remains largely unexplored. To study the relationship between a firm's management practices and how it recruits, retains and dismisses its employees, we link a survey of firm-level management practices to production and employee records from Brazil. We find that firms using structured management practices consistently hire and retain better workers, and fire more selectively. Good production workers match with firms using structured personnel management practices. By contrast, better managers match with firms using structured operations management practices.

Key words: labor allocation, managers, management practices, productivity
JEL Codes: D22; M11; J31

This paper was produced as part of the Centre's Growth Programme. The Centre for Economic Performance is financed by the Economic and Social Research Council.

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 Erik Brynjolfsson, Bob Gibbons, Hilary Hoynes, Lisa Kahn, Raffaella Sadun and Kathryn Shaw 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, NBER Org meeting (fall 2018), SIOE 2019 and EPED 2019 for useful discussions and comments.

Christopher Cornwell, University of Georgia, Terry College of Business. Ian M. Schmutte, University of Georgia, Terry College of Business. Daniela Scur, Cornell University and Centre for Economic Performance, London School of Economics.

Published by
Centre for Economic Performance
London School of Economics and Political Science
Houghton Street
London WC2A 2AE

1 Introduction

Firms' decisions about whom to hire and fire affect not only their own bottom line, but the functioning of the entire labor market. Recent work in labor economics documents the importance of worker-firm matching for productivity (Iranzo et al. 2008; Abowd et al. 2017; Bender et al. 2018), inequality (Card et al. 2013; Alvarez et al. 2018; Song et al. 2019), and wage differentials (Card et al. 2016; Lavetti and Schmutte 2018; Sorkin 2018). But what are the actual processes that generate the observed assignment of workers to firms? Oyer and Schaefer (2011) suggest that to understand labor market matching, economists should focus on the active role played a firm's managers and management practices. However, most studies of the labor market abstract away from how real-world differences in managerial competence affect job matching.[1] The empirical relevance of differences in management practices for the allocation of labor remains largely unexplored.

In this paper, we provide a first look into the relationship between a firm's management practices, the quality of the managers that implement those practices, and the processes by which it recruits, retains and dismisses production workers. We have assembled a detailed dataset that links firm-level survey measures of management practices from the World Management Survey (WMS) to matched employer-employee data from Brazil, the *Relação Anual de Informações Sociais* (RAIS). Based on the WMS data, we characterize each firm as having either *structured* or *unstructured* management practices, with respect to both its management of people and its management of production operations. By "structured" we mean that the firm has formal management systems in place that are independent of the manager implementing them. Using the RAIS data, we construct measures of the quality of each establishment's managerial and non-managerial workforce. The longitudinal structure of RAIS also allows us to track how firms manage workforce quality through their hiring, retention and firing decisions. Finally, we link our WMS-RAIS sample to data from Brazil's industrial survey, the *Pesquisa Industrial Anual* (PIA), to verify that our measures of worker quality and management do, in fact, correlate with productivity.

Our findings are as follows. First, firms with structured management practices hire disproportionately from the top of the worker quality distribution, especially when recruiting managers. Second, these firms are also more successful at keeping their high-quality hires. Their incumbent managers are twice as likely to be high-quality and their advantage among incumbent production workers is almost as large. Third, firms with structured management practices have much lower overall rates of firing, suggesting they screen or motivate workers more effectively. Furthermore,

[1] The assortative matching model of Becker (1973) is the classic example, but in most contemporary discussions of job matching in economics, like Card et al. (2018) or Sorkin (2018), matching happens without the intervention of any particular or specialized managerial structures.

when they do dismiss production workers, firms using structured practices fire more selectively with respect to worker quality. Overall, the use of structured management practices is associated with an increase in worker quality of around one half of a standard deviation for managers, and one-third of a standard deviation for production workers. For both worker groups, around one quarter of the relationship between management practices and worker quality remains after controlling for observed worker and firm characteristics.

If these relationships reflect the direct influence of management practices, we expect them to operate primarily through personnel management. Indeed, for production workers, the positive relationship between management practices and worker quality is explained entirely by the personnel practices index. For managers, by contrast, both the personnel and operations practices indices matter and in roughly equal measure. These results are consistent with a model in which personnel management practices facilitate the recruiting and retention of better production workers and structured operations practices attract better managers (or better managers are required to implement structured practices in both domains. This is the first time these patterns have been documented so clearly in the data.

We contribute to a growing empirical literature in organizational and labor economics studying how management practices affect matching in the labor market. Advances in this area have been made possible by efforts like ours to assemble data on key features of the employment relationship. Focusing just on managers, Bandiera et al. (2015) show risk averse, low-talent managers prefer low-powered incentives, as do firm owners that benefit from retaining control, while more talented managers prefer high-powered incentives. This is consistent with high-quality managers being attracted to firms with more structured management practices, as such firms should have greater accountability and stronger incentives. A central managerial responsibility is the recruitment of new workers, but Hoffman et al. (2018) show that there can be sizeable biases in managers' hiring decisions. They are concerned with the use of information technology to overcome bias, but our work suggests that structured management practices may help discipline managers' decisions about whom to hire.

Our paper is most closely related to Bender et al. (2018), who combine WMS data with German administrative records to study how worker quality mediates the positive relationship between structured management practices and firm productivity. We find a very similar relationship between productivity and worker quality in Brazil, which is striking given differences between the two economies and their workforces. While they report results separately for managers, they do so by treating any worker in the top quartile of their firm's pay distribution as a manager, because there is no manager classification in the German data. In contrast, the RAIS data allow us to observe managers directly via their occupation code, as well as isolate hires, fires and quits for both managerial and non-managerial workers. Thus, we are uniquely able to document how management practices contribute to the selection and sorting of managers and production workers across firms. Our results suggest many new avenues for empirical research, which we discuss in the conclusion.

2 Empirical Setting

We combine three datasets covering Brazilian firms: RAIS, which provides essential information on workers and their jobs; the WMS, which contributes our measures of management practices, and the Annual Industrial Survey (*Pesquisa Industrial Anual - PIA*), our source for firm input and output data.

2.1 Worker quality, occupation, and employment history: RAIS

We first use the RAIS data to construct a measure of worker quality derived from the part of their wage that follows them from job to job. More specifically, we associate worker quality with the estimated worker effects from a decomposition of log wages into worker- and firm-specific components, following the approach introduced by Abowd, Kramarz and Margolis (1999) (henceforth the AKM decomposition).[2] For the wage decomposition, we use the 2003-2013 waves of RAIS to build a sample of employees who are contracted to work at least 30 hours per week, have at least one month of tenure and have complete data on time-varing covariates. We exclude workers in establishments with only one employee, and observations beyond the top and bottom 0.01 percent of the wage distribution. These restrictions leave us with 353,141,951 unique worker-firm-year observations covering 96,499,697 unique workers and 4,433,492 unique establishments.[3]

The wage decomposition involves estimating a two-way fixed-effects model 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 wage of worker i at time t.[4] Our primary interest is in the worker effects, θ_i, which

[2]As many studies have shown, the relationship between AKM worker effects and underlying ability or productivity is unclear theoretically (Shimer 2005; Eeckhout and Kircher 2011; Abowd et al. 2018). However, as we document in Section 3.1, they are strongly correlated with firm productivity. Hence, the "quality" label seems reasonable in the sense that the estimated worker effects reflect a set of attributes that firms find desirable.

