Management Practices, Workforce Selection, and Productivity

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We study the relationship among productivity, management practices, and employee ability using German data combining management practices surveys with employees' longitudinal earnings records. Including human capital reduces the association between productivity and management practices by 30%–50%. Only a small fraction is accounted for by the higher human capital of the average employee at better-managed firms. A larger share is attributable to the human capital of the highest-paid workers, that is, the managers. A similar share is mediated through the pay premiums offered by better-managed firms. We find that better-managed firms recruit and retain workers with higher average human capital.

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I. Introduction

In a typical four-digit manufacturing industry in the United States, establishments at the 90th percentile of total factor productivity (TFP) are about twice as productive as those at the 10th percentile (Syverson 2004, 2011). These very large differences in productivity between establishments are highly persistent, contributing to significant disparities in economic performance over time and across countries.[1] They are also central to a growing body of theoretical research in macroeconomics, industrial organization, and trade. In labor economics, many studies find a strong connection between firm performance and average wages (see Van Reenen 1996 or, for a review, Card et al. 2018, in this issue), suggesting that differences in firm productivity could also help explain cross-sectional wage inequality. Furthermore, several recent papers attribute a significant fraction of the growth in wage inequality across individuals to growing differences between establishments.[2] Since wage differences between firms are closely correlated with performance differences, understanding what drives the dispersion in establishment performance could help us understand why inequality has risen so sharply in recent decades.

As suggested by the seminal work of Ichniowski, Shaw, and Prennushi (1997), a key correlate of plant-level productivity is the adoption of advanced management practices, including employee monitoring, financial incentives, and modern inventory control and workflow techniques.[3] Bloom,

CESifo (Center for Economic Studies and Leibniz-Institut für Wirtschaftsforschung an der Universität München) in Berlin, GRAPE (Group for Research in Applied Economics), Harvard, National Bureau of Economic Research, Stanford, and Zentrum für Europäische Wirtschaftsforschung (ZEW), Mannheim. The Economic and Social Research Council, the European Research Council, the Kauffman Foundation, and the Alfred Sloan Foundation have provided financial support. We received no funding from the global management consultancy firm (McKinsey) we worked with in developing the survey tool. Our partnership with Pedro Castro, Stephen Dorgan, and John Dowdy has been particularly important in the development of the project. We are grateful to Daniela Scur and Renata Lemos for excellent research assistance. Any opinions expressed in this paper are those of the authors and do not necessarily reflect the views of the Deutsche Bundesbank or the Institute for Employment Research. Contact the corresponding author, John Van Reenen, at j.vanreenen@lse.ac.uk. Information concerning access to the data used in this paper is available as supplementary material online.

[1] For example, Bailey, Hulten, and Campbell (1992), Hsieh and Klenow (2009), and Bartelsman, Haltiwanger, and Scarpetta (2013).

[2] See Card, Heining, and Kline (2013) for Germany; Song et al. (2015) or Barth et al. (2016) for the United States; and Faggio, Salvanes, and Van Reenen (2010) for the United Kingdom.

[3] In a prescient precursor of this paper, Ichniowski et al. (1997) conduct a robustness test of their productivity regressions where they include multiple measures of managerial ability on the right-hand side, such as a quadratic in tenure of the line manager and site's human resource (HR) manager or, even more rigorously, a full suite of line and HR manager fixed effects. They find that their HR management

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Sadun, and Van Reenen (2016) construct an index of advanced practices that they interpret as "managerial capital" and argue that it can account for on average a fifth of the 90-10 firm-level spread of TFP within countries and a third of the productivity gap between the United States (the highest-scoring country) and 33 other nations. At the very micro level, Bloom et al. (2013) find a large causal role for such management practices in a field experiment with Indian textile plants.

While some management practices can directly affect productivity, many others—like monitoring, goal setting, and use of incentives—are mediated through employee decision-making and effort. If advanced management practices are complementary with higher-ability employees, as seems plausible, then one would expect firms that use these practices to systematically alter both the skill composition of their workforce and the structure of their pay system, potentially leading to a rise in differential sorting of higher- and lower-skilled workers to more and less productive workplaces.[4]

In this paper, we formally investigate the extent to which management—as proxied by an index of adoption of advanced management practices—influences measured productivity through the channels of workforce selection and pay. Our empirical analysis exploits a unique database of middle-sized German manufacturing plants included in the World Management Survey (WMS; discussed in Bloom and Van Reenen 2007 and in Bloom et al. 2014), linked to employee earnings records from the Integrated Employment Biographies (IEB) of the Institute for Employment Research. The WMS provides detailed survey data on management practices and (through links to the Orbis database) firm-level financial information. The IEB provides longitudinal data on earnings of workers who were employed at these plants, including their pay at previous or subsequent employers, which we use to estimate person-specific measures of earnings capacity for each worker (i.e., worker effects) and plant-specific pay premiums for each workplace (i.e., establishment effects). The worker effects allow us to measure the quality of workers' skills at each plant as well as the relative quality of different employee subgroups. The pay premiums provide a summary measure of the financial incentive system at each plant.

Analyzing these data through the lens of a simple model of firm-specific productivity, we reach three main conclusions. First, plants with higher management scores have higher average worker skills. Plant-specific measures of observed skills (e.g., the fraction of workers with a college degree)

system variable is robust to the inclusion of these, and the coefficients are little changed. We will also find that our management practice variables have a robust correlation with firm productivity, but the coefficient will be strongly attenuated when conditioning on the quality of individual managerial human capital.

[4] Milgrom and Roberts (1990) argue that modern manufacturing processes and organizational methods are highly complementary, leading firms to adopt clusters of practices.

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and of overall skills (as recovered from the person effects in a two-way fixed effects model) have a strong correlation with measured productivity. Nevertheless, only a limited fraction of the overall association of management practices with productivity is mediated through average worker skills. A more important channel is though the skills of the top quartile of employees at a plant—a group that we interpret as the managers. Higher average skill for this group has an independent influence on plant-level productivity (controlling for average worker skills at the plant) and is positively correlated with higher management practice scores. Overall, about one-sixth of the association between productivity and higher management scores is mediated through the average skill level of managers.

A second finding is that plants with higher management scores pay higher wages relative to the market as a whole, controlling for the quality of their workforce. Higher pay premiums account for another 13% of the association of better management practices with productivity.[5]

A third finding is that better-managed firms are able to build up a superior stock of employees through selective hiring and attrition. In particular, examining job inflows and outflows at the plants in our sample, we find that those with higher management scores are more likely to recruit higher-ability workers (measured by the permanent component in their earnings) and are less likely to lay off or fire the highest-skilled workers.

Our paper contributes to at least four existing literatures. First, as noted above we contribute to the growing literature on firm heterogeneity and economic performance (e.g., the survey by De Loecker and Goldberg 2014). Second, we try to understand the causes of the heterogeneity in management practices and the link to workers' skills (e.g., Feng and Valero 2015; Lemos and Scur 2015; Bloom et al. 2016). Third, our finding that management practices are more than simply the sum of the "atoms" of human capital of managers links to work on corporate culture by economists and management scholars (e.g., O'Reilly 1989; Guiso, Sapienza, and Zingales 2013, 2015). Finally, we contribute to the literature on the importance of managers for firm performance (e.g., Bertrand and Schoar 2003; Bennedsen et al. 2007).

The structure of the paper is as follows. Section II describes our empirical framework, Section III the data, and Section IV the results. Some concluding comments are offered in Section V. The online appendixes contain more details about the data and many additional specifications and robustness checks.

[5] In principle, some of this could reflect longer hours or higher levels of performance pay at well-managed firms, features we cannot directly observe in the IEB. However, controlling for these factors in the WMS suggests that this is not the main route.

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II. Empirical Models

A. Conceptual Framework

The classical approach to understanding productivity differences across firms or plants is "reductionist": after properly accounting for differences in capital and other nonlabor inputs per worker, any remaining difference in productivity at a given point in time is by definition a measure of the quality (and/or effort) of the workforce.[6] Lucas (1978) offers a more sophisticated version of this approach that accounts for firm heterogeneity. In his span-of-control model, the talent of the entrepreneur/chief executive officer (CEO) determines the productivity of the firm. More talented CEOs run larger (or more complex) firms, so the relationship between management and productivity boils down to the talent of the CEO.

Although the Lucas (1978) model is powerful and parsimonious, we view the focus on the CEO as overly narrow. Many iconic firms, such as Toyota, GE, IBM, and Lincoln Electric, remain successful even after their CEO dies and/or all of the original managers have left the firm. Management scholars sometimes refer to this as firm "capability" or "corporate culture." Building on this idea, we view the quality of the workforce, the pay strategy of the firm, and the adoption of advanced management practices as jointly endogenous choices that reflect the underlying quality of the management of the firm. We ask to what extent the association between productivity and advanced management practices reflect the impact of higher human capital of all employees at firms that adopt these practices or the higher human capital of the managers.

As a framework for our empirical analysis, we adopt a standard production function approach that incorporates variation across firms in both TFP and the quality of labor. Specifically, suppose that the value of the output of firm j in period t, Y_{jt}, depends on inputs of nonmanagement labor N_{jt}, management labor M_{jt}, intermediate inputs I_{jt}, and capital K_{jt} through a constant returns-to-scale production function:

$$Y_{jt} = \theta_{jt} f\left(Q_{Njt} N_{jt}, Q_{Mjt} M_{jt}, I_{jt}, K_{jt}\right), \tag{1}$$

where θ_{jt} represents TFP in period t and Q_{Njt} and Q_{Mjt} are, respectively, the productivity levels of nonmanagement workers and managers at the firm. We think of better-managed firms as potentially selecting different types of managers and nonmanagement workers and offering different incentive packages—both of which could raise Q_{Mjt} and Q_{Njt}. We also think of these firms as adopting practices and management systems that directly increase θ_{jt}.

[6] Comparisons of productivity are also affected by differences in technology. See Jorgenson (1991) for a brief history of productivity measurement and growth accounting.

