

# MANAGEMENT PRACTICES, WORKFORCE SELECTION, AND PRODUCTIVITY

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## Abstract

Recent research suggests that a non-trivial part of the cross-firm variation in measured productivity is due to differences in use of advanced management practices. Many of these practices – including monitoring, goal setting, and the use of incentives – are mediated through employee decision-making and effort. To the extent that these practices are complementary with workers' skills, better-managed firms will tend to recruit higher-ability workers and adopt pay practices to retain these employees. We use a unique data set that combines detailed survey data on the management practices of German manufacturing establishments with longitudinal earnings records for their employees to study the relationship between productivity, management, worker ability, and pay. As documented by Bloom and Van Reenen (2007) there is a strong partial correlation between management practice scores and firm-level productivity in Germany. In our preferred TFP estimates only a small fraction (about 3%) of this correlation is accounted for by the higher human capital of the *average* employee at better-managed firms. A larger share (about 13%) is attributable to the human capital of the *highest-paid* workers, a group we interpret as representing the managers of the firm. A similar share is mediated through the pay premiums offered by better-managed firms. Looking at employee inflows and outflows, we confirm that better-managed firms systematically recruit and retain workers with higher average human capital. Overall, we conclude that workforce selection and positive pay premiums explain just under 30% of the measured association of productivity with management practices in German manufacturing.

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Keywords: Management practices, productivity, wages

## Disclaimer

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.

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## I. INTRODUCTION

In a typical four-digit manufacturing industry in the U.S., establishments at the 90<sup>th</sup> percentile of total factor productivity (TFP) are about twice as productive as those at the 10<sup>th</sup> 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.<sup>1</sup> 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 Card et al in this volume for a review), 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.<sup>2</sup> 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 work-flow techniques.<sup>3</sup> Bloom, Sadun and Van Reenen (2016) construct an index of advanced practices that they interpret as “managerial capital” and argue that it can account for about 38% of the 90-10 firm-level spread of total factor productivity in the UK and about a third of the productivity gap between the US (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 impact 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

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<sup>1</sup> For example, Bailey, Hulten and Campbell (1992); Hsieh and Klenow (2009); Bartelsman, Haltiwanger and Scarpetta (2013).

<sup>2</sup> See Card, Heining and Kline (2013) for Germany; Song et al (2015) or Barth et al (2014) for the US; Faggio, Salvanes and Van Reenen (2010) for the UK.

<sup>3</sup> In a prescient precursor of this paper, Ichniowski et al (1997) conduct a robustness test where they include multiple measures of managerial ability such as a quadratic in tenure of the line manager and site’s Human Resource (HR) manager or even more rigorously, a full site of line and HR manager fixed effects. They find that their HR management system variable is robust to the inclusion of these and the coefficients are little changed. We will also find our management practice variables have a robust correlation with firm productivity, but the coefficient will be attenuated when conditioning on the quality of individual managerial human capital.

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.<sup>4</sup>

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 WMS (the World Management Survey, discussed by Bloom and Van Reenen, 2007 and 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 a person-specific measure of earnings capacity for each worker, and plant-specific pay premiums for each workplace. 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) 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 through 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.

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

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 percent of the association of better management practices with productivity.<sup>5</sup>

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, we link to work on corporate culture by economists and management scholars (e.g. Guiso et al, 2013, 2015; O'Reilly, 1989). 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 the empirical framework, Section III the data and Section IV the results. Some concluding comments are offered in Section V. The Online Appendices contain more details about the data and many additional specifications and robustness checks.

## **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 non-labor 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.<sup>6</sup> 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-CEO determines the

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<sup>5</sup> 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 WMS suggests that this is not be the main route.

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

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 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 management of the firm. We ask to what extent the association of productivity with 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 total factor productivity and the quality of labor. Specifically, suppose that value of the output of firm  $j$  in period  $t$ ,  $Y_{jt}$ , depends on inputs of non-management labor  $N_{jt}$ , management labor  $M_{jt}$ , intermediate inputs  $I_{jt}$ , and capital  $K_{jt}$ , through a constant returns to scale production function:

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

where  $\theta_{jt}$  represents TFP in period  $t$ , and  $Q_{Mjt}$  and  $Q_{Njt}$  are the productivity levels of non-management workers and managers at the firm. We think of better-managed firms as potentially selecting different types of managers and non-management 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  $\theta_{jt}$ .

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

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

where  $s_0$  is a constant,  $s_N$ ,  $s_M$ ,  $s_I$ , and  $s_K$  are the cost shares of non-management labor, management labor, intermediate inputs, and capital, respectively, and  $\epsilon_{jt}$  is an approximation error.<sup>7</sup> 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.<sup>8</sup> Letting  $L_{jt} = N_{jt} + M_{jt}$  represent total employment and  $s_L = s_M + s_N$  represents the cost share of labor inputs, and defining  $Q_{jt}$  as the geometric average of the productivity levels of managers and non-managers:

$$Q_{jt} \equiv [(Q_{Njt})^{s_N} (Q_{Mjt})^{s_M}]^{1/s_L} . \quad (3)$$

Equation (2) can be rewritten as:

$$\log Y_{jt} = s'_0 + s_L \log L_{jt} + s_I \log I_{jt} + s_K \log K_{jt} + s_L \log Q_{jt} + \log \theta_{jt} + \epsilon_{jt} , \quad (2')$$

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 non-management 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 productivity 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 (1996, henceforth “AKM”), which decomposes wages into worker- and establishment-specific pay components. Specifically, AKM assume that the log of the wage received by worker  $i$  in period  $t$  can be decomposed as:

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

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<sup>7</sup> Note that the  $s$  coefficients in this equation (including both the constant and the factor shares) 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.

<sup>8</sup> 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.

where  $\eta_i$  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)<sup>9</sup>,  $J(i,t)$  is an index function that gives the identity of the workplace of individual  $i$  in period  $t$ ,  $\psi_j$  is a time-invariant wage premium paid to all workers at workplace  $j$ , and  $r_{it}$  is a residual pay component. In this model,  $\eta_i$  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  $\psi_j$  can be interpreted as a measure of the financial incentives associated with continued employment at the firm. AKM 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.<sup>10</sup>

Card, Heining and Kline (2013) (CHK) show that the AKM model provides a relatively good approximation to the structure of wages in Germany, with  $\bar{R}^2$  statistics of around 90 percent. 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 effects estimated by CHK to summarize different workers' abilities and the strength of the financial incentives offered at different workplaces.<sup>11</sup>

Specifically, we use the average of the estimated worker effects for full time employees at a given establishment ( $\bar{\eta}_j$ ) 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.<sup>12</sup> We assume that the average productivity of labor inputs

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

<sup>10</sup> 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 CHK, this rules out mobility based on a “match-specific” component of pay.

<sup>11</sup> 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.