[3]Appendix A provides details of the sample construction and summary statistics on the workers that comprise it.

[4]For the wage variable we take average monthly earnings, reported in 2003 Brazilian Reais, and convert it into an hourly measure. 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

capture the value of portable skills and represent our measure of worker quality. The model x_{it} contains a normalized cubic in labor-market experience interacted with race and gender.[5], [6] 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 and ε_{it} is a mean-zero error. 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 the worker and firm effects.[7]

Similar to other settings — for example, Germany (Card et al. 2013), Portugal (Card et al. 2016) and the US (Abowd et al. 2017) — we find the AKM model provides a comprehensive 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.[8]

Our data allows us to separately measure the average quality of production workers and managers within each establishment. In our RAIS-WMS sample, roughly 5 percent of the employees hold managerial positions, which is consistent with the 4.88 percent share of managers reported in the WMS. We refer to the remaining 95 percent of workers interchangeably as non-managers or production workers.[9] In the WMS firms, average quality is almost twenty times higher for managers than production workers. However, average manager quality is more variable, with a standard deviation of 0.389 compared with 0.305 for production workers.

In addition, RAIS provides detailed employment histories that allow us to track the quality of worker flows into and out of the firm at both the managerial and non-managerial levels. In particular, RAIS records the exact date of hire for each worker, as well as the date and *reason for separation* when a job ends. Thus, we are able to evaluate a firm's hiring, retention and dismissal activity as a function of its management practices, for both managers and production workers.

would have earned for the entire month. All of these calculations are performed by the MTE and included in the raw RAIS data.

[5]For workers whose first employment begins in 2003 or after, experience is the sum of all months they are reported in at least one active employment relationship. For workers whose first employment started prior to 2003, we approximate experience as the greater of potential experience (age-years of schooling-6) or tenure in the first observed job.

[6]Card et al. (2018) note that in a model with year effects, the experience profile is not identified relative to worker effects without a normalization. We normalize the experience profile to be flat at 20 years of experience.

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

[8]Because the AKM decomposition is not our focus, we offer a discussion of only the essential results of estimation here. For interested readers, the Appendix tables B.2 and B.3 report the variance decomposition of wages into the components of the AKM model and the estimated correlations between them.

[9]Our classification of managers is in sharp contrast to Bender et al. (2018), whose German data do not distinguish managerial and nonmanagerial workers. Consequently, they assume all workers in the top quartile of the within-firm pay distribution are managers.

2.2 Structured management practices: WMS

The WMS project employs double-blind surveys to collect data on firms' management practices. Focusing on firms with employment of 50–5,000 workers, WMS analysts interview the senior-most manager at a plant and score their responses on a set of 18 basic management practices. The scores range from 1 to 5 indicating the degree to which formal processes are in place.[10] A higher score implies that a firm has adopted a set of *structured* management practices, which have been causally associated with improvements in productivity (Bloom et al. 2013; 2019).

In our analysis of hiring, retention and dismissal, we distinguish between firms that have structured management practices and those that do not. We average the reported management scores across all 18 practices and define a firm as having "structured personnel management" if its average score is above 3. To choose this threshold, we focus on the explicit meaning of the survey coding. A score of 3 or higher on any practice means that the firm has formal management processes in place. A score below 3 implies that management processes are informal in the sense that they would not be continued if the manager implementing them were to leave the firm.[11] In our regression analysis, we also employ continuous measures of management practices, following the convention of using standardized averages.[12] The average overall management score for the Brazilian firms is 2.67, with a standard deviation of approximately 0.6, implying that the typical establishment may have some structured practices in place, but they are idiosyncratic to a particular manager rather than part of a standard operating procedure. When compared with the overall management score, Brazilian firms score lower (2.52) in personnel management and higher (2.78) in operations management. Because we are focused on how firms build a productive workforce, we also build a separate index of "personnel management" based on the six practices directly relating to hiring, retention and dismissal decisions. We group the other 12 practices, which concern lean operations, monitoring and target-setting, into a single "operations management" index, which we define analogously.[13]

There are 763 unique firms in the Brazilian sample of the WMS: 227 surveyed in 2008 only,

[10] See Bloom and Van Reenen (2007); Bloom et al. (2014) for more information on the WMS.

[11] For example, consider the personnel practice of "performance culture". A score of 1 implies that "people within the firm are rewarded equally irrespective of performance level" while 5 means that "firms strive to outperform the competitors by providing ambitious stretch targets with clear performance related accountability and rewards" In this case, the best score involves formal appraisal and evaluation of employees, with accountability and performance processes to evaluate each worker's contribution to the firm.
N.B. We have adopted the "structured" versus "unstructured" nomenclature to avoid confusing firms that use informal management processes with firms operating in the informal sector, which is a large and important part of the Brazilian economy.

[12] Specifically, we standardize each of the 18 questions, average across each index (overall management, operations and people management) and standardize again. The results are robust to alternative index-building methods.

[13] Similarly to (Bloom et al. 2015) in their work on school management.

228 surveyed in 2013 only, and 308 surveyed in 2008 and 2013. Of the 763 firms, 694 can be matched to our RAIS sample for at least one year (213 in 2008, 214 in 2013 and 267 in both years), yielding 961 total observations between 2008 and 2013.[14]

3 Results

We first show that our measures of management and worker quality are positively associated with productivity. We then examine the relationship between structured management practices and the quality of a firm's hires, retentions and dismissals. Finally, we estimate the unconditional effect of structured practices on worker quality, how much of this effect is mediated through observable worker and firm characteristics and how much can be attributed to personnel versus operations management. We carry out our analysis separately for managers and production workers, revealing important but intuitive differences in how structured management practices are used to build workforce quality at the top and bottom of the organizational hierarchy.

3.1 More productive firms hire higher quality workers

To document the relationship between productivity and worker quality we link data on firm revenue, employment and materials expenditure from the Brazilian annual industrial survey, *Pesquisa Industrial Anual* (PIA) to our WMS-RAIS matched sample of firms.[15] Using the combined data, we estimate models predicting log sales as a function of capital, materials, as well as the overall management practices score and the measured quality of managers and production workers. We also control for industry sub-sector and family or founder ownership. Table I reports the results.