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Using a first-order approximation of the function $f(.)$ and the assumption that marginal products of the four inputs are equal to their factor prices, the log of output can be expressed as

$$\begin{aligned}\log Y_{jt} = {} & s_0 + s_N \log N_{jt} + s_M \log M_{jt} + s_I \log I_{jt} + s_K \log K_{jt} \\ & + s_N \log Q_{Njt} + s_M \log Q_{Mjt} + \log \theta_{jt} + \epsilon_{jt},\end{aligned} \tag{2}$$

where s_0 is a constant; s_N, s_M, s_I, and s_K are the cost shares of nonmanagement labor, management labor, intermediate inputs, and capital, respectively; and ϵ_{jt} is an approximation error.[7] If the employment share of managers in the workforce is approximately constant across firms (as we implicitly assume in our empirical analysis below), this expression can be usefully simplified.[8] Letting $L_{jt} = N_{jt} + M_{jt}$ represent total employment, letting $s_L = s_M + s_N$ represent the cost share of labor inputs, and defining Q_{jt} as the geometric average of the productivity levels of managers and nonmanagers,

$$Q_{jt} \equiv \left[\left(Q_{Njt}\right)^{S_N} \left(Q_{Mjt}\right)^{S_M} \right]^{1/S_L}. \tag{3}$$

Equation (2) can be rewritten as

$$\begin{aligned}\log Y_{jt} = {} & s_0' + s_L \log L_{jt} + s_I \log I_{jt} + s_K \log K_{jt} \\ & + s_L \log Q_{jt} + \log \theta_{jt} + \epsilon_{jt},\end{aligned} \tag{2'}$$

where $s_0' = s_0 + s_N \log(1 - m) + s_M \log m$ and m is the employment share of managers. Notice that (to first order) the appropriately defined average quality measure Q_{jt} fully captures variation in the relative productivity of both management and nonmanagement labor inputs.

B. Management and Productivity

To assess the effects of workforce quality on firm productivity, we need to measure the skill composition of the workforce. The standard approach to measuring labor quality, pioneered by Dennison (1962), is to classify workers into subgroups based on observed characteristics (e.g., by white-collar/blue-collar status or education) and control for the shares of workers in each group. A limitation of this approach is that observed characteristics explain only a small share of the variation in wages across workers or firms, suggesting that there may be a lot of unobserved heterogeneity in the pro-

[7] Note that the s coefficients in this equation (including both the constant share and the factor share) potentially vary with characteristics of the firm, such as industry and size. In our models below, we control for many observed characteristics in recognition of this fact.

[8] Although we have some rough indicators of the proportion of managers in firms, different firms tend to define whether an employee is a "manager" in different ways, so we did not want to rely on this variable.

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ductivity of the workers at different firms. Moreover, the standard approach cannot address the possible impact of wage-based incentives on the productivity of labor.

As an alternative, we build on the simple framework developed by Abowd, Kramarz, and Margolis (1999)—the AKM model—which decomposes wages into worker- and establishment-specific components. Specifically, Abowd et al. (1999) assume that the log of the wage received by worker i in period t can be decomposed as

$$\log w_{it} = \eta_i + \psi_{J(i,t)} + x'_{it}\beta + r_{it}, \tag{4}$$

where η_i is an individual-specific pay component, $x'_{it}\beta$ is a linear index of time-varying individual characteristics (incorporating the effects of experience and calendar time),[9] $J(i, t)$ is an index function that gives the identity of the workplace of individual i in period t, ψ_j is a time-invariant wage premium paid to all workers at workplace j, and r_{it} is a residual pay component. In this model, η_i can be interpreted as a measure of worker i's human capital, incorporating potentially observable factors (like education) as well as unobserved attributes (like cognitive ability or ambition) that raise or lower the worker's productivity regardless of where they work. The pay premium ψ_j can be interpreted as a measure of the financial incentives associated with continued employment at the firm. Abowd et al. (1999) show that under a set of orthogonality assumptions the worker-specific and plant-specific pay components in equation (4) can be estimated without bias using ordinary least squares.[10]

Card et al. (2013) show that the AKM model provides a relatively good approximation of the structure of wages in Germany, with $\bar{R}^2$ statistics of around 90%. They also show that more and less skilled workers receive approximately the same proportional wage premiums at a given establishment—consistent with the simple additive structure of equation (4). Moreover, they argue that the assumptions needed for unbiased estimation of the worker and establishment effects in the AKM model appear to be roughly satisfied in Germany. In particular, the "match-specific" component of the wage residual r_{it} is small in magnitude and uncorrelated with the direction of mobility between firms. Given these findings and the fact that we use the same IEB wage data in our analysis, we use the worker and establishment

[9] We normalize the index $x'_{it}\beta$ to be equal to 0 for individuals of age 40, so η_i measures the permanent individual component of wages at roughly the peak of the lifecycle wage profile.

[10] The most controversial implication of these assumptions is that the residual component of wages is uncorrelated with the entire sequence of firm identifiers in a worker's job history. As discussed by Card et al. (2013), this rules out mobility based on a "match-specific" component of pay.

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effects estimated by Card et al. (2013) to summarize different workers' abilities and the strength of the financial incentives offered at different workplaces.[11]

Specifically, we use the average of the estimated worker effects for full-time employees at a given establishment ($\overline{\hat{\eta}}_j$) as a simple proxy for the average human capital of workers at the plant and the estimated wage premium for full time male workers at the establishment $\hat{\psi}_j$ as a proxy for the size of the financial incentives offered by the firm.[12] We assume that the average productivity of labor inputs at the firm is affected by both factors as well as by the adoption of advanced management practices (indexed by measure Λ_j):

$$\log Q_{jt} = \rho_0 + \rho_1 \overline{\hat{\eta}}_j + \rho_2 \hat{\psi}_j + \rho_3 \Lambda_j + \upsilon_{jt}. \tag{5}$$

Given the scaling of the person effects in equation (4), one might expect that $\rho_1 \approx 1$. Since these effects are measured with error, however, and are unavailable for part-time workers and trainees, we expect some attenuation in the estimated value of ρ_1.[13] The magnitude of the coefficient ρ_2 is less clear. If a firm that pays a 10% higher wage premium is rewarded with 10% higher productivity, then $\rho_2 = 1$. If, on the other hand, higher or lower wage premiums have no effect on productivity, then $\rho_2 = 0$.

TFP may be affected by the ability of the managers at a firm as well as by the firm's adoption of advanced management practices. We assume that TFP (θ_{jt}) can be parameterized as

$$\log \theta_{jt} = \lambda_0 + \lambda_1 \overline{\hat{\eta}}_{Mj} + \lambda_2 \Lambda_j + \varphi_{jt}, \tag{6}$$

where $\overline{\hat{\eta}}_{Mj}$ is the mean value of the estimated person effects for the highest-paid workers at the firm, who we assume represent the managers of the firm. Combining equations (2′), (5), and (6) leads to the following model for output:

[11] Despite the apparent empirical success of the AKM framework, we note that the estimated firm effects are at best a crude summary of the pay policy of a given firm. Moreover, the estimation issues may be more difficult for certain types of firms—e.g., those that are undergoing a management turnaround during the sample period.

[12] Since the IEB data do not include information on hours, Card et al. (2013) limit their estimated models to full-time workers. More than 90% of West German males are full time, so this is not too restrictive. Among women, however, close to a third work part time. As a result of this fact (and the lower participation rate of females), the sample sizes underlying the estimates of Card et al. (2013) are about 80% larger for men than for women, leading to less measurement error in the male effects. For simplicity, we therefore use the establishment wage premiums for men.

[13] Card et al. (2013) estimate the AKM model using data for full-time workers between the ages of 20 and 60, so our average person effect estimates exclude part-time workers, trainees, workers in so-called minijobs, and those under 20 or over 60.

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$$\log Y_{jt} = s_0'' + s_L \log L_{jt} + s_I \log I_{jt} + s_K \log K_{jt} + \pi_1 \overline{\hat{\eta}}_j + \pi_2 \hat{\psi}_j + \pi_3 \overline{\hat{\eta}}_{Mj} + \pi_4 \Lambda_j + \epsilon'_{jt}, \tag{7}$$

where $\pi_1 = s_L\rho_1$, $\pi_2 = s_L\rho_2$, $\pi_3 = \lambda_1$, $\pi_4 = s_L\rho_3 + \lambda_2$, and $\epsilon'_{jt} = \epsilon_{jt} + s_L\upsilon_{jt} + \varphi_{jt}$. Equation (7) is a standard log-linear three-factor production function, augmented with four additional productivity factors: (1) a measure of the average quality of the plant's workforce ($\overline{\hat{\eta}}_j$), (2) a measure of the average wage premium received by workers at the firm ($\hat{\psi}_j$), (3) a measure of the average quality of managers at the firm ($\overline{\hat{\eta}}_{Mj}$), and (4) a measure of the use of advanced management practices (Λ_j).

Since the factor inputs are endogenous, we also estimate log TFP specification where we bring labor, capital, and intermediate inputs to the left-hand side of the equation:

$$\begin{aligned}\log \mathrm{TFP}_{jt} &\equiv \log Y_{jt} - s_L \log L_{jt} - s_I \log I_{jt} - s_K \log K_{jt} \\ &= s_0'' + \pi_1 \overline{\hat{\eta}}_j + \pi_2 \hat{\psi}_j + \pi_3 \overline{\hat{\eta}}_{Mj} + \pi_4 \Lambda_j + \epsilon'_{jt}.\end{aligned} \tag{8}$$

In our empirical analysis below, we compare estimates of equations (7) and (8) to estimates of similar "reduced-form" specifications that exclude the labor quality and wage premium measures and include only the management practices variable. If advanced management practices, higher workforce quality, and enhanced pay are complementary practices that tend to be adopted as a package by better-managed firms, then we expect the coefficient on advanced management practices to be larger in this alternative specification, reflecting an "omitted variable" bias. We also consider controlling for other factors that may influence productivity and workforce quality in equations (7) and (8), such as firm age, industry, ownership type, the degree of product market competition, and so on.

In addition to examining how the productivity-management relationship changes after conditioning on employee ability and the firm-specific pay premium, we also examine directly the cross-firm relationship between the ability distribution and management practice scores. We first check whether firms with high management practice scores employ people of above-average ability, especially in managerial ability (the upper quartile of the within-firm pay distribution). We then investigate the extent to which the positive correlation between management practices and the average ability of the workforce is due to selective recruiting and retention of higher-ability workers by better-managed firms. We tackle this question by analyzing leavers and joiners at the firms in our data between 2004 and 2009 (the dates when the first and last management surveys took place). Using estimates of worker ability based on data from the pre-2003 period, we ask whether the better-managed firms disproportionately recruit and retain those of higher ability (and find that they do).

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III. Data

Our empirical analysis combines data for the German firms in the WMS with longitudinal earnings records from the Institute for Employment Research (Dorner et al. 2010). In this section, we briefly describe the two underlying data sets and our procedure for forming the matched WMS-IEB database.

A. The WMS Database

The WMS was developed by Bloom and Van Reenen (2007) as an instrument for eliciting reliable information on the use of key management practices. The WMS relies on an interview-based evaluation tool that scores participating firms from 1 ("worst practice") to 5 ("best practice") in three broad areas.[14] The first is monitoring: how well does the firm track what goes on inside its plant(s) and use this for continuous improvement? The second is goal setting: does the firm set appropriate targets, track closely aligned outcomes, and take appropriate action if the two are inconsistent? A third area is incentives/people management: does the firm promote and reward employees on the basis of performance and systematically try to hire and retain the best employees?[15]

To obtain accurate responses, the WMS uses a double-blind protocol. Responding plant managers are not informed that they are being scored or shown the scoring grid. They are told only that they are being "interviewed about management practices for a piece of work." Likewise, WMS interviewers are not given any information about the firm.