<sup>12</sup> Since the IEB data do not include information on hours, CHK limit their estimated models to full time workers. Over 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 CHK estimates are about

at the firm is affected by both factors, as well as by the adoption of advanced management practices (indexed by a measure  $\Lambda_j$ ):

$$\log Q_{jt} = \rho_0 + \rho_1 \bar{\eta}_j + \rho_2 \hat{\psi}_j + \rho_3 \Lambda_j + v_{jt}. \quad (5)$$

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  $\rho_1$ .<sup>13</sup> The magnitude of the coefficient  $\rho_2$  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 ( $\theta_{jt}$ ) can be parameterized as:

$$\log \theta_{jt} = \lambda_0 + \lambda_1 \bar{\eta}_{Mj} + \lambda_2 \Lambda_j + \varphi_{jt}, \quad (6)$$

where  $\bar{\eta}_{Mj}$  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:

$$\begin{aligned} \log Y_{jt} = & s''_0 + s_L \log L_{jt} + s_I \log I_{jt} + s_K \log K_{jt} \\ & + \pi_1 \bar{\eta}_j + \pi_2 \hat{\psi}_j + \pi_3 \bar{\eta}_{Mj} + \pi_4 \Lambda_j + \epsilon'_{jt} \end{aligned} \quad (7)$$

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  $\epsilon'_{jt} = \epsilon_{jt} + s_L v_{jt} + \varphi_{jt}$ . Equation (7) is a standard log-linear 3-factor production function, augmented with four additional productivity factors: (1) a measure of the average quality of the plant's workforce ( $\bar{\eta}_j$ ); (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 ( $\bar{\eta}_{Mj}$ ); and (4) a measure of the use of advanced management practices ( $\Lambda_j$ ).

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:

$$\begin{aligned} \log TFP_{jt} \equiv & \log Y_{jt} - s_L \log L_{jt} - s_I \log I_{jt} - s_K \log K_{jt} \\ = & s''_0 + \pi_1 \bar{\eta}_j + \pi_2 \hat{\psi}_j + \pi_3 \bar{\eta}_{Mj} + \pi_4 \Lambda_j + \epsilon'_{jt} \end{aligned} \quad (8)$$

In our empirical analysis below we compare estimates of equations (7) and (8) to estimates of similar "reduced form" specifications that excludes the labor quality and wage premium measures and include

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80% larger for men than women, leading to less measurement error in the male effects. For simplicity, we therefore use the establishment wage premiums for men.

<sup>13</sup> CHK 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 "mini-jobs", and those under 20 or over 60.



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, etc.

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).

### **III. DATA**

Our empirical analysis combines data for the German firms in the World Management Management Survey 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 data base.

#### ***a. The WMS Data Base***

The WMS was developed by Bloom and Van Reenen (2007) as an instrument for eliciting reliable information on the use of advanced management practices. The WMS relies on an interview-based evaluation tool that scores participating firms from one (“worst practice”) to five (“best practice”) in three broad areas.<sup>14</sup> The first is *monitoring*: how well does the firm track what goes on inside its plant(s)

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<sup>14</sup> 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 CFO management style, capturing (for example) differences in strategy over mergers and acquisitions.

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 based on performance, and systematically try to hire and retain the best employees?<sup>15</sup>

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 only told 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 Appendix Table B1.

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 data base. Firms with under 50 workers were excluded from the universe because many small firms do not use (or need) 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 pre-conceived 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.<sup>16</sup> 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 also 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

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<sup>15</sup> These practices are similar to those emphasized in earlier work on management practices, by for example Ichniowski, Prennushi and Shaw (1997) and Black and Lynch (2001).

<sup>16</sup> The survey also collects information on a set of “noise controls” about the interview itself, including the time of day and 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 our regression analysis.

from the BVD ORBIS data base (which included 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 to 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 only available 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).<sup>17</sup>

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 these and then z-scoring this average. This process yields a management practice score with mean zero and standard deviation one.

#### ***b. Worker-Level Data from the IEB***

The worker-level data used in our analysis come from the Integrated Employment Biographies (IEB) data base maintained by the IAB. For each job lasting a day or more, the IEB includes employee information such as age, gender and education, employer information such as industry and location, and job-spell-based information on characteristics such 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.

Online Appendix A3 describes how we merge firms in the WMS to establishments in the IEB data, primarily using the firm name and address information in both datasets. Overall, we were able to link 361 of the 365 firm in the WMS to an establishment identifier in the IEB. We then searched the IEB data base 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 construct 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.

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<sup>17</sup> 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.

To measure worker skills and the wage premiums offered by different firms we use the estimated worker and firm effects estimated by CHK. CHK 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, CHK limit their analysis to full time workers: no worker effects are available for part time employees or those who hold so-called mini-jobs.<sup>18</sup> Henceforth when we refer to "wages", the reader should bear in mind we are referring to daily wages (rather than the hourly wage). Another limitation of the IEB data is that daily wage is censored for about 10% of men and 2% of women. CHK use a Tobit model to allocate earnings for the censored cases. (A similar procedure was used by Dustmann, Ludsteck, and Schonberg, 2009, who also provide some information on the quality of the Tobit approximation to the upper tail of wages in Germany).

CHK estimated separate models for full-time male and female workers age 20-60 in four overlapping intervals: 1985-1991, 1990-1996, 1996-2002 and 2002-2009. For all our analysis we use the worker effects from the 1996-2002 interval, as this pre-dates the measurement of management in 2004 and beyond, except for the outflow analysis where we use the 2002-2009 period.

Overall we have estimated person effects for 79% 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 CHK). 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 in the period from 2003 to 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

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<sup>18</sup> 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.

on maternity leave, people moving from self-employment or a job in the civil service,<sup>19</sup> 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 datasets to our merged WMS-IEB sample. We use BVD ORBIS for firm-level information on sales, intermediate inputs (materials) and capital. From the OECD STAN dataset we have 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 Dataset***

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 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. 27% of all workers at these firms are female and 12% have a university degree.

The next two rows of the table show the average cost shares of intermediate inputs and labor inputs, based on industry-wide averages for German firms reported in the STAN data set. The input share of intermediate inputs is relatively large (67% on average) while the average labor share is 23%. 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, non-family 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% who are family owned and 13% 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 IVD, below.

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<sup>19</sup> Self-employed workers and civil servants are excluded from the IEB.

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 of 1, like we do with the management score.<sup>20</sup> We have estimated employee fixed effects for just under four-fifths of the workers who can be matched to a WMS firm.<sup>21</sup>

## IV. RESULTS

### *a. 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 panel 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 lower-middle of the skill distribution. As discussed in more detail below, Figures 1 and 2 imply that firms with more advanced management practices have somewhat lower dispersion in daily wages but wider dispersion in worker skills.<sup>22</sup>

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<sup>20</sup> The estimated person and firm effects in an AKM model are only identified up to a linear constant. Since the male and female models are estimated separately, the person effects are normalized differently. We re-center the male and female effects to have mean zero across all firms in our sample, then average the person effects for males and females, then standardize the resulting mean.

<sup>21</sup> The coverage is smaller in East Germany, where we can only merge an ability measure if the employee has been in a connected with a West German firm. We show robustness to dropping all East German firms.

<sup>22</sup> CHK show that over the past three decades establishments in West Germany have become more specialized in terms of the distribution of occupations. Contrary to our expectations, Figure 2 suggests that this tendency is not more pronounced among middle sized manufacturing firms with higher management scores.

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-scatter plot 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 labelled “employee ability”). There is clearly an upward sloping relationship as revealed by the line of best fit. Figure 4 is a similar bin-scatter 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).

Next we examine the correlates of firm productivity. Figure 5 shows the non-parametric 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).<sup>23</sup>

### ***b. Correlates of Management Practice Scores***

To provide more contextual information on the relationship between workforce quality and management 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 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.<sup>24</sup> The estimates in column (1) confirm the findings from Bloom and Van Reenen (2007) that larger firms in Germany have significantly higher management scores and family owned firms significantly lower management scores (we discuss the family firm results more detail in sub-section IVD below).