Columns (1) and (2) exclude the factor inputs. Higher overall management scores — that is, structured management practices — strongly predict sales, and, conditional on management, so does overall worker quality.[16] Adding the factor inputs in Column (3) reduces the estimated management-score and worker-quality coefficients by about one-half and two-thirds, respectively,

[14] Employees are matched to their employers through a code assigned by the *Cadastro Nacional da Pessoa Jurídica* (CNPJ), which also allows a match to the WMS and PIA. Of the 763 WMS firms, 745 have valid CNPJ identifiers. The two sources match quite closely for the set of variables that are recorded in both, specifically the share of female employees, the share of employees with a college degree, and weekly hours worked. Table B.1 provides the full descriptive statistics for the matched RAIS-WMS firms.

[15] 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.

[16] This is consistent with previous production function results using this measure (Bloom et al. 2019; 2016; Lemos and Scur 2019)

though both are still significant at the 1% level. These findings are remarkably consistent with with results reported for Germany in Bender et al. (2018), despite the differences between the two countries' economies.

Columns (4)-(6) exploit the unique ability RAIS provides to cleanly distinguish managers from non-managers.[17] Column (4) indicates that worker quality at both levels matters for productivity, but the variation loads to a much greater degree on managers: the manager quality coefficient estimate of .078 is more than twice that of production workers. Column (5) shows that the results are robust to controlling for the share of workers with a college degree, an often-used proxy for worker quality. Adding the AKM firm effect in Column (6) renders the relationship between average production worker quality and sales insignificant. However, the estimated management-score and manager-quality coefficient remain highly significant, albeit with slightly smaller magnitudes. These results are consistent with managers being primarily responsible for value generation. They also suggest that higher wages may be one tool firms use to attract better production workers and motivate them to work harder.

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

Having established that worker quality — especially manager quality — is important for productivity, we turn to the hiring, retention and firing activity of the firms in our sample, distinguishing those with structured management practices from those with unstructured practices.

3.2.1 Hiring

Figure 1 illustrates differences in the quality of hired managers (panel A) and production workers (panel B) between firms with structured management practices and those without in the 2008 data.[18] The horizontal axis shows the worker's rank in the overall distribution of workers hired in 2008. The vertial axis plots that worker's rank in the distribution of workers hired into firms with structured management (blue solid line) and unstructured management (green dashed line). Intuitively, if all firms hire randomly with respect to worker quality, both curves would sit on the 45 degree line. This is clearly not the case. At every point in the distribution, the quality of workers hired by firms with structured management is above that of firms with unstructured management.

To offer a concrete example, observe that the median manager working in a firm with unstructured management practices is in the 42nd percentile of the overall manager quality distribution. In contrast, the median manager working in a firm with structured management practices was hired

[17] Disaggregating causes us to lose about 14 percent of the sample because of missing data on worker type.
[18] We use only data for 2008 in this graph, but the pattern is consistent across all other years.

from the 59th percentile of the overall manager quality distribution. For production workers, the median production worker hired into an unstructured management practices firm is in the 48th 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

Hiring from the top will have less impact if high-quality hires are not retained. We classify 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 classify them as either "high-quality" or "low-quality" 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 share of low quality production workers in firms with structured management increases gradually after 2007, and this can be partly explained by the loss in overall employment share by unstructured firms over time.[19] Employees at the bottom of the quality distribution are more likely to suffer a job separation, and some are being hired by growing firms that use structured management practices.

3.2.3 Dismissals

The ability to fire is an important tool for managing the workforce. Our analysis suggests that firms with structured management practices use it more judiciously. Unlike other linked employer-employee datasets, RAIS includes the reason for separation, allowing us to distinguish jobs that ended due to firing from those that ended because the worker quit.[20] 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.[21]

[19] 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. Figure B.1 in the Appendix depicts the pattern.

[20] 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.

[21] 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.

Two features of the data stand out. First, firms with structured management practices have lower levels of 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, firms with structured practices shed workers of lower quality than firms with unstructured practices, suggesting that those without structured practices make more mistakes in firing. The patterns in the graphs indicate that the mistakes may more pronounced in the upper part of the worker quality distribution.

3.3 Management practices and worker quality

The patterns depicted in Figures 1, 2 and 3 provide new evidence that structured management practices are important for building a stable, high-quality workforce. Now, we quantify how much of the role of management is mediated through the observable worker and firm characteristics and how much is attributable to structured personnel practices guiding hiring and retention decisions. Using the sample of all workers employed by WMS between 2003-2013, we estimate a series of regressions relating worker quality to management practices:

$$WorkerQuality_{ij} = \alpha + \beta MGMT_j + X_{ij}\gamma_1 + Z_j\gamma_2 + u_{ij}, \tag{2}$$

where $WorkerQuality_{ij}$ is the $\hat{\theta}$ z-score for worker i in firm j, standardized relative to its distribution across all workers in the analysis sample; $MGMT_j$ is a transformation of the employer's management practices score; and X_{ij} and Z_j contain worker and firm characteristics, respectively.[22]

We first estimate the unconditional effect of management practices on worker quality for different measures of the key variables. Then, using the overall index of management practices (z-management) for $MGMT$, we incrementally introduce worker characteristics (age, number of hours worked per week, gender, race and education level) and firm characteristics (multinational status, the share of unionized workers, firm age, log of employment and industry effects). Finally, we decompose the overall management practices index into the personnel and operations indices (z-people and z-operations) described in 2.2. Table II presents the results. Consistent with the figures, we carry out this exercise separately for managers (Panel A) and for production workers (Panel B).

Analogously to Figure 2, Column (1) uses a top-quintile indicator for worker quality and structured-practices indicator for $MGMT$. Firms with structured management are 15 percentage points more likely to have a manager from the top quintile of worker quality and 11 percentage points more likely to have a production worker from the top quintile. Switching to

[22] We index worker characteristics by i and j because all worker characteristics are reported by the employer and are subject to change when workers change jobs (Cornwell et al. 2017).

$WorkerQuality$ as the dependent variable, Column (2) shows that managers in firms with structured management are almost half a standard deviation higher quality, while production workers are of just under a third of a standard deviation higher quality. Column (3) replaces structured-practices indicator with the overall management practices index (z-management). This specification suggests that a standard deviation increase in the management index is associated with a quarter (.250) of a standard deviation increase in manager quality and about one-fifth (.185) of a standard deviation increase in production worker quality. Note that it would take a half standard deviation improvement in management practices to move the median firm into the structured practices classification.