The interview script consists of open-ended questions rather than yes/no queries or checklists. For example, the first question on monitoring practices is "Tell me how you monitor your production process." The questions continue, focusing on actual practices and examples, until the interviewer can make an accurate assessment of the firm's practices in a certain area. The full interview script is reported in online appendix B.

The survey universe for the German component of the WMS consisted of medium-sized manufacturing firms (employing between 50 and 5,000 workers) selected from the Orbis database. Firms with less than 50 workers were excluded from the universe because many small firms do not use (or need)

[14] The survey tool used in the WMS was developed from a scorecard used by McKinsey, an international management consulting company. Not all aspects of management behavior are captured by the WMS. For example, Bertrand and Schoar (2003) focus on CEO and chief financial officer management style, capturing, e.g., differences in strategy over mergers and acquisitions.

[15] These practices are similar to those emphasized in earlier work on management practices by, e.g., Ichniowski, Prennushi, and Shaw (1997) and Black and Lynch (2001).

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advanced management practices. Large firms were excluded to ensure that the responses from a single plant manager are broadly representative of the firm's overall practices. The exclusion of large firms also makes it unlikely that the WMS interviewer would have any preconceived impressions about the firm or its management practices.

The WMS survey is targeted at plant managers, who are typically senior enough to have a good understanding of management practices but not so senior as to be detached from day-to-day operations.[16] To insure high response rates and reliable answers, the WMS was conducted by MBA-type students with some business experience and training. German firms in the WMS were contacted prior to the survey with a letter of endorsement from the Bundesbank, the independent German central bank. Moreover, interviewees were never asked for financial data; instead, these data were obtained directly from the Orbis database (which includes financial data for both public and private firms). Finally, the interviewers were encouraged to be persistent, so they typically conducted two interviews a day lasting about 45 minutes each and spent the rest of their time contacting managers to schedule interviews. These protocols helped yield a 58.6% response rate in Germany, which was uncorrelated with the (independently collected) performance measures.

German firms in the WMS were interviewed in four waves: 2004, 2006, 2009, and 2014. Since the estimated worker and firm effects are available only for the years up to 2009, we only use the first three survey waves, which included 365 medium-sized manufacturing firms, some of which were interviewed two or three times (we cluster standard errors at the firm level to deal with this).[17]

Our main measure of management quality was constructed by z-scoring (normalizing to mean 0, standard deviation 1) the 18 individual questions in the WMS, averaging them, and then z-scoring the average. This process yields a management practice score with mean 0 and standard deviation 1.

B. Worker-Level Data from the IEB

The worker-level data used in our analysis come from the IEB database maintained by the Institute for Employment Research. For each job lasting

[16] The survey also collects information on a set of "noise controls" about the interview itself, including the time of day and the day of the week the interview occurred, characteristics of the interviewee, and the identity of the interviewer. We check whether our results are robust to including these controls in our regression analysis.

[17] We also looked at the panel dimension of management practices within firms, but the longitudinal aspect exists for a relatively small number of firms and there is not enough real-time series variation (given measurement error) to identify any significant relationships.

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a day or more in the German social security system, the IEB includes employee information, such as age, gender, and education; employer information, such as industry and location; and job spell–based information on such characteristics as full-time or part-time status, average daily wages, and occupation. It also includes information on benefit spells for workers who are receiving regular unemployment benefits or unemployment assistance. Dorner et al. (2010) provide more information on the sources of data used to create the IEB data.

Section A3 of online appendix A describes how we merge firms in the WMS to establishments in the IEB data, primarily using the firm name and address information in both data sets. Overall, we were able to link 361 of the 365 firms in the WMS to an establishment identifier in the IEB. We then searched the IEB database to identify all individuals who had worked at one (or more) of the matched firms for at least one day between 2002 and 2009. We located a total of 251,872 workers who met this criterion. For some of our descriptive correlations and for our analysis of productivity, we constructed a panel data set using employee rosters as of June 30 to define the set of workers at a given firm in a given year.

To measure worker skills and the wage premiums offered by different firms, we use the estimated worker and firm effects produced by Card et al. (2013). They convert the job spell information in the IEB into a longitudinal panel with information on a worker's main job in each year and estimate a version of equation (4) by ordinary least squares. A limitation of the IEB data is that there is no information on usual hours of work during a job spell. For this reason, Card et al. (2013) limit their analysis to full-time workers: no worker effects are available for part-time employees or those who hold so-called minijobs.[18] Henceforth, when we refer to "wages," the reader should bear in mind that we are referring to daily wages (rather than the hourly wage). Another limitation of the IEB data is that daily wages are censored for about 10% of men and 2% of women. Card et al. (2013) use a Tobit model to allocate earnings for the censored cases. (A similar procedure was used by Dustmann, Ludsteck, and Schönberg [2009], who also provide some information on the quality of the Tobit approximation to the upper tail of wages in Germany).

Card et al. (2013) estimated separate models for full-time male and female workers aged 20–60 in four overlapping intervals: 1985–1991, 1990–1996, 1996–2002, and 2002–2009. For all of our analyses we use the worker effects from the 1996–2002 interval, as this predates the measurement of management in 2004 and beyond, except for the outflow analysis, for which we use the 2002–2009 period.

[18] They also exclude job spells where a worker is in training and spells worked by individuals younger than 20, older than 60, or with less than 1 year of potential labor market experience.

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Overall, we have estimated person effects for 74% of all workers in the matched WMS firms (98% of the relevant population of workers in these firms—e.g., excluding part-timers and workers at firms in East Germany, which were excluded by Card et al. [2013]). In all firm-level models, we control for a quadratic function of the coverage ratio (the proportion of workers in the firm for which we have employee fixed effects) to partially control for any systematic sample-selectivity biases.

For our inflow and outflow analysis, we construct average information by firm on workers who join a sample firm or leave a sample firm during the period 2003–2009. Specifically, we focus on three types of joiners: job-to-job joiners, who transition from some other firm to a sample firm with no more than 2 months between the end of the previous job and the start of the new job; joiners from unemployment, who transition from a spell of registered unemployment to a sample firm with no more than 2 months between the end of the unemployment spell and the start of the new job; and all other joiners. The latter group includes new labor market entrants, recent immigrants, people who have been on maternity leave, people moving from self-employment or a job in the civil service,[19] and people with longer gaps between their prior job or benefit spell. Likewise, we focus on three types of leavers: job-to-job leavers, who move to a new firm within 2 months of leaving a sample firm; leavers to unemployment, who enter a spell of registered unemployment within 2 months of leaving a job at a sample firm; and all other leavers.

We also match in several other data sets to our merged WMS-IEB sample. We use Orbis as a source for firm-level information on sales, intermediate inputs (materials), and capital. From the Organization for Economic Cooperation and Development (OECD) STAN data set we extracted industry-level average data on gross output and labor costs, which we match to the WMS plants at the three-digit level to estimate cost shares. We use the 2000–2009 averages from the STAN data to approximately match the time period of the management data.

C. Overview of the Matched WMS and IEB Data Set

Panel A of table 1 gives an overview of the key characteristics of the firms included in our matched WMS-IEB sample (exact definitions of the variables are presented in online app. table A1). The firms are distributed across 15 of the 16 German federal states, with 13% in East Germany. On average, sample firms have been in business for 64 years, employ 440 workers, and pay a daily wage of just over €100. Twenty-seven percent of all workers at these firms are female, and 12% have a university degree.

[19] Self-employed workers and civil servants are excluded from the IEB.

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Table 1
Descriptive Statistics for Matched World Management Survey (WMS)–Integrated Employment Biographies (IEB) Sample

	A. Firms				
	Mean	Median	Minimum	Maximum	SD
Orbis data:					
Firm located in East Germany	.13	.00	.00	1.00	.34
Log of book value of capital	9.89	10.18	2.71	13.82	1.69
Log of intermediate inputs	11.29	11.78	8.44	14.47	1.07
OECD data:					
Intermediate input revenue share (industry data)	.67	.67	.57	.89	.05
Share of labor in revenue (industry level)	.23	.23	.04	.30	.04
WMS data:					
Firm age (years)	64.34	42.50	1.00	489.67	62.79
Number of competitors:					
No competitors	.01	.00	.00	1.00	.09
Less than five competitors	.41	.00	.00	1.00	.49
Five or more competitors	.59	1.00	.00	1.00	.59
Ownership:					
Family owned	.23	.00	.00	1.00	.42
Founder owned	.05	.00	.00	1.00	.21
Manager owned	.03	.00	.00	1.00	.18
Nonfamily private owned	.22	.00	.00	1.00	.42
Institutionally owned	.13	.00	.00	1.00	.33
Other ownership	.06	.00	.00	1.00	.25
Ownership unknown	.28	.00	.00	1.00	.45
Management score	.00	.06	−3.25	2.68	1.00
IEB data:					
Number of workers	440.02	238	1	6,971	642.90
Median daily wage (€)	101.58	99.51	37.21	172.60	28.46
Proportion of female workers	.27	.22	.00	.89	.17
Share of employees with university degree	.12	.08	.00	.80	.13
IEB/CHK data:					
CHK coverage (share of employees with worker effects)	.79	.87	.01	1.00	.25
Average employee ability (CHK worker effects)	.00	−.19	− 5.56	3.40	1.00
Average managerial ability (CHK top-paid worker effects)	.00	−.00	− 6.24	2.71	1.00
Firm wage fixed effect (CHK pay premium)	.00	.080	− 4.48	3.54	1.00

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Table 1 (*Continued*)

	B. Employees	
	Inflows to Sample Firms from the Specified Labor Market State	Outflows from Sample Firms to the Specified Labor Market State
Unemployment	19,013	40,093
Jobs	70,675	75,023
Nonparticipation	32,748	17,584
Total	122,436	132,600

NOTE.—In panel A, the sample includes 361 firms from the 2004, 2006, and 2009 waves of WMS data matched to IEB data on workers (590 firm-year surveys across all three waves). In panel B, the sample includes individuals in the IEB data who joined or exited firms in the WMS-IEB matched panel between 2003 and 2009. See online app. table A1 for more information on data sources and definitions. CHK = Card, Heining, and Kline (2013).

The merged revenue share data from the OECD STAN data set show that intermediate inputs comprise a relatively high share of revenues (67% on average), while labor costs account for 23% of revenues. Thus, labor costs account for just over two-thirds of value added.