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<sup>23</sup> Kernel density plots of employee and managerial ability are presented in online Figure A1, both overall and broken down by high and low WMS management score firms.

<sup>24</sup> 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).

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 Table A2 we show this finding is also robust to including other measures of observable human capital (experience, age and tenure), none of which have a large or significant correlation with management scores. 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 co-vary together.

## **IVB Quantifying the Channels Linking Management Practices to Productivity**

### ***a. 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, 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. 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, Sadun and Van Reenen (2016). The coefficient on the management score variable falls to 0.20 when we control for average employee ability (column (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.<sup>25</sup> 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

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<sup>25</sup> 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 RCTs and non-experimental regressions across all countries (Bloom et al, 2014).



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.

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 2, 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. Panel A shows a bin-scatter plot relating the estimated firm-specific wage premiums to  $\ln(\text{sales per worker})$ . These are positively related, as has also been documented in other countries (e.g. Card, Cardoso and Kline, 2015, for Portugal and Abowd, Kramarz and Margolis, 1999, for France). Panel B presents a bin-scatter plot 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 Table A7).

In column (6) of Table 3 we introduce the firm-specific wage premium as an additional control. As expected given the scatter plots, 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).

Columns (7)-(10) of Table 3 present estimates for production function specifications that control for labor, capital, and intermediate inputs.<sup>26</sup> 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 80%. Evidently, more advanced management practices are more likely to be adopted by firms with more capital intensive production

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<sup>26</sup> 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 and impute the value of intermediate inputs if it was missing.

techniques that also use larger shares of intermediate inputs. Controlling for these factors, the coefficient implies that a one standard deviation unit 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. 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 using principal components, and by looking at subsets of the question-specific scores. For example, online Table A6 presents a series of models similar to ones in Table 3, but using 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.

### ***b. 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. Moreover, the coefficients on labor, capital and materials are allowed to vary across detailed sub-industries 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 cost shares, an assumption which 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 24% ( $= (0.08-0.06)/0.08$ ). Controlling for managerial ability reduces the management practice coefficient by another 14% and controlling for the firm wage premium

reduces it by another 16%. So altogether the reduced form association of TFP with 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 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 13% and establishment fixed effects in pay a further 13%. The fraction accounted for by average employee ability falls compared to 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:

- (1) equation (5), which relates overall workforce quality to average human capital ( $\bar{\eta}_j$ ), the firm's pay premium ( $\hat{\psi}_j$ ), and observed management practices ( $\Lambda_j$ ) (with coefficients  $\rho_1$ ,  $\rho_2$ , and  $\rho_3$ , respectively)
- (2) equation (6), which relates TFP to managerial human capital  $\bar{\eta}_{Mj}$  and management practices (with coefficients  $\lambda_1$  and  $\lambda_2$ , respectively)
- (3) 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  $\rho_1$ ,  $\rho_2$ ,  $\lambda_1$ , 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  $\rho_1$ , and  $\rho_2$  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  $\lambda_1$  (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 outside the 20-60 age range. Third, there is some slippage introduced by the presence of multi-plant establishments in our sample, since we only merge firms to a single establishment in the IEB data base.<sup>27</sup> 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.

We also conclude from the pattern of coefficients on the management practice variables (e.g., between columns (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 sub-section to see whether there is any direct evidence that some of the role of management practices operates via selection.

### **IVC. 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

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<sup>27</sup>The establishment identified in the IEB can actually combine 2 or more plants if the plants are all in the same location and assigned the same narrow industry code.

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%). Likewise many job leavers exit to unemployment (30%) or to other destinations (13%).<sup>28</sup>

Table 6 presents an analysis of the relationship between management ability measures and the fraction of new recruits at a firm with estimated employee effects at or above various percentiles of the overall distribution among all new recruits. The employee effects for this analysis are those estimated by CHK 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 10<sup>th</sup>, 25<sup>th</sup>, 50<sup>th</sup>, 75<sup>th</sup> and 90<sup>th</sup> 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 in the period from 1996 to 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; and a richer set of specifications (Panel B) that also control for firm size. In both specifications the coefficient on the management score is positive at every percentile, and particularly strong for workers in the top of the distribution. In the specifications without size controls the management score coefficients for the 75<sup>th</sup> and 90<sup>th</sup> 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 90<sup>th</sup> 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.<sup>29</sup> 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.

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<sup>28</sup> 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).

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

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 the models in Table 7 is the average value of the person effect for leavers who move to unemployment, normalized by deviating from the mean person effect at the firm among all employees in the previous year. Thus, the coefficients reflect the impact of higher management ability on the *differential* layoff/firing rate of higher or lower-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 (in column (3)) and whether the individual was college educated (column (4)). Interestingly, these controls tend to increase the magnitude of the management score coefficient, suggesting that the “quality preference” of better-managed firms is stronger within traditionally measured skill groups than between groups.<sup>30</sup>

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.<sup>31</sup> 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 which 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.<sup>32</sup>

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<sup>30</sup> 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 that the firm policy variables are most likely to be seen when looking at exits to unemployment.

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

<sup>32</sup> 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% ( $= 0.004 * 0.067 / 0.007$ ) 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% ( $= 0.031 * 0.014 / 0.007$ ). Putting the inflows and outflows channels together implies 11% of the ability gap is closed per year.

## IVD. 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 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  $\ln(\text{wages})$  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, though 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 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, 2015).

### *Family Ownership and Governance*

All our regressions include controls for family ownership. We were particularly interested in family ownership, as this has been the subject of much previous research.<sup>33</sup> 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. In the production function.<sup>34</sup> This is consistent with some of the association being due to weaker managerial talent in family run firms. We also found a negative correlation of family ownership with productivity in Tables 3 and 4, although this was not statistically significant.

We probed the results further by distinguishing between firms whose CEO was selected by primogeniture (i.e. was a son or daughter, 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 Table 2 and 3.<sup>35</sup> However, in the TFP specifications of Table 4 the coefficient on primogeniture was negative and significant.<sup>36</sup> The broad consistency of these patterns is with earlier studies is reassuring, although the smaller sample size of our dataset makes us cautious about drawing too strong conclusions over family firms.

### *Other Outcomes*

We also investigated many other outcomes discussed in the Appendix. We examined whether there was faster wage growth (as a proxy for promotion) for the more able employees in better managed firms (online Appendix Table A5). Interacting management scores and worker ability together in the wage growth equation we did find that better managed firms seemed to promote high ability workers more quickly, but the coefficient was insignificant.

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

<sup>34</sup> The negative association of management with family ownership is particularly strong and significant for targets and operations management. It is insignificant for people and monitoring management.

<sup>35</sup> For example, in a specification like column (1) in Table 2, the coefficient (standard error) on primogeniture was -0.316 (0.210) compared to -0.100(0.171) for the coefficient on family ownership.

<sup>36</sup> For example, in a specification like column (5) in Table 4 the coefficient (standard error) on primogeniture was -0.181 (0.075) compared to -0.056(0.060) for the coefficient on family ownership.



### *Average Wage bill vs. AKM*

Another question is whether our approach of using the 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 higher TFP 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  $\ln(\text{wages})$  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 the previous column. 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 significantly more than simply the average of individual wages of the workers currently in the firm.<sup>37</sup>

## **V. CONCLUSIONS**

In this paper we have examined whether some core management practices found to be important for firm productivity (e.g. in Bloom and Van Reenen, 2007; Bloom et al, 2016) are due to the higher ability of employees, especially managers, in these firm. 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 fixed effects from wage equations in the manner of Abowd et al (1999). This approach also provides us with information on ability of the top quartile of workers, who

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<sup>37</sup> 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.