Columns (4) and (5) examine the degree to which the effect of management practices on quality is mediated through worker and firm characteristics. Worker characteristics explain about 60% for both managers and production workers (Column (4)), reducing the estimated coefficients of z-management to .107 and .084. This suggests that structured management practices produce higher quality workforces in large part by hiring and retaining on the basis of observable predictors of worker quality, such as education and experience. Adding firm characteristics further attenuates the management index coefficient estimates – to .061 for managers and 0.051 for production workers (Column (5)). Hence, part of the relationship between management and worker quality also arises from high-quality workers sorting into firms with particular characteristics associated with structured management, for instance, toward larger, multinational firms. While worker and firm characteristics account for about three-quarters of the overall management effect on worker quality, a significant role for structured practices remains. Firms with high management scores given their observed characteristics tend to employ workers of high quality given their observed characteristics.

Ideally, we would like to to determine whether structured management practices actually enable firms to select higher quality workers more effectively. Unfortunately, this is not possible with our data because we cannot rule out sorting on the basis of other unobserved worker or firm characteristics. However, if structured practices do drive the selection of higher quality workers, the process should operate primarily through personnel management. When we decompose the overall management-practices index into the personnel and operations indices, we find that the variation loads roughly evenly onto z-people and z-operations for managers, and entirely onto z-people for production workers. For managers, the estimated coefficients of z-people and z-operations are .030 and .037, both of which are significant at the 10% level. For production workers, on the other hand, the estimated coefficient of z-people is .055, which is statistically significant, while the z-operations coefficient estimate is essentially zero. These results are consistent with a model in which structured personnel management practices drive the recruitment and retention of high-quality production workers, while high-quality managers are attracted to firms with better overall management practices.

The relationships presented in Table II are new and intuitive. They suggest that structured personnel practices are important for building a stock of high-quality *production* workers. This makes sense, as many of the personnel management practices measured by WMS are oriented toward production workers. As production workers are not in charge of setting the managerial practices in the firm, causality should run from practices to better production-worker quality. For managers, both operations and people management practices are similarly correlated with manager quality. It could be that more structured operations management practices facilitate matches with better managerial talent, as better managers prefer working in environments where there are well-defined targets, accountability, and performance evaluation policies in place. On the other hand, it could be that the causality runs the other way, with higher quality managers implementing more structured operations practices. Both explanations are likely correct, but determining which channel is most important is a subject for future research.

4 Conclusion

A firm's management practices can be viewed as a type of technology that can influence its productivity. An important channel of influence is workforce quality. In this paper, we provide the most complete examination to date of how differences in managerial technology — the structures and processes in place at the firm — contribute to differences between firms in manager and production-worker quality.

Key to our analysis is our Brazilian empirical setting, which links administrative information on firms and their employees with empirically vetted measures of management practices and productivity data. With our analysis sample, we can uniquely observe the flow components of workforce construction (hiring, retention and firing), detailed worker employment records (from which we infer occupation-specific worker quality), a firm's managerial structure and measures of inputs and output.

We show that firms with structured management practices — formal processes that transcend individual managers — consistently hire and retain a larger share of the best managers and production workers, and are more discerning when dismissing employees. When we distinguish between personnel and operations practices, we find that both are roughly equally important for manager quality, but production-worker quality is related only to personnel practices. This follows from personnel management practices being specifically designed for evaluating and motivating production workers, while the operations practices are primarily concerned with general production activities overseen by managers.

While the findings we report are new and important, we concede our inability to make strong causal claims about the relationship between management practices and the quality of a firm's workforce. This problem afflicts most studies that use survey data on management practices, and ours is no exception. On balance, we believe the evidence is consistent with a model in which structured personnel practices lead to the selection and retention of high-quality production workers, while high-quality managers are attracted to firms with better overall management practices. Additionally, our measure of worker quality may not completely reflect the ways in which firms rank workers for purposes of recruiting. We rely on the fact that worker quality, as we define it, correlates positively with firm productivity. In doing so, we obtain results that simultaneously validate the our measures of management practices by showing the stated behavior of firm managers is consistent with the employment decisions observed in the administrative data.

Our analysis opens several important avenues for future work. First, we find that about half of the relationship between the use of structured management practices and worker quality is explained by observable characteristics. Do structured management practices commit firms to screen more effectively on such characteristics, overcoming the sort of managerial biases documented in Hoffman et al. (2018). In a similar vein, do structured practices help firms develop stronger signals of worker productivity, thereby limiting statistical discrimination?

Second, there is scope to say more about the role of managers in the adoption of structured management practices. We have repeated observations on some WMS firms, many of which change management practices between 2008 and 2013. Using this panel feature of our data, we can examine how workforce quality varies with those changes. The panel will allow us to track the transmission of management-practice effects across firms that have employed the same manager.

Finally, we have only shown that management practices affect the average quality of a firm's managers and production workers. What role do management practices play in environments where team production is important? Do structured practices aid in the assembly of the right combination of complementary skills? Or, are firms with complex production processes requiring teams of workers with diverse skills more likely to adopt structured practices? Our new dataset opens the possibility of answering such questions in future work.

References

Abowd, J. M., Kramarz, F. and Margolis, D. N. (1999). High wage workers and high wage firms, *Econometrica* **67**(2): 251–333.

Abowd, J. M., Kramarz, F., Pèrez-Duarte, S. and Schmutte, I. M. (2018). Sorting between and within industries: A testable model of assortative matching, *Annals of Economics and Statistics* (129): 1–32.

Abowd, J. M., McKinney, K. L. and Schmutte, I. M. (2017). Modeling endogenous mobility in earnings determination, *Journal of Business & Economic Statistics* **0**(ja): 0–0.

Alvarez, J., Benguria, F., Engbom, N. and Moser, C. (2018). Firms and the decline in earnings inequality in Brazil, *American Economic Journal: Macroeconomics* **10**(1): 149–89.

Bandiera, O., Guiso, L., Prat, A. and Sadun, R. (2015). Matching firms, managers, and incentives, *Journal of Labor Economics* **33**(3): 623 – 681.

Becker, G. S. (1973). A theory of marriage: Part I, *Journal of Political Economy* **81**(4): 813–846.

Bender, S., Bloom, N., Card, D., Van Reenen, J. and Wolter, S. (2018). Management practices, workforce selection, and productivity, *Journal of Labor Economics* **36**(S1): S371–S409.

Bloom, N., Brynjolfsson, E., Foster, L., Jarmin, R., Patnaik, M., Saporta-Eksten, I. and Van Reenen, J. (2019). What drives differences in management practices?, *American Economic Review* **109**(5): 1648–83.

Bloom, N., Eifert, B., Mahajan, A., McKenzie, D. and Roberts, J. (2013). Does management matter? Evidence from India, *The Quarterly Journal of Economics* **128**: 1–51.