From the WMS we also have information on ownership structure—for example, whether the firm is family owned, nonfamily privately owned, or institutionally owned (typically by a local government or quasi-governmental agency). The sample includes firms in a wide range of ownership types, including about 23% that are family owned and 13% that are institutionally owned. We condition on these ownership dummies throughout our analysis and discuss differences between family-owned firms and other types of firms in Section IV.C below.

Finally, the remaining rows of panel A show sample statistics for the WMS management score and for the average estimated worker effects and establishment-level wage premiums. For ease of interpretation, we standardize the estimated worker and firm effects to have mean 0 and standard deviation 1, as we do with the management score.[20] We have estimated employee fixed effects for just under four-fifths of the workers who can be matched to a WMS firm.[21]

[20] The estimated person and firm effects in an AKM model are identified only up to a linear constant. Since the male and female models are estimated separately, the person effects are normalized differently. We recenter the male and female effects to have mean 0 across all firms in our sample, then average the person effects for males and females, then standardize the resulting mean.

[21] The coverage rate is lower in East Germany, where we can merge only the worker effects of Card et al. (2013) for employees who were observed working at a West German firm. We show that the results are robust to dropping all East German firms.

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IV. Results

Descriptive analysis.—We begin our analysis of the relationship between management quality, workforce selection, and productivity with some simple descriptive comparisons. Figures 1 and 2 show how the distributions of wages and estimated employee effects, respectively, differ between firms with relatively high management scores and other firms. To construct figure 1, we begin by finding the quintiles of daily wages for all workers who are matched to a firm in the WMS sample. We then identified the "best-managed firms"—those with management scores in the top 10% of firms in the sample—and all other firms (i.e., those with management scores in the bottom 90%) and calculated the fractions of workers in each wage quintile at the two groups of firms. As shown in the right-hand part of figure 1, the best-managed firms have a relatively high share of workers in the top wage quintile (26%) and a relatively low share in the bottom quintile (13.4%).

To construct figure 2, we followed the same procedure but used the estimated employee effects, which proxy for the long-run human capital of the workforce. The differences between the best-managed firms and all other firms are a little different using this measure. The best-managed firms have more workers in the top two quintiles than other firms but no fewer in the bottom quintile. Instead, the gap is made up by a shortfall in the shares of workers in quintiles 2 and 3 of the person effects—the middle part of the skill distribution. As discussed in more detail below, figures 1 and 2 imply that firms with more advanced management practices have a somewhat lower dispersion in daily wages but a wider dispersion in worker skills.[22]

More insight into the potential complementarity between advanced management practices and the human capital distribution of the workforce is provided in figures 3 and 4. Figure 3 is a simple bin scatterplot of average management scores (on the *Y*-axis) against the average human capital of all employees in a firm, as measured by the average employee effect (on the *X*-axis labeled "Average employee Fixed Effect"). There is clearly an upward-sloping relationship. Figure 4 is a similar bin scatterplot using measures of management scores and mean employee effects that have been residualized to control for the effect of firm size. The positive relationship between management quality and the average human capital of the workforce is particularly strong after controlling for firm size, which previous work has shown is very strongly correlated with management practice scores (e.g., Bloom et al. 2014).

[22] Card et al. (2013) show that over the past 3 decades establishments in West Germany have become more specialized in terms of the distribution of occupations. Contrary to our expectations, fig. 2 suggests that this tendency is not more pronounced among middle-sized manufacturing firms with higher management scores.

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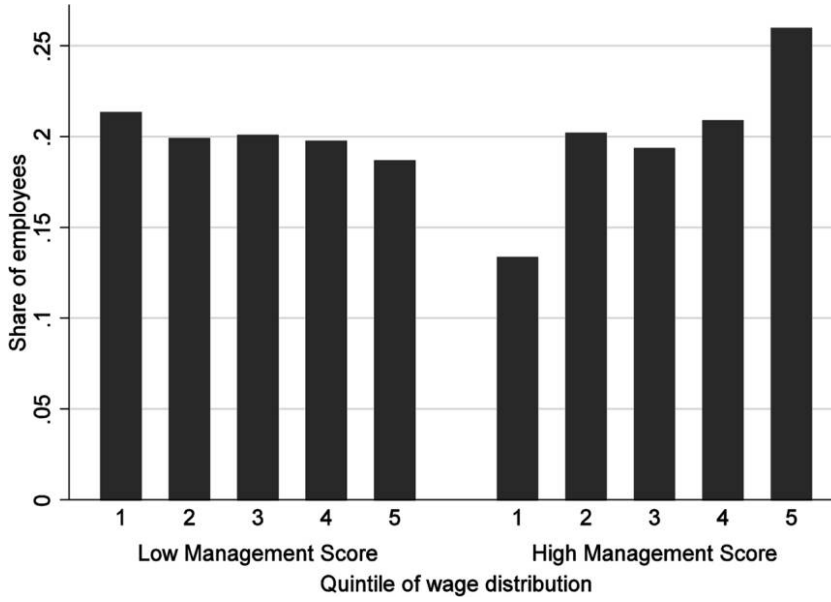


FIG. 1.—Fraction of workers of different wage quintiles in firms with low versus high management scores. High-management-score firms are those in the top decile of the World Management Survey management score, and low-management-score firms are all other firms. We bin all workers into quintiles based on the overall distributions of wages (bin 1 = lowest 20%; bin 5 = highest 20%). We then tabulate the fractions of workers in each quintile at firms with high management scores and those with low management scores.

Next we examine the correlates of firm productivity. Figure 5 shows the nonparametric relationship between labor productivity (measured by log sales per worker) and the WMS management score. As noted by Bloom and Van Reenen (2007), there is a positive relationship between the two even after controlling for firm size. Figure 6 presents an analogous scatterplot for productivity and the average employee fixed effects. There is also a clear positive relationship here, motivating our question of whether the impact of management practices on productivity is mediated through employee talent. Interestingly, the relationship is quite convex, hinting at a greater role for the skill level of managers in determining productivity, as specified in equation (6).[23]

Correlates of management practice scores.—To provide more contextual information on the relationship between workforce quality and manage-

[23] Kernel density plots of employee and managerial ability are presented in online app. fig. A1, both overall and broken down by high and low WMS management score firms.

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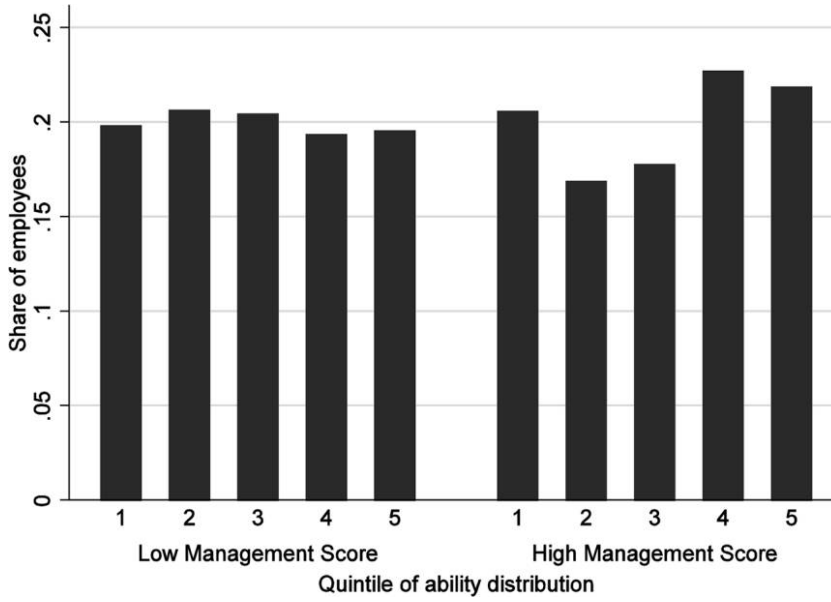


FIG. 2.—Fraction of workers of different ability quintiles (as measured by AKM [Abowd-Kramarz-Margolis] individual fixed effect) in firms with low versus high management scores. High-management-score firms are those in the top decile of the World Management Survey management score, and low-management-score firms are all other firms. We bin all workers into quintiles based on the overall distributions of worker ability (as measured by worker fixed effects; bin 1 = lowest 20%; bin 5 = highest 20%). We then tabulate the fractions of workers in each quintile at firms with high management scores and those with low management scores.

ment practices, we estimated a series of simple regression models, summarized in table 2, that relate the management *z*-score at each firm to measures of employee quality and other firm characteristics. All of the specifications also control for firm size, the share of female workers, ownership status, the number of competitors, firm age, three-digit industry, survey year, and location in East Germany.[24] The estimates in column 1 confirm the findings from Bloom and Van Reenen (2007) that larger firms in Germany have significantly higher management scores while family-owned firms have significantly lower management scores (we discuss the family firm results in more detail in Sec. IV.C below).

[24] Note that to avoid losing observations due to missing values for the control variables, we set missing values to the sample mean and include a dummy for an imputed value. Only a handful of firms have missing data for most control variables, but 92 firms have missing data on capital (which is not included in table 2 but is used in later tables).

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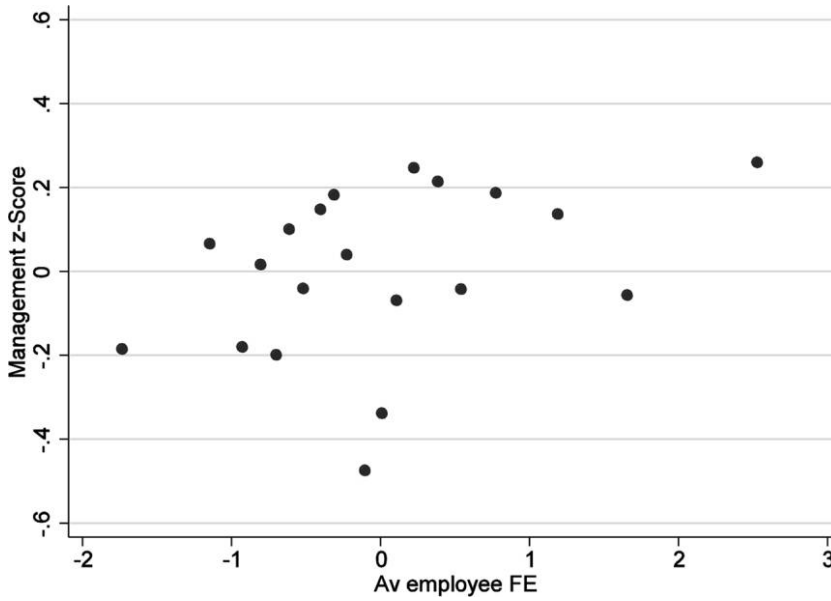


FIG. 3.—Correlation between management score and employee ability (not controlling for firm size). The figure shows the bin scatter of management scores against vigintiles of employee ability, as measured by the mean firm-level average of estimated employee effects (from the period 1996–2002). Management scores and employee ability are both standardized to have mean 0 and standard deviation 1. FE = fixed effect.