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, Heining and Kline (2013) have documented a large (and increasing) degree of firm-specific wage premia in this 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 to 50 percent (with our preferred estimates at the low end of this range). Although we can never 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 – employee ability relationship, we show that well managed firms have a larger stock of higher ability workers employees. High management score firms 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 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 its sum of parts. We believe 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 a low disutility of effort will be disproportionately sorted into the 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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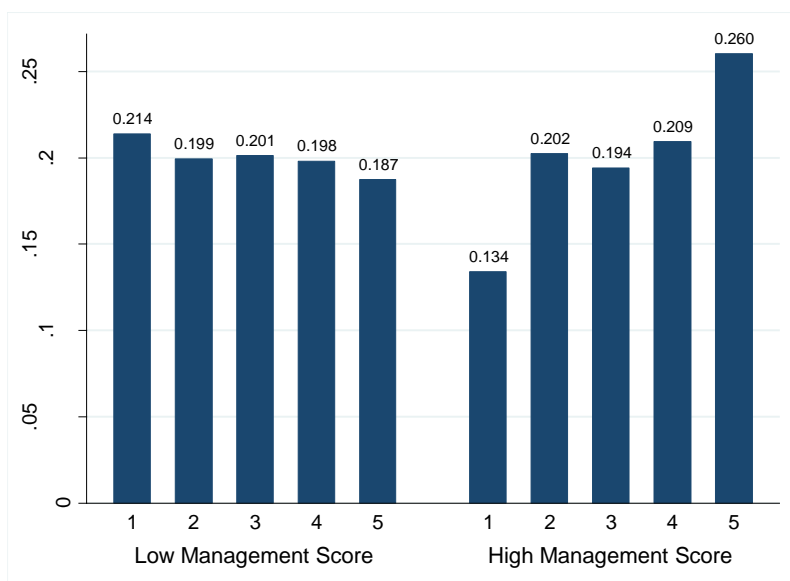
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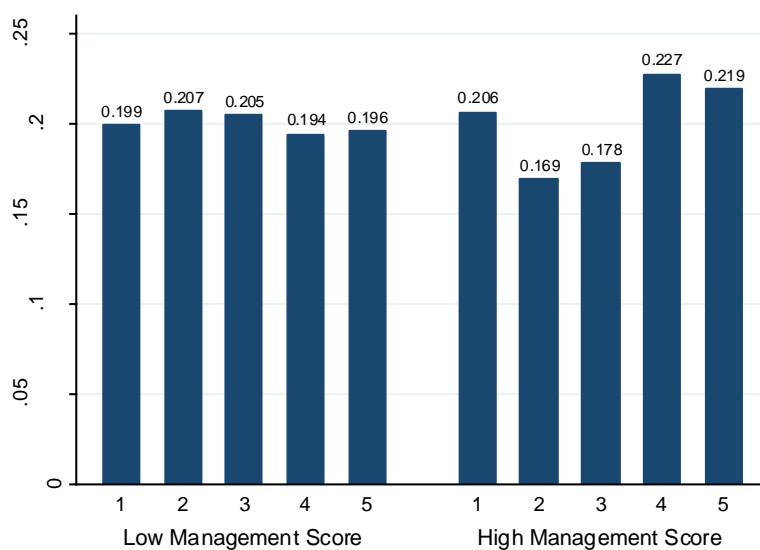
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**Figure 1: Fraction of workers of different wage quintiles in low vs high managed score firms**

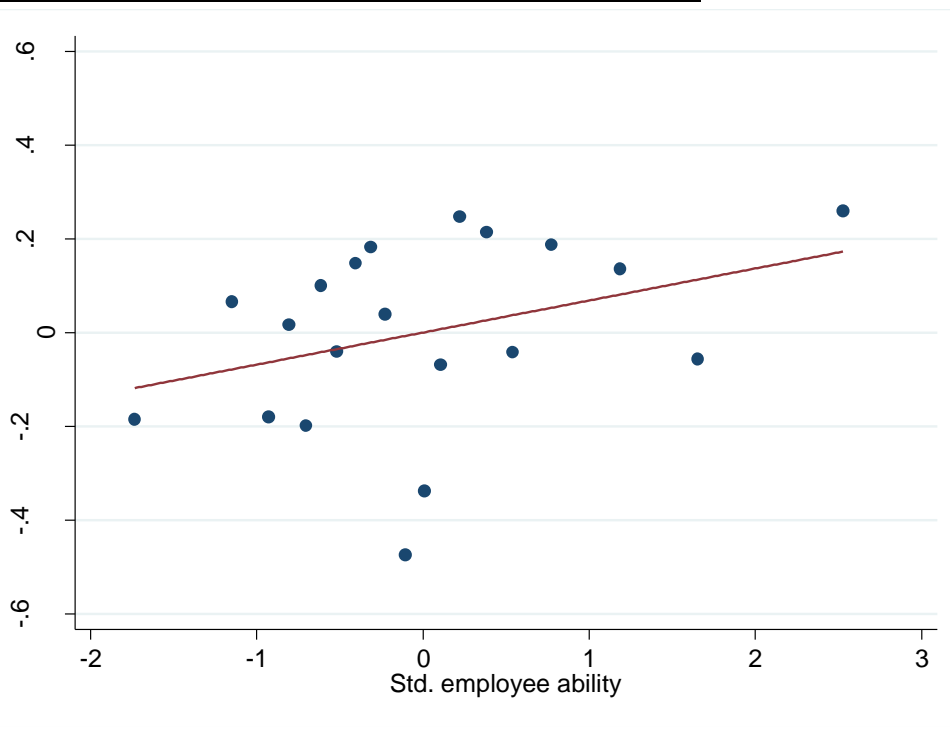


**Figure 2: Fraction of workers of different ability quintiles (as measured by AKM individual fixed effect) in low vs high managed score firms**



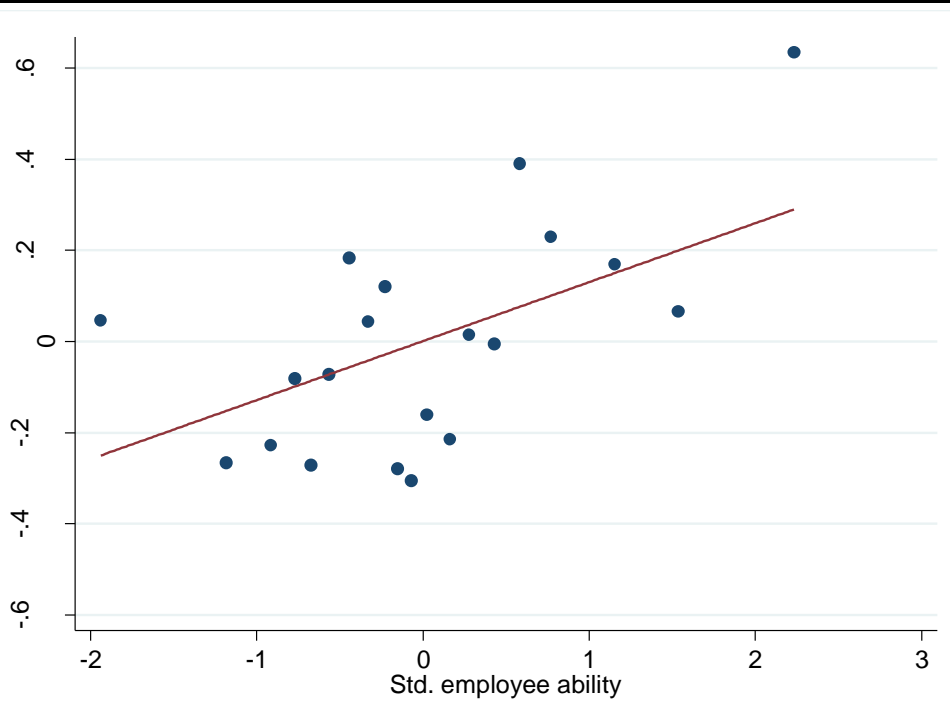
**Notes:** “High Management Score” firms are those in the top decile of the WMS management score. “Low Management Score” firms are all other firms. We bin all workers into quintiles based on the overall distributions of wages or worker ability (as measured by worker fixed effects). Bin 1=lowest 20% and bin 5 = highest 20%. We then tabulate the fractions of workers in each quintile at firms in the top 10% of management scores and all other firms.