Bloom, N., Lemos, R., Sadun, R. and Reenen, J. V. (2015). Does management matter in schools?, *The Economic Journal* **125**: 647–674.

Bloom, N., Lemos, R., Sadun, R., Scur, D. and Van Reenen, J. (2014). The new empirical economics of management, *Journal of the European Economic Association* **12**(4).

Bloom, N., Sadun, R. and Van Reenen, J. (2016). Management as a technology?, *Working Paper 22327*, National Bureau of Economic Research.

Bloom, N. and Van Reenen, J. (2007). Measuring and explaining management practices across firms and countries, *The Quarterly Journal of Economics* **122**(4): 1351–1408.

Card, D., Cardoso, A. R., Heining, J. and Kline, P. (2018). Firms and labor market inequality: Evidence and some theory, *Journal of Labor Economics* **36**(S1): S13–S70.

Card, D., Cardoso, A. R. and Kline, P. (2016). Bargaining, sorting, and the gender wage gap: Quantifying the impact of firms on the relative pay of women, *The Quarterly Journal of Economics* **131**(2): 633.

Card, D., Heining, J. and Kline, P. (2013). Workplace heterogeneity and the rise of West German wage inequality, *Quarterly Journal of Economics* **128**(3): 967–1015.

Cornwell, C., Rivera, J. and Schmutte, I. M. (2017). Wage discrimination when identity is subjective: Evidence from changes in employer-reported race, **52**(3): 719.

Eeckhout, J. and Kircher, P. (2011). Identifying sorting–in theory, *Review of Economic Studies* **78**: 872–906.

Hoffman, M., Kahn, L. B. and Li, D. (2018). Discretion in hiring, *The Quarterly Journal of Economics* **133**(2): 765–800.

Iranzo, S., Schivardi, F. and Tosetti, E. (2008). Skill dispersion and firm productivity: An analysis with matched employer-employee data, *Journal of Labor Economics* **26**: 247–285.

Lavetti, K. and Schmutte, I. M. (2018). Estimating compensating wage differentials with endogenous job mobility, *Working paper*, University of Georgia.

Lemos, R. and Scur, D. (2019). The ties that bind: implicit contracts and management practices in family-run firms.

Oyer, P. and Schaefer, S. (2011). Personnel economics: Hiring and incentives, Vol. 4 of *Handbook of Labor Economics*, Elsevier, pp. 1769 – 1823.

Shimer, R. (2005). The assignment of workers to jobs in an economy with coordination frictions, *Journal of Political Economy* **113**: 996.

Song, J., Price, D. J., Guvenen, F., Bloom, N. and von Wachter, T. (2019). Firming up inequality, *The Quarterly Journal of Economics* **134**(1): 1–50.

Sorkin, I. (2018). Ranking firms using revealed preference, *The Quarterly Journal of Economics* **133**(3): 1331–1393.

Tables and Figures

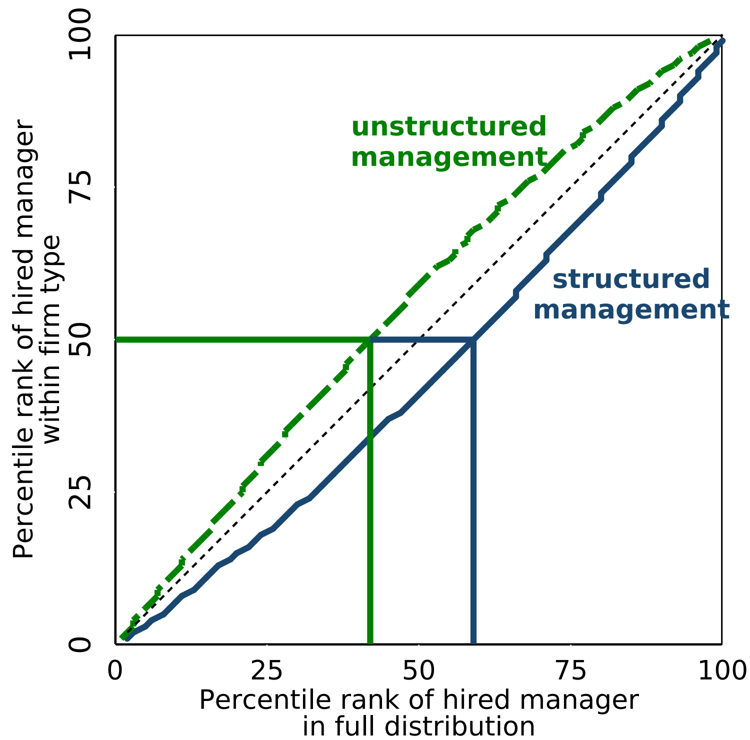
Table I: Production function estimates: WMS-RAIS-PIA matched data

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-AKM firm effect						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

*Standard errors in parentheses. Significance stars omitted.
Notes: Where indicated, the estimated models include factor inputs (the log of capital, raw materials, and the number of employees), industry dummies, and ownership type (whether the firm is a family-owned). The data are prepared by merging the PIA industrial survey to the WMS-RAIS matched sample of firms described in Section 2.2.