The model presented in column 2 of table 2 relates management scores to mean employee quality and confirms the strong positive correlation suggested in figures 3 and 4. The specification in column 3 focuses on mean ability of the top quarter of employees, which we assume is a measure of the human capital of the firm's managers. The coefficient on "managerial ability" is over a third larger than that on average employee ability (0.294 vs. 0.216). Column 4 enters both measures and shows that it is managerial ability that matters more—the coefficient on average employee ability remains positive but is statistically insignificant conditional on managerial ability. As shown in column 5, this result is robust to controlling for another measure of average human capital, the share of college-educated workers at the firm. In online appendix table A2, we show that this finding is also robust to including other measures of observable human capital (experience, age, and tenure). Overall, the specifications in table 2 confirm that the management practice scores and human capital (especially managerial ability) are complementary in the sense that they covary together.

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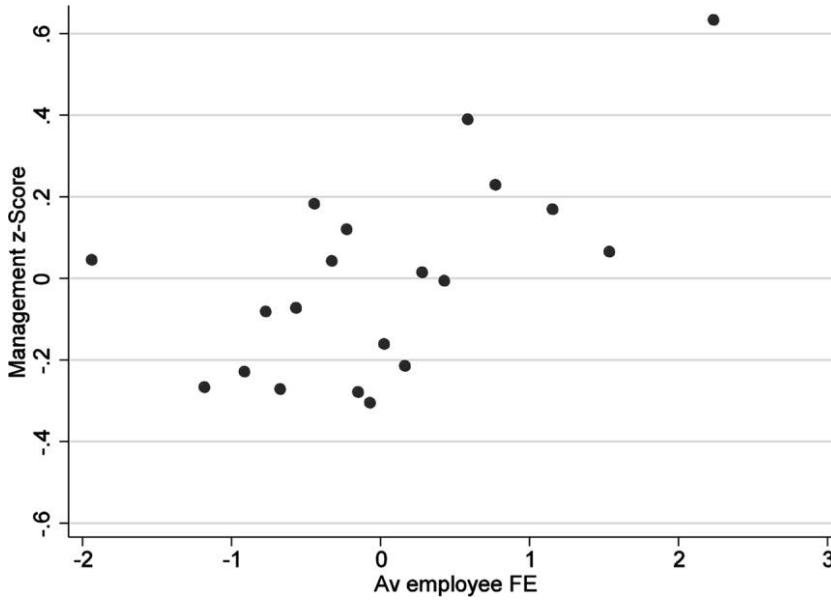


FIG. 4.—Correlation between management score and employee ability, controlling for size. The figure shows the bin scatter of management scores against vigintiles of employee ability, as measured by the mean firm-level average of estimated employee effects (from the period 1996–2002). Both variables are residualized by regressing the underlying variable on ln(employment). FE = fixed effect.

A. Quantifying the Channels Linking Management Practices to Productivity

Analysis based on production function estimation.—We begin our analysis of productivity in table 3 with a straightforward production-function approach, as in equation (7). The basic specifications in columns 1–4 control for labor inputs only, while the models in columns 5 and 6 include labor and capital inputs and those in columns 7–10 include labor, capital, and intermediate inputs.

Looking first at the specifications that exclude capital and intermediate inputs, the estimates in column 1 show that the WMS management score variable has a relatively large partial correlation with productivity (0.26) when there are no controls for worker ability. This implies that a 1 standard deviation increase in the management score is associated with a 30% (26 log point) increase in labor productivity. The magnitude of this coefficient is similar to the coefficient from a parallel specification fit to the overall WMS sample covering 34 countries, reported by Bloom et al. (2016). The coefficient on the management score variable falls to 0.20 when we control for

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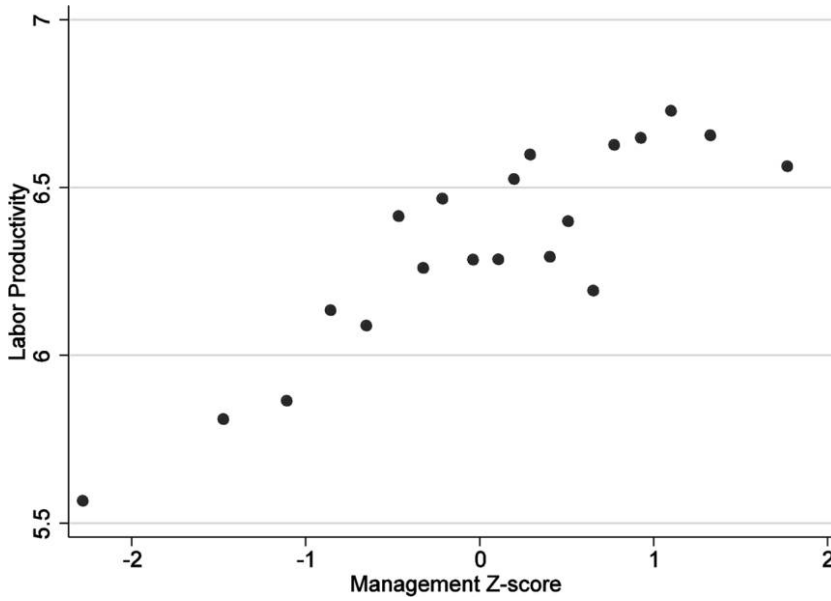


FIG. 5.—Positive correlation between ln(labor productivity) and World Management Survey management scores. The figure shows the bin scatter of ln(sales per worker) against vigintiles of management scores. Both variables are residualized by regressing the underlying variable on ln(employment).

average employee ability (col. 2), to 0.15 when we control for both average worker ability and managerial ability, and to 0.13 when we add a further control for the share of college-educated workers.[25] Thus, without taking account of variation in capital and intermediate inputs, one would conclude that up to about one-half of the (relatively large) effect of management scores on productivity is accounted for by the fact that firms with more-advanced management practices hire better-quality workers—particularly in the upper stratum of the skill distribution.

Column 5 of table 3 introduces a control for the book value of the capital stock. Despite the well-known limitations of book value–based capital measures, this variable has a large positive coefficient that is relatively precisely estimated. Introducing capital into the production function leads to a relatively large reduction (about 40%) in the coefficient on the management score and to noticeable declines in the coefficients on average worker ability, managerial ability, and the fraction of college graduates. Nevertheless, all four remain at least marginally significant.

[25] In this column, a standard deviation increase in management scores is associated with a 13% increase in productivity, which is similar to the findings of the Indian randomized controlled trials and nonexperimental regressions across all countries (Bloom et al. 2014).

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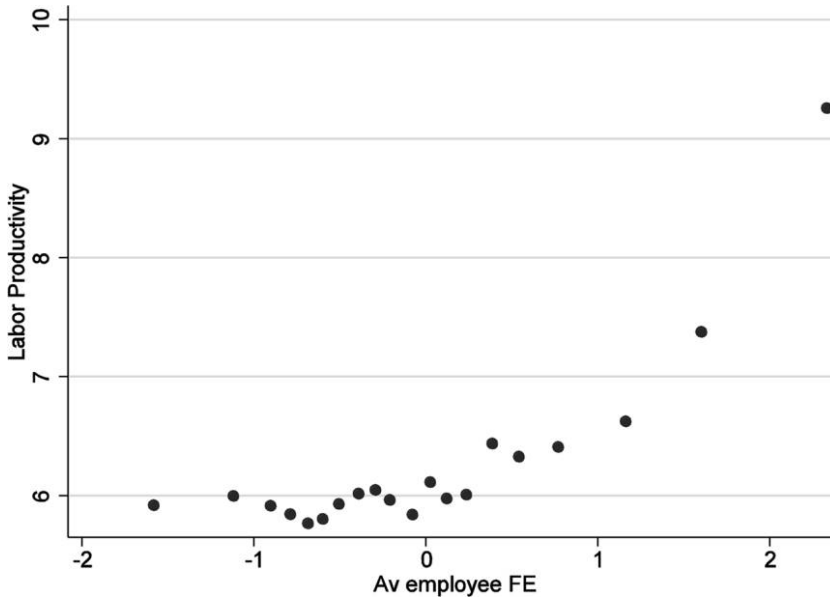


FIG. 6.—Increasing productivity in employee ability, especially for high levels of ability. The figure shows the bin scatter of ln(sales per worker) against vigintiles of mean worker ability, as measured by mean employee fixed effects. Both variables are residualized by regressing the underlying variable on ln(employment).

So far we have focused on the impact of measures of worker quality on the measured effect of the managerial score variable. As discussed in Section II, however, firm-specific pay policies may also affect productivity if they are used by the firm to reward greater effort. Some descriptive evidence on this mechanism is presented in figure 7. Figure 7*A* shows a bin scatterplot relating the estimated firm-specific wage premiums to ln(sales per worker). These are positively related, as has also been documented in other countries (e.g., see Card, Cardoso, and Kline [2016] for Portugal and Abowd et al. [1999] for France). Figure 7*B* presents a bin scatterplot of the wage premiums against the WMS management scores. Again, there is a strong positive relationship, suggesting that firms that use advanced management practices tend to pay higher wages to their workers relative to the outside labor market. When we regress the firm fixed effects on management scores, we find a significant and positive correlation, with or without the other controls (see online app. table A7).

In column 6 of table 3, we introduce the firm-specific wage premium as an additional control. As expected given the scatterplots, the coefficient on this variable is positive and significant. Its inclusion also leads to a further reduction in the effect of the management score variable (to 0.07).

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Table 2
Correlations between Firm Management and Average Employee and Managerial Ability

	Management *z*-Score				
	(1)	(2)	(3)	(4)	(5)
Mean employee ability		.216***		.029	−.093
		(.078)		(.090)	(.112)
Mean managerial ability			.294***	.277***	.258***
			(.071)	(.091)	(.095)
ln(number of employees)	.208***	.237***	.261***	.264***	.263***
	(.046)	(.049)	(.048)	(.050)	(.050)
% of employees with college degree					1.022**
					(.452)
Family	−.262**	−.223*	−.210	−.207	−.214*
	(.131)	(.132)	(.129)	(.130)	(.129)
Founder	−.384	−.325	−.244	−.243	−.259
	(.287)	(.277)	(.274)	(.274)	(.271)
Institution	−.240	−.239	−.245	−.244	−.249
	(.184)	(.181)	(.177)	(.178)	(.180)
Manager	−.256	−.164	−.255	−.244	−.229
	(.320)	(.313)	(.293)	(.290)	(.292)
Other	−.068	−.031	−.059	−.057	−.039
	(.172)	(.174)	(.181)	(.181)	(.181)
Firms	354	354	354	354	354
Observations	588	588	588	588	588

NOTE.—All standard errors are clustered by 354 firms (in parentheses under coefficients estimated by ordinary least squares). Management score and employee ability measures are *z*-scored to have mean 0 and standard deviation 1. All columns include a dummy for whether the firm is located in East Germany, the share of female workers, the number of competitors, a cubic in the coverage rate (fraction of employees where we can calculate the CHK ability measures), firm age, a dummy for unknown ownership status, three-digit industry dummies, and time dummies; the reference category for ownership is nonfamily privately owned. Employee ability is the mean level of individual fixed effect measured over the period 1996–2002. Managerial ability is the mean employee ability in the top quartile of the within-firm distribution. CHK = Card, Heining, and Kline (2013).