**Figure 3: Correlation of Management Score and employee ability**



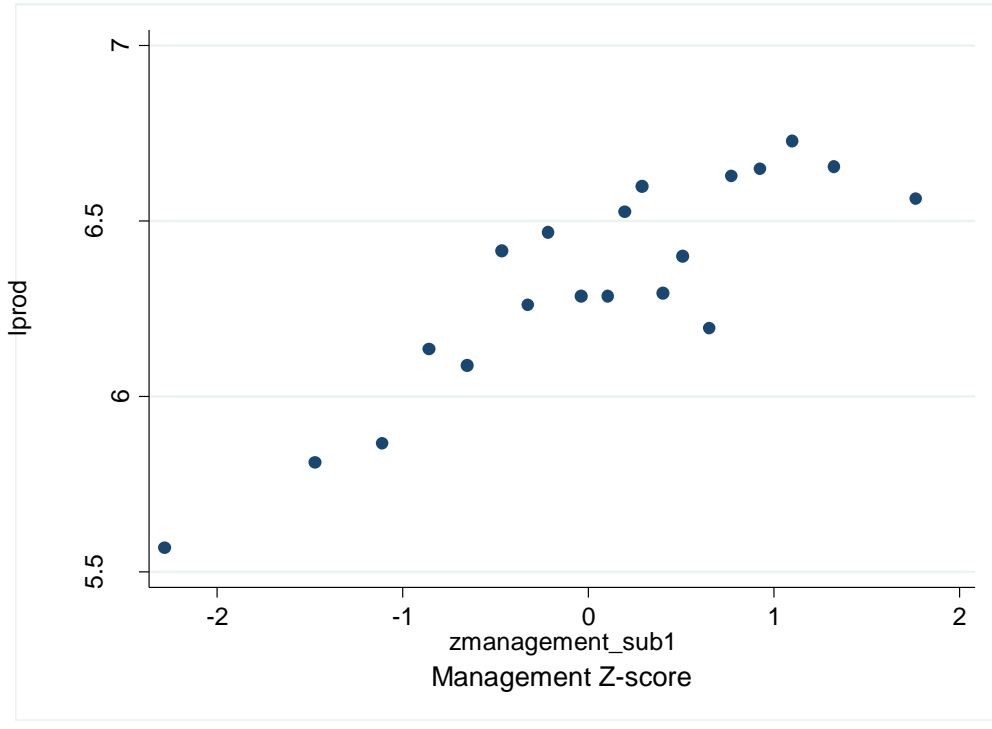
**Notes:** The figure shows bin scatter of management scores against vigintiles of employee ability, as measured by the mean firm-level average of estimated employee effects (from the 1996-2002 period). Management scores and employee ability are both standardized to have mean 0 and standard deviation 1.

**Figure 4: Correlation of Management Score and employee ability controlling for size**



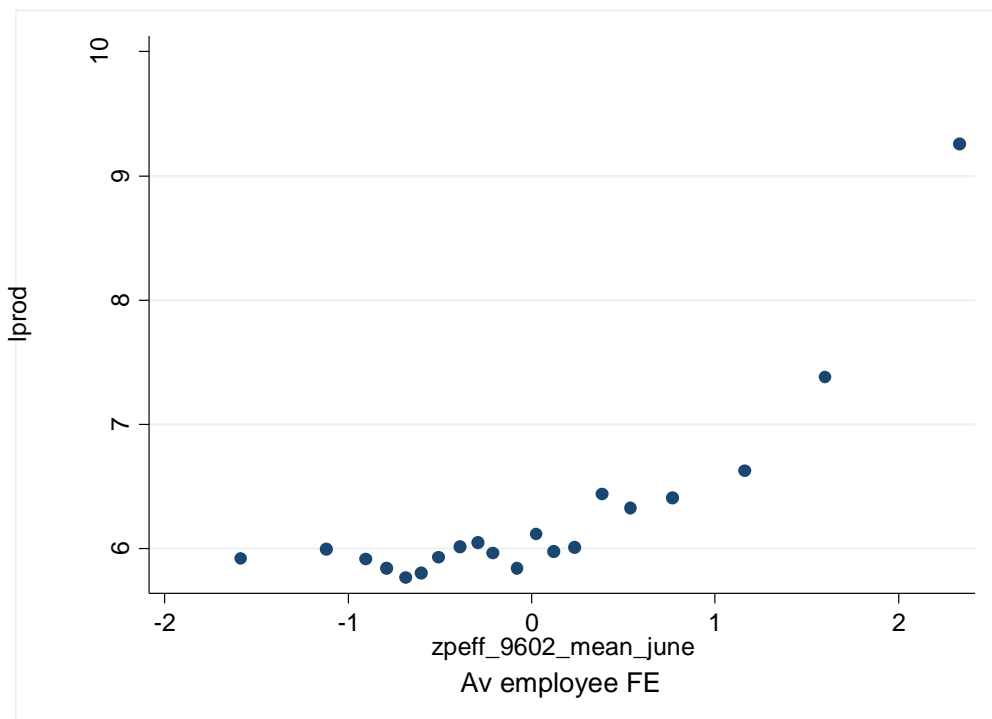
**Notes:** The figure shows bin scatter of management scores against vigintiles of employee ability, as measured by the mean firm-level average of estimated employee effects (from the 1996-2002 period). Both variables are residualized by regressing the underlying variable on  $\ln(\text{employment})$ .

**Figure 5: Positive Correlation of Ln(Labor Productivity) and WMS Management scores**



**Notes:** The figure shows bin scatter of ln(sales per worker) against vigintiles of management scores. Both variables are residualized by regressing the underlying variable on ln(employment).