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

(a) Managers



(b) Production workers

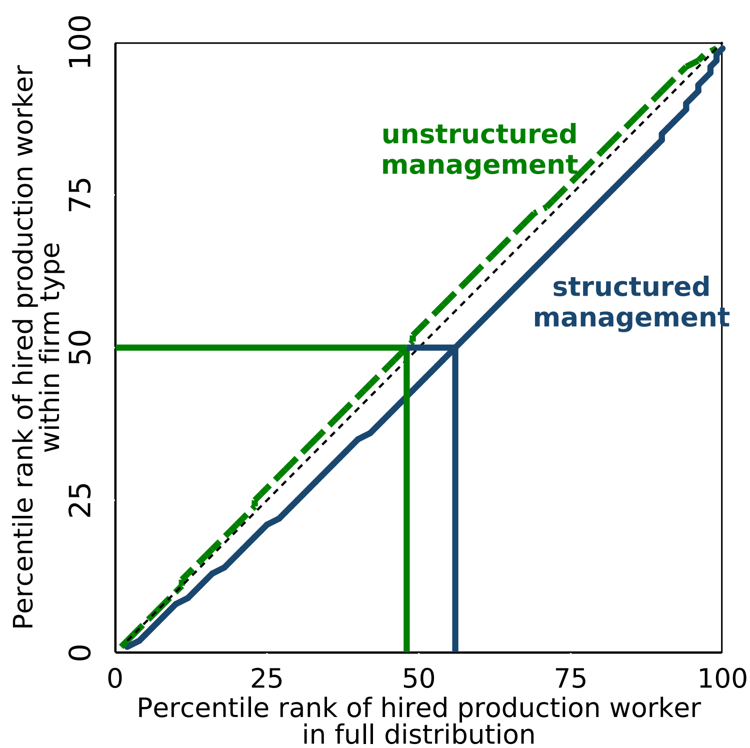
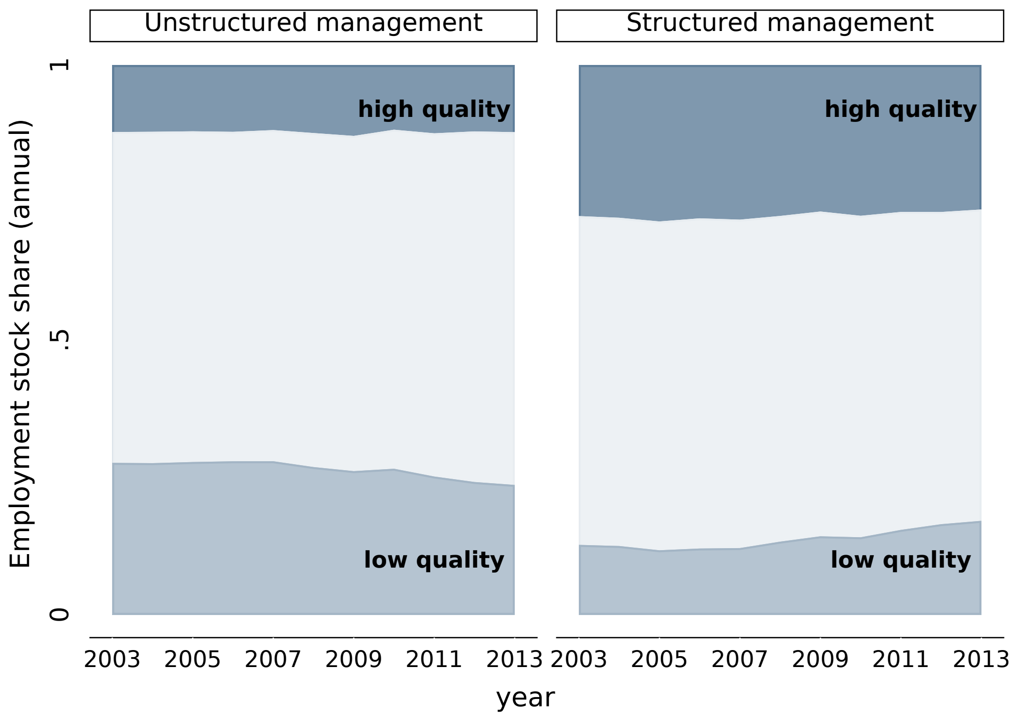


Figure 2: Quality distribution of managers and production workers in continuing jobs