* Statistically significant at the 10% level.
** Statistically significant at the 5% level.
*** Statistically significant at the 1% level.

Columns 7–10 of table 3 present estimates for production function specifications that control for labor, capital, and intermediate inputs (materials).[26] The baseline model in column 7 includes only the management score variable and controls for factor inputs. Relative to the parallel specification in column 1, the coefficient on management practices is reduced by around four-fifths. Evidently, more advanced management practices are more likely to be adopted by firms with more capital intensive production techniques that also use larger shares of intermediate inputs. Controlling for these factors,

[26] Information on intermediate inputs is missing for a sizeable fraction of firms in Orbis, leading to a 30% reduction in sample size. Unlike the case for other control variables, we decided not to try to impute the value of intermediate inputs if it was missing.

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Table 3
Production Functions

	ln(Sales)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Management score	.264***	.199***	.150***	.129***	.074*	.066*	.043**	.035**	.033*	.029
	(.052)	(.046)	(.042)	(.042)	(.038)	(.038)	(.020)	(.017)	(.017)	(.018)
Employee ability		.821***	.597***	.375***	.250**	.252**		.110*	.083	.058
		(.144)	(.101)	(.105)	(.098)	(.110)		(.060)	(.073)	(.075)
Managerial ability			.363***	.329***	.184*	.155		.082*	.082*	.082*
			(.107)	(.100)	(.099)	(.102)		(.048)	(.049)	(.049)
% of employees with college degree				1.873***	1.308***	1.308***			.192	.282
				(.642)	(.465)	(.454)			(.232)	(.226)
ln(labor)	.315***	.446***	.589***	.591***	.389***	.389***	.055***	.129***	.130***	.132***
	(.067)	(.067)	(.071)	(.071)	(.062)	(.060)	(.019)	(.028)	(.029)	(.026)
ln(capital)					.431***	.421***	.204***	.181***	.181***	.176***
					(.048)	(.047)	(.023)	(.022)	(.023)	(.022)
ln(materials)							.696***	.667***	.663***	.661***
							(.035)	(.032)	(.035)	(.034)
ln(firm effect − wages)						.110**				.039*
						(.051)				(.023)
Firms	333	333	333	333	333	333	229	229	229	229
Observations	560	560	560	560	560	560	378	378	378	378

NOTE.—All standard errors are clustered by firm (in parentheses under coefficients estimated by ordinary least squares). Management score and employee ability are standardized to have mean 0 and standard deviation 1. All columns include a dummy for East German firms, the share of female workers, five ownership dummies, dummies for numbers of competitors, firm age, a cubic in the coverage rate, industry dummies, and time dummies. Mean employee ability is the mean level of individual fixed effect measured over the period 1996–2002. Mean managerial ability is employee ability in the top quartile of the within-firm distribution.

* Statistically significant at the 10% level.
** Statistically significant at the 5% level.
*** Statistically significant at the 1% level.

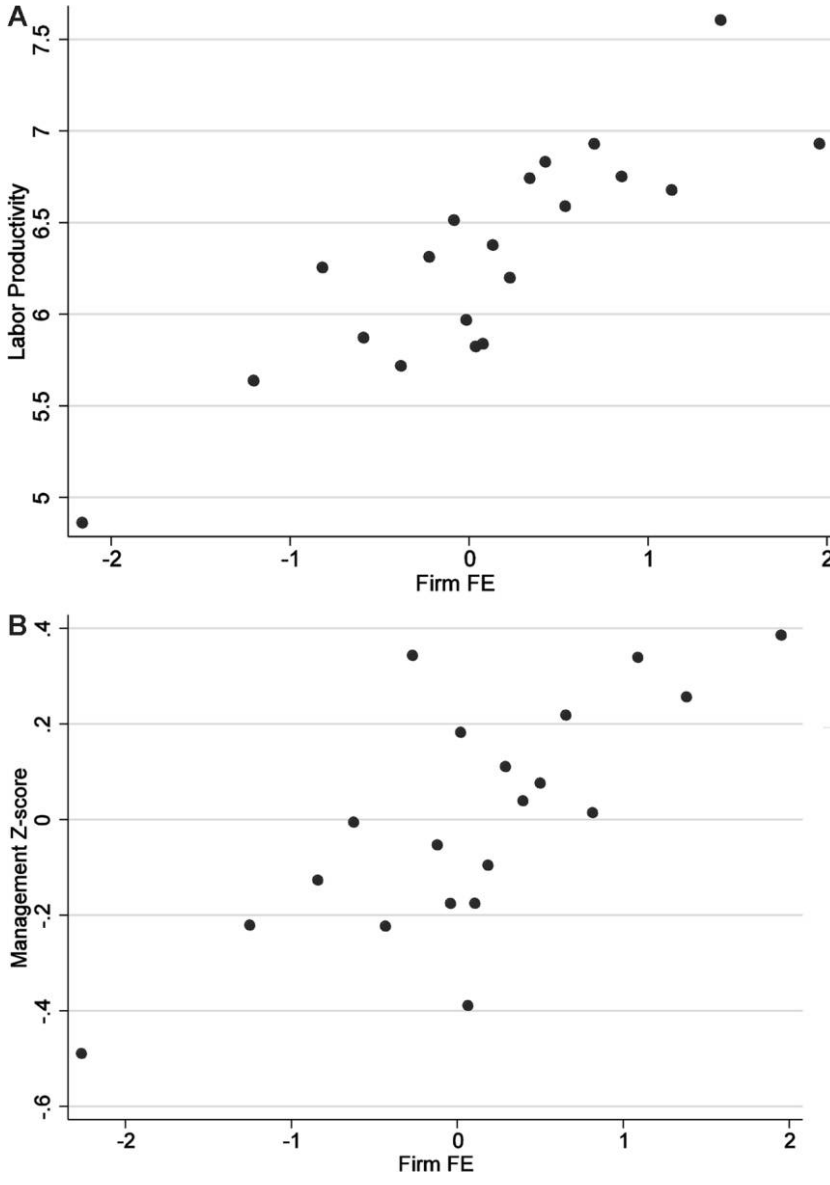


FIG. 7.—Correlation between firm fixed effect (in wage equation) and World Management Survey (WMS) management practice score and productivity. *A*, Labor productivity and firm fixed effect. *B*, WMS management score and firm fixed effect. The figures show the bin scatter of ln(sales per worker) (*A*) or management scores (*B*) against vigintiles of estimated firm-specific wage premium ("Firm FE"). Both bin scatterplots control for firm size. FE = fixed effect.

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the coefficient implies that a 1 standard deviation increase in management practices is associated with a 4.3% increase in productivity. Column 8 adds the two worker-ability measures to the three-factor production function. Both variables are marginally significant, and their addition reduces the management-TFP relationship to 0.035. In column 9, management practices and ability remain significant even conditional on the share of college-educated workers. Finally, in column 10 we add in the estimated firm-specific pay premium, which leads to a reduction in the point estimates for the effects of the management score and worker-quality variables. With only 229 firms included in the analysis, we have reached the limits of the data to distinguish between the different channels.

The models summarized in table 3 use a simple average of the 18 management questions on the WMS survey as a measure of management practices. We have checked the robustness of our findings by using other ways of summarizing the WMS questions, such as principal components and looking at subsets of the question-specific scores. For example, online appendix table A6 presents a series of models similar to the ones in table 3 but uses the first principal component of all 18 questions. Overall, the results are qualitatively and quantitatively similar to those based on simple averages of the *z*-scores.

Analysis based on TFP.—In table 4, we implement our preferred TFP specification based on equation (8). This approach has the advantage relative to the production approach used in table 3 of moving the conventional factor inputs (labor, capital, and materials) from the right-hand side to left-hand side of the regression, reducing the effects of measurement errors and endogeneity biases for these variables. Moreover, the coefficients on labor, capital, and materials are allowed to vary across detailed subindustries according to their respective cost shares. On the other hand, a TFP approach assumes that the output elasticities with respect to the three-factor inputs are equal to their factor shares, an assumption that may not be correct.

In general, the broad pattern of results in table 4 is similar to the pattern in table 3. The more parsimonious specification, however, allows us to estimate the key parameters more precisely. The first four columns of the table present models where we exclude the firm size, industry, and ownership controls, whereas the last four columns present models with these controls included (as in table 3). As we move from column 1 to column 2, we observe that the controlling for employee quality reduces the management practice coefficient by about a quarter. Controlling for managerial ability in column 3 reduces the management practice coefficient by another 14%, and controlling for the firm wage premium in column 4 reduces it by another 16%. So altogether the reduced-form association between TFP and management is roughly halved when we introduce these additional controls.

We repeat the specifications of columns 1–4 in the last four columns of table 4 but include more extensive controls. The results show a qualitatively

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Table 4
Total Factor Productivity (TFP) Specifications

	ln(TFP)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Management score	.081***	.062***	.053***	.044**	.048***	.047***	.041**	.036**
	(.021)	(.020)	(.019)	(.018)	(.018)	(.017)	(.017)	(.017)
Mean employee ability		.176***	.113***	.103***		.198***	.141**	.113*
		(.025)	(.034)	(.033)		(.060)	(.058)	(.060)
Mean managerial ability			.062*	.059*			.055	.052
			(.035)	(.034)			(.034)	(.034)
Firm effect (in wages)				.070***				.051**
				(.018)				(.020)
General controls	No	No	No	No	Yes	Yes	Yes	Yes
Firms	229	229	229	229	229	229	229	229
Observations	378	378	378	378	378	378	378	378

NOTE.—All standard errors are clustered by firm (in parentheses under coefficients estimated by ordinary least squares). Management score, managerial ability, and employee ability are all standardized. TFP is measured by ln(sales) minus the cost-weighted ln(inputs), where inputs are labor, capital, and materials. All columns include industry dummies, year dummies, and firm size. General controls are a dummy for East German firms, the share of female workers, five ownership dummies, dummies for numbers of competitors, firm age, and a cubic in the coverage rate. Mean employee ability is the mean level of individual fixed effect measured over the period 1996–2002. Mean managerial ability is employee ability in the top quartile of the within-firm distribution.