**Figure 6: Productivity is increasing in employee ability, especially for high levels of ability**

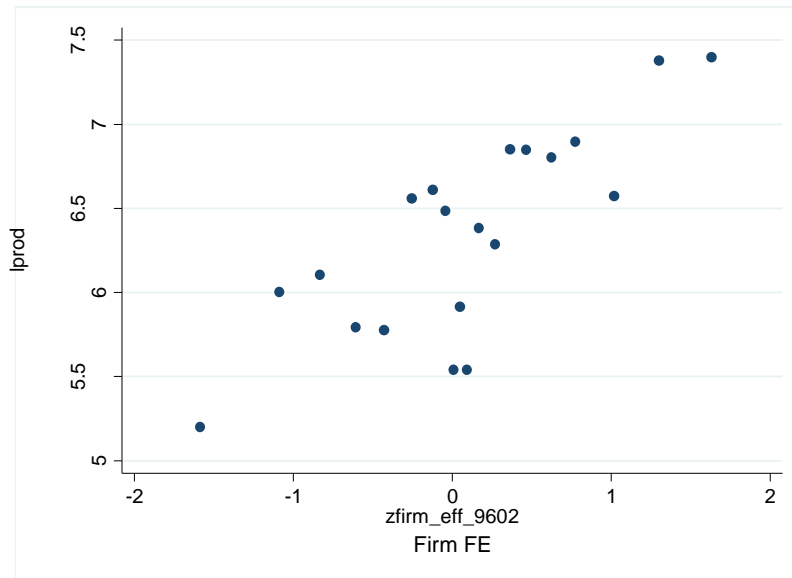


**Notes:** The figure shows bin scatter of ln(sales per worker) against vigintiles of mean worker ability, as measured by mean employee fixed effects. Both variables are residualized by regressing the underlying variable on ln(employment).

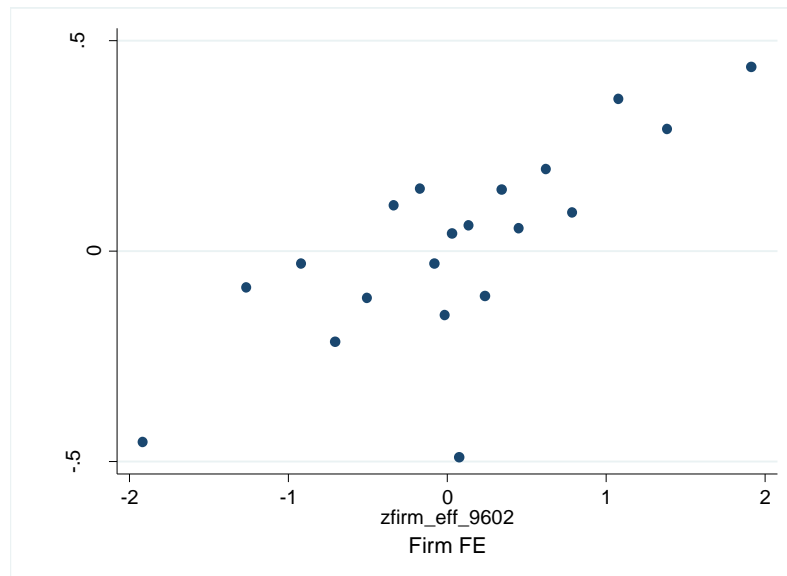


**Figure 7: Firm Fixed effect (in wage equation) is correlated with WMS Management Practice Score and Productivity**

**Panel A: Labor Productivity and Firm Fixed Effect**



**Panel B: WMS Management Score and Firm Fixed Effect**



**Notes:** The figures show bin scatter of  $\ln(\text{sales per worker})$  in Panel A or management scores in Panel B against vigintiles of estimated firm-specific wage premium (“Firm FE”).

**Table 1: Descriptive Statistics for Firms in Matched WMS-IEB Sample**

<b>Panel A: Firms (DATASET)</b>	<b>Mean</b>	<b>Median</b>	<b>Min</b>	<b>Max</b>	<b>SD</b>
Firm located in East Germany (ORBIS)	0.13	0.00	0.00	100	0.34
Firm age (WMS)	64.34	42.50	1.00	489.67	62.79
Number of workers in IEB	440.02	238	1.00	6971	642.9
Proportion Female Workers in IEB	0.27	0.22	0.00	0.89	0.17
Share Employees with University degree (IEB)	0.12	0.08	0.00	0.80	0.13
Median daily wage (IEB)	101.58	99.51	37.21	172.60	28.46
Log of Book Value of Capital (ORBIS)	9.89	10.18	2.71	13.82	1.69
Log of Intermediate Inputs (ORBIS)	11.29	11.78	8.44	14.47	1.07
Intermediate Input Revenue Share (OECD, Ind. Data)	0.67	0.67	0.57	0.89	0.05
Share of Labor in Revenue (OECD, Industry Level)	0.23	0.23	0.04	0.30	0.04
Firm has no competitors (WMS)	0.01	0.00	0.00	1.00	0.09
Firm has less than 5 competitors (WMS)	0.41	0.00	0.00	1.00	0.49
Firm has 5 or more competitors(WMS)	0.59	1.00	0.00	1.00	0.59
Firm is family owned (WMS)	0.23	0.00	0.00	1.00	0.42
Firm is founder owned (WMS)	0.05	0.00	0.00	1.00	0.21
Firm is manager owned (WMS)	0.03	0.00	0.00	1.00	0.18
Firm is non-family private owned (WMS)	0.22	0.00	0.00	1.00	0.42
Firm is institutionally owned (WMS)	0.13	0.00	0.00	1.00	0.33
Other ownership (WMS)	0.06	0.00	0.00	1.00	0.25
Ownership unknown (WMS)	0.28	0.00	0.00	1.00	0.45
Management Score (WMS)	0.00	0.06	-3.25	2.68	1.00
CHK coverage (share employees with worker effects)	0.79	0.87	0.01	1.00	0.25
Average employee ability (CHK worker effects)	0.00	-0.186	-5.56	3.40	1.00
Average managerial ability (CHK top-paid worker effects)	0.00	-0.00	-6.24	2.71	1.00
Firm Wage Fixed Effect (CHK pay premium)	0.00	0.080	-4.48	3.54	1.00

**Notes:** Sample includes 361 firms from 2004, 2006 and 2009 waves of WMS data matched to IEB data on workers. (590 firm-year surveys across all three waves). See Table A1 for more information on data sources and definitions.

**Table 1: Descriptive Statistics for Firms in Matched WMS-IEB Sample – contd.**

**Panel B: Individuals**

<b>Variables</b>	<b>Inflows to our firms from the specified labor market state</b>	<b>Outflows from our firms to the specified labor market state</b>
Unemployment	19,013	40,093
Jobs	70,675	75,023
Non-participation	32,748	17,584
Total	122,436	132,600

**Notes:** Sample includes individuals in the IEB data who joined or exited firms in the WMS-IEB matched panel between 2003 and 2009.

**Table 2: Correlations of Firm Management with Average employee and managerial ability**

<b>Dependent Variable:</b>	(1) Management z-Score	(2) Management z-Score	(3) Management z-Score	(4) Management z-Score	(5) Management z-Score
<b>Mean employee ability</b>		0.216*** (0.078)		0.029 (0.090)	-0.093 (0.112)
<b>Mean managerial ability</b>			0.294*** (0.071)	0.277*** (0.091)	0.258*** (0.095)
<b>Ln(Number of Employees)</b>	0.208*** (0.046)	0.237*** (0.049)	0.261*** (0.048)	0.264*** (0.050)	0.263*** (0.050)
<b>% Employees with college</b>					1.022** (0.452)
<b>Family</b>	-0.262** (0.131)	-0.223* (0.132)	-0.210 (0.129)	-0.207 (0.130)	-0.214* (0.129)
<b>Founder</b>	-0.384 (0.287)	-0.325 (0.277)	-0.244 (0.274)	-0.243 (0.274)	-0.259 (0.271)
<b>Institution</b>	-0.240 (0.184)	-0.239 (0.181)	-0.245 (0.177)	-0.244 (0.178)	-0.249 (0.180)
<b>Manager</b>	-0.256 (0.320)	-0.164 (0.313)	-0.255 (0.293)	-0.244 (0.290)	-0.229 (0.292)
<b>Other</b>	-0.068 (0.172)	-0.031 (0.174)	-0.059 (0.181)	-0.057 (0.181)	-0.039 (0.181)
<b>Omitted reference category for ownership is “private non-family owned”</b>					
<b>Firms</b>	354	354	354	354	354
<b>Observations</b>	588	588	588	588	588

**Notes:** \*\*\* indicates significance at the 1% level, \*\* at the 5% level and \* at the 10% level. All standard errors clustered by 354 firms (in parentheses under coefficients estimated by OLS). Management score and employee ability measures are z-scored to have mean zero and standard deviation one. All columns include a dummy for if 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 CHK ability measures), firm age, a dummy for unknown ownership status, three digit industry dummies and time dummies. Employee ability is mean level of individual fixed effect measured over 1996-2002 period. Managerial ability is mean employee ability in the top quartile of the within firm distribution.