(a) Managers



(b) Production workers

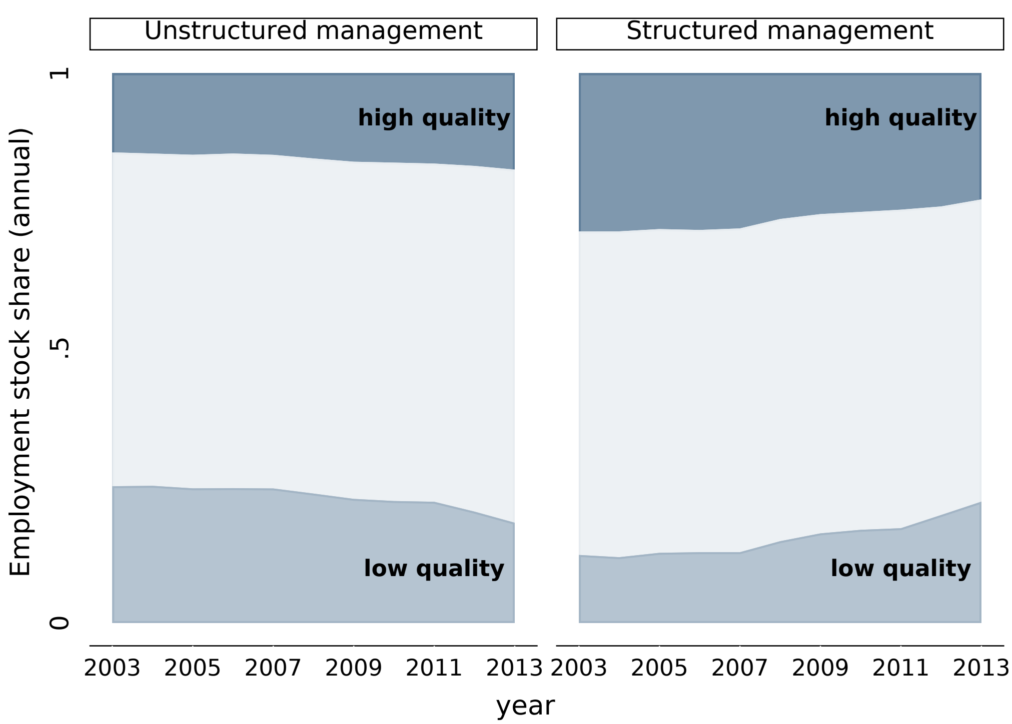


Figure 3: Firing rates for managers and production workers by worker quality

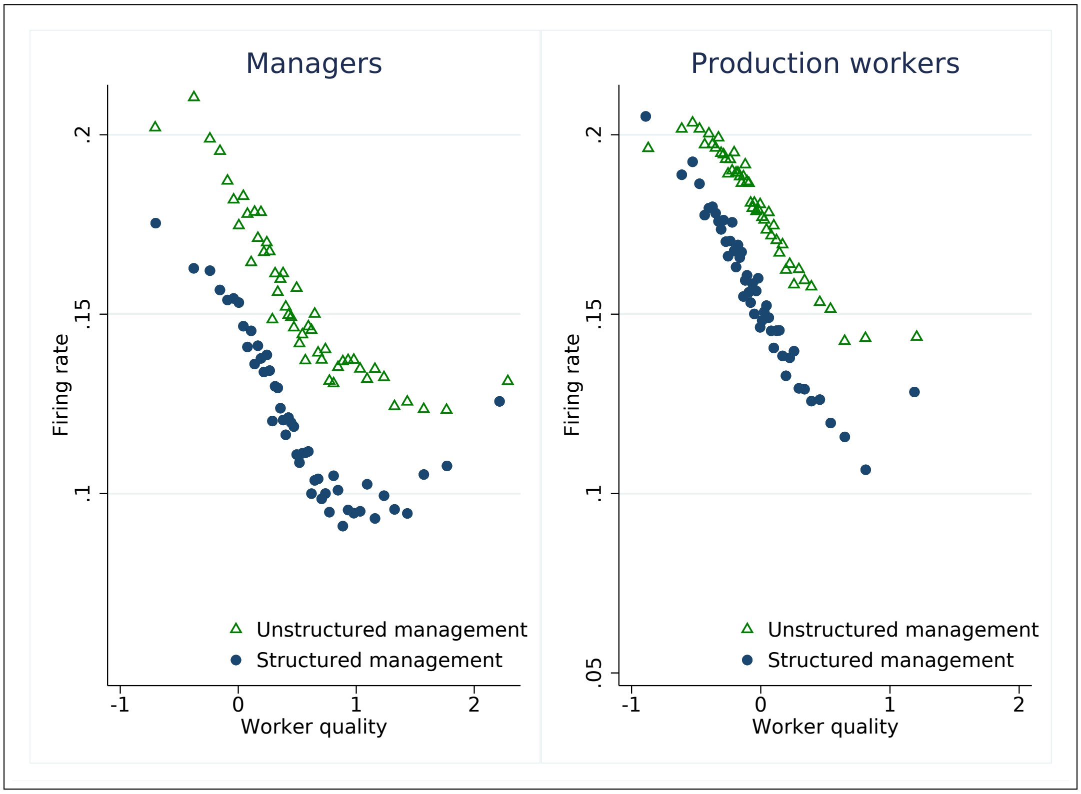


Table II: Management practices and worker quality: Employees of WMS firms in 2003–2013

	Panel A: Managers					
	(1) worker in top quintile	(2) z-worker quality	(3) z-worker quality	(4) z-worker quality	(5) z-worker quality	(6) z-worker quality
Management indicator						
Structured practices = 1	0.150	0.482				
	[0.000]	[0.000]				
	(0.021)	(0.057)				
Management indices						
z-management			0.250	0.107	0.061	
			[0.000]	[0.000]	[0.000]	
			(0.028)	(0.012)	(0.012)	
z-people						0.030
						[0.077]
						(0.017)
z-operations						0.037
						[0.050]
						(0.019)
Year controls	Y	Y	Y	Y	Y	Y
Worker controls				Y	Y	Y
Firm controls					Y	Y
Observations	239915	239915	239915	239915	239915	239915
R^2	0.0356	0.0820	0.0973	0.554	0.559	0.559
# Firms	724	724	724	724	724	724

	Panel B: Production workers					
	(1) worker in top quintile	(2) z-worker quality	(3) z-worker quality	(4) z-worker quality	(5) z-worker quality	(6) z-worker quality
Management indicator						
Structured practices = 1	0.105	0.315				
	[0.000]	[0.000]				
	(0.023)	(0.068)				
Management indices						
z-management			0.185	0.084	0.051	
			[0.000]	[0.000]	[0.009]	
			(0.030)	(0.017)	(0.020)	
z-people						0.055
						[0.069]
						(0.030)
z-operations						0.002
						[0.962]
						(0.033)
Year controls	Y	Y	Y	Y	Y	Y
Worker controls				Y	Y	Y
Firm controls					Y	Y
Observations	897926	897926	897926	897926	897926	897926
R^2	0.0169	0.0454	0.0567	0.399	0.403	0.404
# Firms	725	725	725	725	725	725

* p-values in square brackets, standard errors in parentheses.
Notes: Analysis sample includes all employees engaged in WMS firms between 2003–2013. We keep the variable names as "z-worker quality" to underscore that the measure was estimated using the full sample, and the regressions are simply done on the sub-sample of managers and workers separately, without re-estimating the values. The dependent variable in Column (1) is an indicator for whether the worker is in the top quintile of the worker quality distribution. The dependent variable in all other columns is our worker quality measure (estimated AKM person effect, θ) standardized relative to the worker population. The explanatory variables are standardized measures of either the overall average management score, or the average using only the people or operations management questions from the WMS. The set of worker controls includes age, number of hours worked per week, gender, race and education level. The set of firm controls includes multinational status, the share of unionized workers, firm age and log of firm size (number of employees), and industry effects.

Appendix for Cornwell, Schmutte, and Scur "Building a productive workforce: the role of structured management practices," August 5, 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.[23] 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 managerial and non-managerial 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).[24] 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.

[23]Because individual characteristics are reported by the employer, they can change as workers move from job to job. Cornwell, Rivera and Schmutte (2017) 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.

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

Many of the establishments in RAIS do not have any workers in occupations classified as managerial according to the rule above. However, a third digit of '0' in the occupation 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.

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 contract types 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 Data for Estimating the AKM Model

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.

B Appendix Tables and Figures

Table B.1: Summary statistics for matched WMS-RAIS firms

	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
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: The sample 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. 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 B.2: AKM decomposition of variance in log wages: RAIS 2003–2013

	Variance Component	Share of Total
Total Variance of Log Wage	0.472	100.0
Variance Component:		
Var(Worker Effect θ)	0.235	49.8%
Var(Establishment Effect ψ)	0.088	18.5%
$Var(X\beta)$	0.046	9.7%
Var(Residual)	0.044	9.2%
$2 \times Cov(\theta, \psi)$	0.095	20.2%
$2 \times Cov(X\beta, \theta)$	-0.034	-7.3%
$2 \times Cov(X\beta, \psi)$	$-.001$	$-.00\%$

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

Table B.3: 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)