* Statistically significant at the 10% level.
** Statistically significant at the 5% level.
*** Statistically significant at the 1% level.

similar pattern, although the fraction of the management coefficient explained by the other controls is smaller (the original management association of 0.048 is reduced by about 30% by the final column). Employee ability accounts for only 3%, managerial ability for 13%, and establishment fixed effects in pay for a further 13%. The fraction accounted for by average employee ability falls compared with the first four columns because we are now controlling for the share of employees with a college degree throughout. This suggests that in understanding the productivity-management practice correlation, the unobserved component of human capital for average workers (recovered by the average of the AKM person effects for all workers at the firm) matters less than the corresponding measure of human capital for managers at the firm.

We summarize our estimation results and their implications for our simple structural model in table 5. Recall that the model consists of three equations:

i. equation (5), which relates overall workforce quality to average human capital ($\bar{\hat{\eta}}_j$), the firm's pay premium ($\hat{\psi}_j$), and observed management practices (Λ_j) with coefficients ρ_1, ρ_2, and ρ_3, respectively;

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ii. equation (6), which relates TFP to managerial human capital $\bar{\hat{\eta}}_{Mj}$ and management practices with coefficients λ_1 and λ_2, respectively; and
iii. equation (8), which is a log-linearized three-factor production function with coefficients equal to the cost shares of the factors.

From the reduced-form coefficients associated with these three equations, we can recover estimates of ρ_1, ρ_2, λ_1, and the composite management effect $s_L\rho_3 + \lambda_2$.

Table 5 shows the reduced-form parameter estimates and the associated estimates of the structural parameters ρ_1 and ρ_2 from the basic TFP specification in column 4 of table 4, the extended TFP specification in column 8 of table 4, and the production function estimates in column 10 of table 3. Reassuringly, the estimated reduced-form and structural parameters are fairly similar across these three specifications. The implied values of $\widehat{\rho_1}$ (the effect of higher average human capital on labor quality) are between 0.4 and 0.5, the implied values of $\widehat{\rho_2}$ (the effect of a higher pay premium on labor quality) are between 0.2 and 0.3, the implied values of λ_1 (the effect of a higher human capital of managers on TFP) are between 0.05 and 0.08, and composite effects of (standardized) management ability on TFP are between 0.03 and 0.04.

While the estimates of the effect of workers' average human capital on labor quality ($\widehat{\rho_1}$) are relatively large, they are still far below 1.0, which is the expected effect if a 1% increase in the average person effect at a firm leads to a 1% increase in labor quality. There are three likely explanations for the gap. First, the worker effects are estimated with error. Second, the firm-wide average skill measure excludes part-timers, trainees, and workers out-

Table 5
Implied Structural Estimates

	Symbol (1)	Structural Parameters (2)	Reduced-Form Coefficient (3)	TFP Basic (4)	TFP Full (5)	Production Function (6)
Management score	Λ_j	$s_L\rho_3 + \lambda_2$	π_4	.044	.036	.029
Mean employee ability	$\bar{\hat{\eta}}_j$	$s_L\rho_1$	π_1	.103	.113	.058
		$\widehat{\rho_1}$		*.447*	*.491*	*.439*
Mean managerial ability	$\bar{\hat{\eta}}_{Mj}$	λ_1	π_3	.059	.052	.082
Firm effect (in wages)	$\hat{\psi}_j$	$s_L\rho_2$	π_2	.070	.051	.039
		$\widehat{\rho_2}$		*.304*	*.222*	*.295*

NOTE.—These are estimates of equation (7). Column 4 uses estimates from table 4, col. 4; col. 5 uses estimates from table 4, col. 8; and col. 6 uses estimates from table 3, col. 10. We use the empirical average labor share in revenues of 23% (see table 1) for the estimates of the structural parameters ($\widehat{\rho_1}$ and $\widehat{\rho_2}$, in italics) in cols. 4 and 5 and the estimate of the coefficient on labor from table 3, col. 10, of 0.132 in col. 6.

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side the 20–60 age range. Third, there is some slippage introduced by the presence of multiplant establishments in our sample, since we merge firms to only a single establishment in the IEB database.[27] We suspect that all three factors lead to some attenuation in the measured effect of average worker quality.

Our finding that higher firm-specific wage premiums contribute to average productivity, albeit less than proportionally, is also interesting. Taken at face value, point estimates for $\widehat{\rho_2}$ in the range of 0.20 to 0.30 suggest that firms receive only a partial productivity offset from offering higher pay. Again, we suspect that the estimates could be attenuated by measurement errors in the AKM procedure and by slippage in the match between firms and establishments.

Finally, the finding that average managerial quality has an independent association with TFP, holding constant the average quality of the workforce, provides empirical support for the channel emphasized in Lucas's (1978) original span-of-control model and many subsequent models of the effect of managers on TFP. But the importance of management practices over and above managerial ability is novel to our paper.

We also conclude from the pattern of coefficients on the management practice variables (e.g., between cols. 1 and 4 in table 4) that the observed association of productivity with management practices in simpler specifications represents a combination of direct and indirect effects via workforce selection and pay practices. We turn in the next subsection to see whether there is any direct evidence that some of the role of management practices operates via selection.

B. Inflows and Outflows

We have shown that firms with a more highly skilled workforce—and in particular more highly skilled workers in the top quartile of the pay distribution—tend to have better management practices and higher productivity. We now investigate in more detail how firms come to have higher-ability employees by looking at the inflows and outflows of workers to our firms.

As background, panel B of table 1 shows the total numbers of individuals we observe in the IEB data who join or leave one of the matched WMS firms. In total, we observe 122,436 joiners and 132,600 leavers (roughly 350 joiners and leavers per firm, on average). Most inflows (58%) and most outflows (57%) are job-to-job transitions, but substantial fractions of new hires come from unemployment (16%) and from other sources (27%). Like-

[27] The establishment identified in the IEB can actually combine two or more plants if the plants are all in the same location and assigned the same narrow industry code.

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Table 6
Inflows from Employment and Unemployment

	Percentile of the Ability of Different Quantiles of the Inflow Distribution				
	10% (1)	25% (2)	50% (3)	75% (4)	90% (5)
	A. Not Including Size Control				
Management score	.003	.003	.006	.016**	.019***
	(.002)	(.004)	(.005)	(.006)	(.006)
% college	.081***	.212***	.304***	.075	.090
	(.013)	(.029)	(.052)	(.086)	(.057)
	B. Including Size Control				
Management score	.003	.004	.005	.007	.010*
	(.002)	(.004)	(.006)	(.007)	(.006)
% college	.081***	.202***	.314***	.123	.139**
	(.015)	(.030)	(.050)	(.088)	(.062)
Firm size: ln(labor)	.000	−.005	.005	.026***	.026***
	(.002)	(.004)	(.007)	(.007)	(.007)
Observations	355	355	355	355	355

NOTE.—All standard errors are clustered by firm (in parentheses under coefficients estimated by ordinary least squares based on 89,688 inflows from employment and unemployment in these firms). The management score is standardized. All columns control for an East Germany dummy, competition, ownership, ln(firm age), female share, and industry.
* Statistically significant at the 10% level.
** Statistically significant at the 5% level.
*** Statistically significant at the 1% level.

wise, many job leavers exit to unemployment (30%) or to other destinations (13%).[28]

Table 6 presents an analysis of the relationship between management ability measures and the fraction of new recruits at a firm with estimated employee ability at or above various percentiles of the overall distribution among all new recruits. As with previous tables, the employee effects are those estimated by Card et al. (2013) for the period 1996–2002, prior to the start of the jobs under analysis here. Each column of the table shows the coefficient of the management ability index in a model for the fraction of new recruits with person effects at or above the percentile listed in the column heading (the 10th, 25th, 50th, 75th, and 90th percentiles, respectively). In column 5, for example, the dependent variable is the proportion of workers who were in the top decile of the ability distribution based on their estimated person effects during the period 1996–2002. We present two sets of specifications: a simpler set of models (panel A) that control for location, ownership, industry, female share, and production market competition,

[28] Recall that the third category includes "out of the labor force" as well as employment in jobs outside the coverage of the IEB (self-employment and the civil service).

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Table 7
Outflows to Unemployment

	ln(Average Ability of Outflow) – ln(Average Ability of Incumbents)			
	(1)	(2)	(3)	(4)
Management score	−.091*	−.115**	−.106*	−.133**
	(.053)	(.058)	(.060)	(.057)
Average age of outflows			.048***	.041***
			(.016)	(.015)
% of college of outflows				4.887***
				(.861)
General controls	No	Yes	Yes	Yes
Firms	347	347	347	347

NOTE.—All standard errors are clustered by firm (in parentheses under coefficients estimated by ordinary least squares based on 40,093 outflows to unemployment in these firms). Column 1 includes dummies for industry and coverage of AKM (Abowd-Kramarz-Margolis) effects; other columns additionally include a dummy for East German firms, share of female workers, share of workers with university degrees, firm age, and dummies for competition and ownership.
* Statistically significant at the 10% level.
** Statistically significant at the 5% level.
*** Statistically significant at the 1% level.

and a richer specification (panel B) that also controls for firm size. In both specifications, the coefficient on the management score is positive at every percentile and is particularly strong for workers in the top of the distribution. In the specifications without size controls, the management score coefficients for the 75th and 90th percentiles are highly significant. As shown in the second panel, these effects are attenuated once we control for firm size, but the coefficient in the 90th percentile model remains marginally significant. Online appendix tables A3 and A4 repeat the analysis, fitting separate models for inflows from a previous job and from unemployment.[29] The results are broadly robust to disaggregating in this way. Overall, we conclude that better-managed firms are a little more likely to recruit workers from the upper tail of the ability distribution.

Table 7 turns to the relationship between management ability and the composition of outflows to unemployment. These flows are particularly interesting because they arguably reflect termination decisions by the firm (i.e., decisions to fire or lay off a worker) rather than decisions by workers to move to another job or withdraw from the labor force. The dependent variable in all of the models is the average value of the person effect for leavers who move to unemployment, normalized by differencing from the mean person effect at the firm among all employees in the previous year.

[29] Haltiwanger, Hyatt, and McEntarfer (2015) show that there are differential patterns by firm size (and firm wage) for job-to-job flows compared with other type of flows.

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Thus, the coefficients reflect the impact of higher management ability on the differential layoff/firing rate of higher-ability workers.