**Table 3: Production Functions**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
<b>Dependent Variable:</b>	<b>Ln(sales)</b>	<b>Ln(sales)</b>	<b>Ln(sales)</b>	<b>Ln(sales)</b>	<b>Ln(sales)</b>	<b>Ln(sales)</b>	<b>Ln(sales)</b>	<b>Ln(sales)</b>	<b>Ln(sales)</b>	<b>Ln(sales)</b>
<b>Management Score</b>	0.264*** (0.052)	0.199*** (0.046)	0.150*** (0.042)	0.129*** (0.042)	0.0743* (0.038)	0.066* (0.038)	0.043** (0.020)	0.035** (0.017)	0.033* (0.017)	0.029 (0.018)
<b>Employee Ability</b>		0.821*** (0.144)	0.597*** (0.101)	0.375*** (0.105)	0.250** (0.098)	0.252** (0.110)		0.110* (0.060)	0.083 (0.073)	0.058 (0.075)
<b>Managerial ability</b>			0.363*** (0.107)	0.329*** (0.100)	0.184* (0.099)	0.155 (0.102)		0.082* (0.048)	0.082* (0.049)	0.082* (0.049)
<b>% Employees with College degree</b>				1.873*** (0.642)	1.308*** (0.465)	1.308*** (0.454)			0.192 (0.232)	0.282 (0.226)
<b>Ln(Labor)</b>	0.315*** (0.067)	0.446*** (0.067)	0.589*** (0.071)	0.591*** (0.071)	0.389*** (0.062)	0.389*** (0.060)	0.055*** (0.019)	0.129*** (0.028)	0.130*** (0.029)	0.132*** (0.026)
<b>Ln(Capital)</b>					0.431*** (0.048)	0.421*** (0.047)	0.204*** (0.023)	0.181*** (0.022)	0.181*** (0.023)	0.176*** (0.022)
<b>Ln(Materials)</b>							0.696*** (0.035)	0.667*** (0.032)	0.663*** (0.035)	0.661*** (0.034)
<b>Ln(firm effect-wages)</b>						0.110** (0.051)				0.039* (0.023)
<b>Firms</b>	333	333	333	333	333	333	229	229	229	229
<b>Observations</b>	560	560	560	560	560	560	378	378	378	378

**Notes:** \*\*\* indicates significance at the 1% level, \*\* at the 5% level and \* at the 10% level. All standard errors clustered by firm (in parentheses under coefficients estimated by OLS). Management score and employee ability is standardized. All columns include a dummy for East German firms, the share of female workers, 5 ownership dummies, dummies for numbers of competitors, firm age, a cubic in the coverage rate, industry dummies and time dummies. Mean Employee ability is mean level of individual fixed effect measured over 1996-2002 period. Mean Managerial ability is employee ability in the top quartile of the within firm distribution.

**Table 4: TFP Specifications**

<b>Dependent Variable:</b>	(1) <b>LnTFP</b>	(2) <b>LnTFP</b>	(3) <b>LnTFP</b>	(4) <b>LnTFP</b>	(5) <b>LnTFP</b>	(6) <b>LnTFP</b>	(7) <b>LnTFP</b>	(8) <b>LnTFP</b>
<b>Management Score</b>	0.081*** (0.021)	0.062*** (0.020)	0.053*** (0.019)	0.044** (0.018)	0.048*** (0.0184)	0.047*** (0.017)	0.041** (0.017)	0.036** (0.017)
<b>Mean Employee ability</b>		0.176*** (0.025)	0.113*** (0.034)	0.103*** (0.033)		0.198*** (0.060)	0.141** (0.058)	0.113* (0.060)
<b>Mean Managerial ability</b>			0.062* (0.035)	0.059* (0.034)			0.055 (0.034)	0.052 (0.034)
<b>Firm effect (in wages)</b>				0.070*** (0.018)				0.051** (0.020)
<b>General Controls</b>	No	No	No	No	Yes	Yes	Yes	Yes
<b>Firms</b>	229	229	229	229	229	229	229	229
<b>Observations</b>	378	378	378	378	378	378	378	378

**Notes:** \*\*\* indicates significance at the 1% level, \*\* at the 5% level and \* at the 10% level. All standard errors clustered by firm (in parentheses under coefficients estimated by OLS). Management score, managerial ability and employee ability are all standardized. All columns include industry dummies, year dummies and firm size. “General controls” are: a dummy for East German firms, the share of female workers, 5 ownership dummies, dummies for numbers of competitors, firm age and a cubic in the coverage rate. Mean Employee ability is mean level of individual fixed effect measured over 1996-2002 period. Mean Managerial ability is employee ability in the top quartile of the within firm distribution.

**Table 5: Implied Structural Estimates**

<b>Variable:</b>	(1) <b>Symbol</b>	(2) <b>Structural Parameters</b>	(3) <b>Reduced form coefficient</b>	(4) <b>TFP basic</b>	(5) <b>TFP Full</b>	(6) <b>Production Function</b>
<b>Management Score</b>	$\Lambda_j$	$s_L \rho_3 + \lambda_2$	$\pi_4$	0.044	0.036	0.029
<b>Mean Employee ability</b>	$\bar{\eta}_j$	$s_L \rho_1$ $\widehat{\rho}_1$	$\pi_1$	0.103 <i>0.447</i>	0.113 <i>0.491</i>	0.058 <i>0.439</i>
<b>Mean Managerial ability</b>	$\bar{\eta}_{Mj}$	$\lambda_1$	$\pi_3$	0.059	0.052	0.082
<b>Firm effect (in wages)</b>	$\hat{\psi}_j$	$s_L \rho_2$ $\widehat{\rho}_2$	$\pi_2$	0.070 <i>0.304</i>	0.051 <i>0.222</i>	0.039 <i>0.295</i>

**Notes:** These are estimates of equation (7). Column (4) uses estimates from Table 4 column (4); column (5) uses estimates from Table 4 column (8), column (6) uses estimates from Table 3 column (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 columns (4) and (5) and the estimate of the coefficient on labor from Table 3 column (10) of 0.132 in column (6).