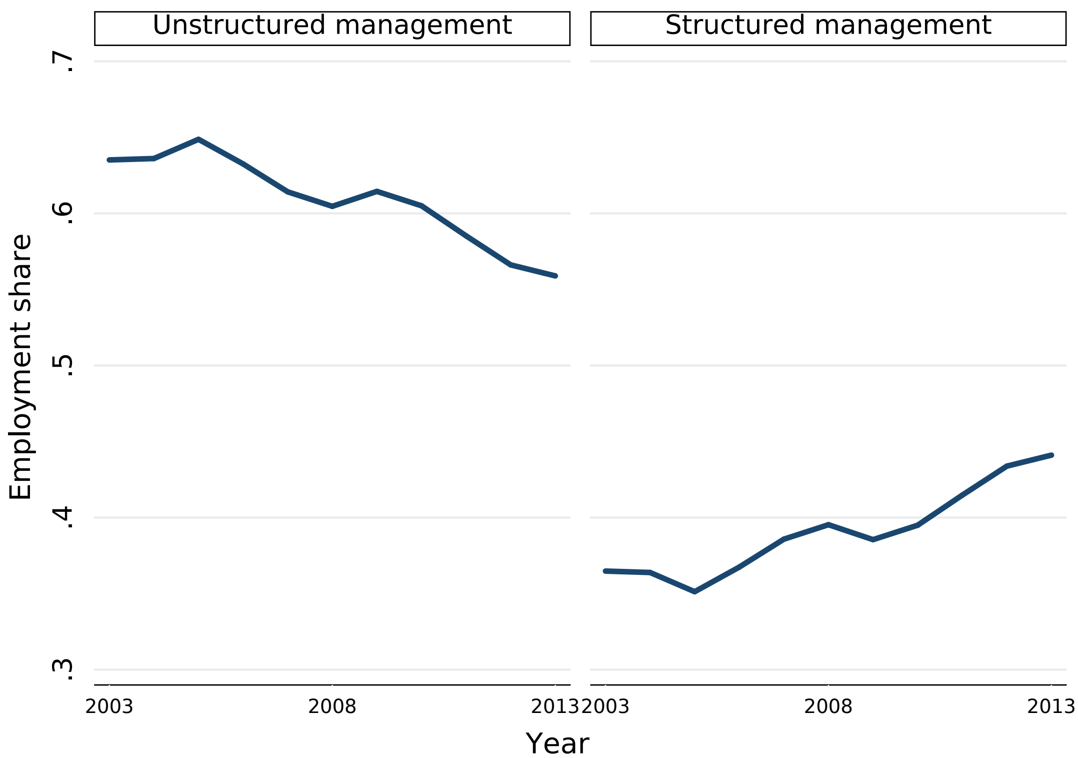


Figure B.1: Employment shares in structured and unstructured firms

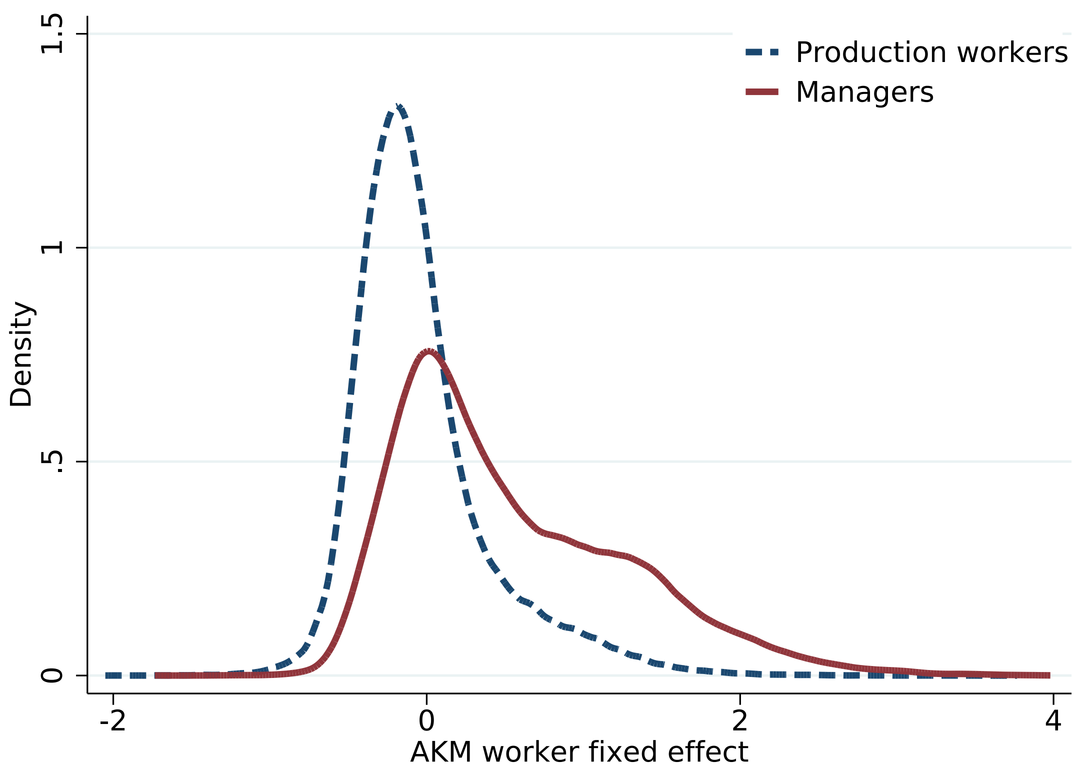


Figure B.2: Distribution of AKM Worker Fixed Effect for Managers and Nonmanagers

CENTRE FOR ECONOMIC PERFORMANCE
Recent Discussion Papers

1643	Paul Dolan Georgios Kavetsos Christian Krekel Dimitris Mavridis Robert Metcalfe Claudia Senik Stefan Szymanski Nicolas R. Ziebarth	Quantifying the Intangible Impact of the Olympics Using Subjective Well-Being Data
1642	Xavier Jaravel Erick Sager	What are the Price Effects of Trade? Evidence from the US and Implications for Quantitative Trade Models
1641	Johannes Boehm Jan Sonntag	Vertical Integration and Foreclosure: Evidence from Production Network Data
1640	Teodora Borota Fabrice Defever Giammario Impullitti	Innovation Union: Costs and Benefits of Innovation Policy Coordination
1639	Monica Langella Alan Manning	Residential Mobility and Unemployment in the UK
1638	Christos Genakos Mario Pagliero	Competition and Pass-Through: Evidence from Isolated Markets
1637	Holger Breinlich Elsa Leromain Dennis Novy Thomas Sampson	Voting With Their Money: Brexit and Outward Investment by UK Firms
1636	Maria Sanchez-Vidal	Retail Shocks and City Structure
1635	Felipe Carozzi Sefi Roth	Dirty Density: Air Quality and the Density of American Cities

1634	Nicholas Bloom John Van Reenen Heidi Williams	A Toolkit of Policies to Promote Innovation
1633	Stephan E. Maurer Ferdinand Rauch	Economic Geography Aspects of the Panama Canal
1632	Nikhil Datta	Willing to Pay for Security: A Discrete Choice Experiment to Analyse Labour Supply Preferences
1631	Gabriel M. Ahlfeldt Volker Nitsch Nicolai Wendland	Ease Versus Noise: Long-Run Changes in the Value of Transport (Dis)amenities
1630	Grace Lordan Alistair McGuire	Widening the High School Curriculum to Include Soft Skill Training: Impacts on Health, Behaviour, Emotional Wellbeing and Occupational Aspirations
1629	Per-Anders Edin Tiernan Evans Georg Graetz Sofia Hernnäs Guy Michaels	Individual Consequences of Occupational Decline
1628	Pawel Bukowski Filip Novokmet	Between Communism and Capitalism: Long-Term Inequality in Poland, 1892-2015
1627	Thomas Sampson	Technology Gaps, Trade and Income
1626	Andrea Ichino Martin Olsson Barbara Petrongolo Peter Skogman Thoursie	Economic Incentives, Home Production and Gender Identity Norms

The Centre for Economic Performance Publications Unit
Tel: +44 (0)20 7955 7673 Email info@cep.lse.ac.uk
Website: http://cep.lse.ac.uk Twitter: @CEP_LSE