The results in table 7 suggest that firms with higher management scores are significantly less likely to fire or lay off their relatively high-ability workers. This correlation remains robust in column 2 to more general controls for firm size, location, the shares of college-educated and female workers, firm age, competition, and ownership. Nevertheless, one might be concerned that the relative skill level of workers who are laid off or fired from a particular firm is correlated with some other characteristics of the worker. Consequently, we also experimented with conditioning on some of the observable characteristics of the outflow group, such as age (col. 3) and whether the individual was college educated (col. 4). Interestingly, including these controls in column 4 increases the magnitude of the management score coefficient compared with column 2, suggesting that the "quality preference" of better-managed firms is stronger within traditionally measured skill groups than between groups.[30]

Tables 6 and 7 together confirm that firms with high WMS management scores select higher-ability employees and exit lower-ability employees to a greater extent than other firms.[31] This is a clear mechanism through which they end up with a larger fraction of high-ability incumbent employees. We estimate that it would take about 9 years for a firm that moved from the bottom 90% into the top decile of WMS management scores to converge to the average employee ability score of its peers purely through improving the quality of the inflows and outflows.[32]

C. Extensions and Robustness

Management practices and the within-plant dispersion of wages and ability.—So far we have focused on the importance of management practices for

[30] We repeated these specifications looking at outflows to jobs at other firms. Although the results were of a similar sign, they were generally weaker, which is consistent with our prior finding that the firm policy variables are most likely to be seen when looking at exits to unemployment.

[31] We tried decomposing the management score into its 18 components to see whether there was any systematic pattern between inflows and outflows and types of management practices. We found that 32 of the 36 coefficients were correctly signed, but we did not see any clear pattern of groups of practices being particularly important.

[32] If we compare firms in the top decile of management to the rest, there is a difference of 0.007 (0.554 vs. 0.547) in the average employee fixed effect. The difference in the average employee ability of joiners from the labor force between these two groups of firms is 0.004 (0.555 vs. 0.551), but the inflow rates are similar at 6.7%. Hence, improving the quality of inflows will bridge 4.5% ($=0.004 \times 0.076/0.007$) of the employee ability gap per year. The ability difference of outflows to unemployment is larger at 0.014, but the mean outflow rate is only 3.1%, which makes a contribution of 6.5% ($=0.031 \times 0.014/0.007$). Putting the inflows and outflows channels together implies that 11% of the ability gap is closed per year.

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the differences in mean levels of productivity and worker ability across firms. In part, this focus is driven by the recent literature emphasizing the role of widening between-firm inequality in overall labor market inequality. But an interesting question is whether advanced management practices are also related to the degree of within-firm inequality.

We investigate this issue in table 8. We begin in columns 1 and 2 with specifications that take the 90-10 difference in ln(wages) at each firm in our sample as the dependent variable. As suggested by the pattern in figure 1, there is a modest negative correlation between use of advanced management practices and within-firm wage inequality, although the effect is at best only marginally significant. In columns 3 and 4, we use the coefficient of variation in log daily wages as an alternative measure of within-firm dispersion. This measure of within-firm inequality is strongly negatively correlated with the firm's management score, with or without other controls in the model. Columns 5–8 present a parallel set of models, taking as a dependent variable the corresponding measure of within-firm inequality in worker quality, as measured by the estimated employee effects. (We emphasize that these employee effects are estimated using wage data from a period preceding the time window here.) Again, the findings are consistent with the simple graphical evidence in figure 2, suggesting that better-managed firms have a slightly wider distribution of worker skill.

Overall, the conclusion from table 8 is that firms with high management scores tend to have a little more dispersion in skills and a little less dispersion in overall wages. The opposite signs imply that better-managed firms tend to implement "equalizing" pay policies that offset their more unequal skill distributions—a pattern that is inconsistent with the additive proportional pay premium imposed by the AKM specification. We believe that additional work on the relationship between within-firm inequality and management

Table 8
Within-Firm Heterogeneity of Wages and Employee Ability

	90-10 ln(Wages)		Coefficient of Variation in Log Wages		90-10 ln(Employee Ability)		Coefficient of Variation in ln(Employee Ability)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Management score	−.037*	−.030*	−.097***	−.030**	.027*	.015	.035**	.023
	(.022)	(.017)	(.020)	(.012)	(.014)	(.012)	(.016)	(.015)
General controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	571	571	571	571	571	571	571	571

NOTE.—All standard errors are clustered by firm (in parentheses under coefficients estimated by ordinary least squares based on 348 firms). Controls are size, industry, firm age, a dummy for East Germany, a cubic in the coverage rate, ownership, and competition.
* Statistically significant at the 10% level.
** Statistically significant at the 5% level.
*** Statistically significant at the 1% level.

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practices could be a fruitful area for additional research with larger samples. One interesting question is whether advanced management practices are related to the use of outsourcing practices, which in some cases at least lead to a reduction in the variation in skill levels at the firm (e.g., Goldschmidt and Schmieder 2017).

Family ownership and governance.—All of our regressions include controls for family ownership. We were particularly interested in family ownership, as this has been the subject of much previous research.[33] Consistent with the patterns identified in earlier work, our models suggest that family-owned firms have significantly lower management scores than private, non-family-owned firms. Part of this appears to be related to human capital. For example, the coefficient on family ownership in the management regressions of table 2 falls from a significant −0.262 in column 1 to an insignificant −0.207 in column 4, with most of this fall being due to managerial ability.[34] This is consistent with some of the association being due to weaker managerial talent in family-run firms.[35]

We probed the results further by distinguishing between firms whose CEO was selected by primogeniture (i.e., was the eldest son, grandson, etc. of the founder) and those whose CEO was not. Although the coefficient was more negative than the basic indicator for family ownership, it was imprecisely determined and not significantly lower in specifications like those in tables 2 and 3.[36] However, in the TFP specifications of table 4 the coefficient on primogeniture was negative and significant.[37] The broad consistency of these patterns with those of earlier studies is reassuring, although the smaller sample size of our data set makes us cautious about drawing too strong a conclusion over family firms.

Other outcomes.—We also investigated many other outcomes discussed in the online appendixes. We examined whether there was faster wage growth (as a proxy for promotion) for the more able employees in better-managed firms (online app. table A5). But when interacting management scores and

[33] For deeper investigations into the role of family firms, see Sraer and Thesmar (2007), Bertrand and Schoar (2006), and Bloom and Van Reenen (2007).

[34] The negative association between management and family ownership is particularly strong and significant for targets and operations management. It is insignificant for people and monitoring management.

[35] We also found a negative correlation between family ownership and productivity in tables 3 and 4, although this was not statistically significant.

[36] For example, in a specification like col. 1 in table 2, the coefficient (standard error) on primogeniture was −0.316 (0.210), compared with −0.100 (0.171) for the coefficient on family ownership.

[37] For example, in a specification like col. 5 in table 4, the coefficient (standard error) on primogeniture was −0.181 (0.075), compared with −0.056 (0.060) for the coefficient on family ownership.

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worker ability together in the wage growth equation, we found that the coefficient was insignificant.

Average wage bill versus AKM.—Another question is whether our approach of using AKM fixed effects to proxy for worker, managerial, and firm "quality" buys us any more information than simply conditioning on average wages. There is a tradition in firm-level productivity analysis of using the wage bill instead of employment as a measure of "labor services" (e.g., Hsieh and Klenow 2009). Under competitive markets and perfect substitutability between heterogeneous workers, this seems an attractive approach, as the wage bill is usually available in firm accounts, whereas individual wages are not.

Online appendix table A8 investigates this issue, beginning in column 1 with the basic TFP specification from column 1 of table 4. In column 2, we include the log of the average wage bill per employee, taken from the firm-wide Orbis accounts. Consistent with existing work, this suggests that TFP is higher in firms with higher average "accounting wages," as the coefficient is positive and (weakly) significant, increasing the R^2 from 0.561 to 0.575. If instead of the accounting wage we include our preferred AKM controls, there is a larger increase in the R^2, to 0.685. Furthermore, the average wage estimated from firm accounts is now insignificant conditional on our controls for employee and firm fixed effects in column 4. In column 5, we include the average of the individual ln(wages) from the IEB. This is much more powerful than the accounting measure (which probably has greater measurement error), explaining 0.679 of the variance, almost as much as our AKM measures in column 4. Nevertheless, including our AKM measures gives additional information over and above the simple average individual wage, with employee and managerial ability remaining significant (the joint F-test of the three AKM terms is 9.84, which is significant at the 1% level). The bottom line from this is that our AKM approach adds much more information than simply using the wage bill and/or simply using the average of individual wages of the workers currently in the firm.[38]

V. Conclusions

In this paper, we have examined whether some core management practices found to be important for firm productivity (e.g., Bloom and Van Reenen 2007; Bloom et al. 2016) are due to the higher ability of employees, especially managers, in these firms. We merge German administrative employee-employer data (the IEB) with the WMS management data. We estimate an overall measure of individual ability for each worker using the employee

[38] As with table 2, we also considered controlling for a number of other observable measures of human capital, such as general experience and tenure in the job or firm in the TFP regressions, but these did not make any substantial difference to the results.

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fixed effects from wage equations in the manner of Abowd et al. (1999). This approach also provides us with information on the ability of the top quartile of workers, who we interpret as the firm's managers, and with an estimate of the average pay premium paid by the firm relative to the outside labor market. Card et al. (2013) have documented a large (and increasing) degree of firm-specific wage premia in these data, consistent with evidence in many other countries.

We show several interesting stylized facts in our data. First, we find a strong relationship between average employee ability and management practices. This is particularly strong at the top end of the ability distribution, suggesting that managerial ability is important in explaining why some firms have high management scores (over and above average worker human capital). When we estimate production functions, we find that firms with higher worker and managerial human capital have higher productivity. However, the WMS management scores remain significant in production functions and TFP equations even after conditioning on all measures of employee ability. Including human capital reduces the association of productivity with management by between 30% and 50% (with our preferred estimates at the low end of this range). Although we cannot rule out the idea that there could be further aspects of human capital we are not accounting for, the continued importance of management practices for firm performance regressions is striking.

Delving further into the management score—the employee-ability relationship—we show that well-managed firms have a larger stock of higher-ability workers. Firms with high management scores accomplish this at least in part by selection. They are able to recruit workers from higher points of the ability distribution and remove those from the lower part of the distribution. This is revealed through our analysis of inflows and outflows of workers.

Taken as a whole, our results suggest that human capital, especially managerial human capital, is important for the capability to sustain successful management practices. However, there appears to be information in the management practice scores that predicts the existence of productivity that is not reducible to the "atoms" of human capital employed in the firm. This could be what some scholars have termed "corporate culture"—something that makes a firm more than simply the sum of its parts. We believe that this is a fascinating research path to pursue, as it links economics with other areas of social science.

In short, individuals who are "lucky" enough to have high ability or low disutility of effort will be disproportionately sorted into high-paying, more productive, and better-managed firms. Hence, their existing wage advantages in a world with homogenous firms are magnified by the presence of heterogeneous management practices. This is another force adding to existing inequalities in the labor market.

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