**Table 6: Inflows from Employment and Unemployment**

Dependent Variable:	(1)	(2)	(3)	(4)	(5)
Percentile	Percentile of the ability of different quantiles of the inflow distribution				
	10%	25%	50%	75%	90%
<b>Panel A. No Size Control</b>					
Management Score	0.003 (0.002)	0.003 (0.004)	0.006 (0.005)	0.016** (0.006)	0.019*** (0.006)
% college	0.081*** (0.013)	0.212*** (0.029)	0.304*** (0.052)	0.075 (0.086)	0.090 (0.057)
<b>Panel B. Including Size Control</b>					
Management Score	0.003 (0.002)	0.004 (0.004)	0.005 (0.006)	0.007 (0.007)	0.010* (0.006)
% college	0.081*** (0.015)	0.202*** (0.030)	0.314*** (0.050)	0.123 (0.088)	0.139** (0.062)
Firm Size: Ln(labor)	0.000 (0.002)	-0.005 (0.004)	0.005 (0.007)	0.026*** (0.007)	0.026*** (0.007)
Observations	355	355	355	355	355

**Notes:** \*\*\* indicates significance at the 1% level, \*\* at the 5% level and \* at the 10% level. All standard errors clustered by firm in parentheses under coefficients estimates by OLS 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.



**Table 7: Outflows to Unemployment**

	(1)	(2)	(3)	(4)
<b>Dependent variable:</b>	<b>Ln(Average ability of outflow) – ln(Average ability of incumbents)</b>			
Management Score	-0.091* (0.053)	-0.115** (0.058)	-0.106* (0.060)	-0.133** (0.057)
Average age of outflows			0.048*** (0.016)	0.041*** (0.015)
% college of outflows				4.887*** (0.861)
General Controls	No	Yes	Yes	Yes
Firms	347	347	347	347

**Notes:** \*\*\* indicates significance at the 1% level, \*\* at the 5% level and \* at the 10% level. All standard errors clustered by firm in parentheses under coefficients estimates by OLS based on 40,093 outflows to unemployment in these firms. Column (1) includes dummies for industry and coverage of AKM effects, other column additional include a dummy East German firms, share of female workers, share of workers with university degrees, firm age, and dummies for competition and ownership.

**Table 8: Within firm heterogeneity of wages and employee ability**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<b>Dependent Variable:</b>	<b>90-10 ln(wages)</b>		<b>Coefficient of variation in log wages</b>		<b>90-10 ln(employee ability)</b>		<b>Coefficient of variation in ln(employee ability)</b>	
<b>Management Score</b>	-0.037* (0.022)	-0.030* (0.017)	-0.097*** (0.020)	-0.030** (0.012)	0.027* (0.014)	0.015 (0.012)	0.035** (0.016)	0.023 (0.015)
<b>Observations</b>	571	571	571	571	571	571	571	571
<b>Firms</b>	No	Yes	No	Yes	No	Yes	No	Yes

**Notes:** \*\*\* indicates significance at the 1% level, \*\* at the 5% level and \* at the 10% level. All standard errors clustered by firm in parentheses under coefficients estimated by OLS based on 348 firms . “Controls” are size, industry, firm age, East Germany dummy, cubic in coverage rate, ownership and competition.

# ONLINE APPENDICES: NOT INTENDED FOR PUBLICATION

## APPENDIX A: DATA

### A1. Management and Accounting Data

We overview the WMS data here. More information on an earlier version of the dataset can be found in Bloom, Sadun and Van Reenen (2016). More details on the management survey in general (including datasets, methods and an on-line benchmarking tool) is available on <http://worldmanagementsurvey.org/>.

Our sampling frame was based on the Bureau van Dijk (BVD) ORBIS dataset. This provided sufficient information on companies to conduct a stratified telephone survey (company name, address, industry and a size indicator). BVD has accounting information on employment, sales and (for most German firms) capital. Apart from size, we did not insist on having accounting information to form the sampling population. In every country, including Germany, the sampling frame for the management survey was all firms with a manufacturing primary industry code (SIC 1987 code between 2000 and 3999), with between 50 and 5,000 employees in the most recent year prior to the survey.

Interviewers were each given a randomly selected list of firms from the sampling frame. This should therefore be representative of medium sized manufacturing firms. In addition to randomly surveying from the sampling frame described above we also re-surveyed firms in 2006 and 2009 that we interviewed in the 2004 survey wave used in Bloom and Van Reenen (2007). This was a sample of 732 firms from France, Germany, the UK and the US. In 2009 we also resurveyed all firms interviewed in 2006.

Accounting databases are used to generate our management survey, but how does this compare to Census data? In Bloom, Sadun and Van Reenen (2012) we analyze this in more detail. For example, we compare the number of employees for different size bands from our sample with the figures for the corresponding manufacturing populations obtained from national Census Bureau data from each of the countries. There are several reasons for mismatch between Census data and firm level accounts.<sup>38</sup> Despite these potential differences, the broad picture is that the sample matches up reasonably with the population of medium sized manufacturing firms. This suggests our sampling frame covers near to the population of all firms for most countries

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<sup>38</sup> First, even though we only use unconsolidated firm accounts, employment may include some jobs in overseas branches. Second, the time of when employment is recorded in a Census year will differ from that recorded in firm accounts. Third, the precise definition of “enterprise” in the Census may not correspond to the “firm” in company accounts. Fourth, we keep firms whose primary industry is manufacturing whereas Census data includes only plants whose primary industry code is manufacturing. Fifth, there may be duplication of employment in accounting databases due to the treatment of consolidated accounts. Finally, reporting of employment is not mandatory for the accounts of all firms in all countries.

Of the German firms we contacted 58.6% took part in the survey: a high success rate given the voluntary nature of participation, which was aided by our endorsement letter from the Bundesbank (the German Central Bank). Of the remaining firms 27.2% refused to be surveyed, while the remaining 14.2% were in the process of being scheduled when the survey ended. In Bloom, Sadun and Van Reenen (2016) we analyze the probability of being interviewed. Larger firms and multinationals were more likely to agree to be interviewed, although the size of this effect is not large or statistically significant – firms were about 4 percentage points more likely for a doubling in size. Further, the decision to be interviewed is uncorrelated with revenues per worker, a basic productivity measure. This is an important result as it suggests we are not interviewing particularly high or low performing firms. Firm age and return on capital are also uncorrelated with the response rate.

We have firm accounting data on sales, employment, capital, intermediate inputs, profits, shareholder equity, long-term debt, market values (for quoted firms) and wages (where available). BVD have extensive information on ownership structure, so we can use this to identify whether the firm was part of a multinational enterprise. We also asked specific questions on the multinational status of the firm (whether it owned plants abroad and the country where the parent company is headquartered) to be able to distinguish domestic multinationals from foreign multinationals. We collected many variables through our survey including information on plant size, skills, organization, etc. as described in the main text.

Management Practices were scored following the methodology of Bloom and Van Reenen (2007), with practices grouped into three areas: *monitoring* (eight practices), *targets/goal-setting* (five practices) and *incentives* (five practices). The monitoring section focuses on the introduction of lean manufacturing techniques, the documentation of processes improvements, the tracking of performance of individuals, reviewing performance, and consequence management. The targets section examines the type of targets, the realism of the targets, the transparency of targets and the range and interconnection of targets. Finally, the incentives section includes promotion criteria, pay and bonuses, and fixing or firing bad performers, where best practice is deemed the approach that gives strong rewards for those with both ability and effort. Our management measure averages the z-scores of all 18 dimensions and then z-scores again this average. Details of all the questions are in Appendix B.

## **A2. Estimating Employee and Firm Fixed Effects in the IEB**

We follow Card et al (2013) in estimating the worker and firm fixed effects (see their online appendix for more details, [http://qje.oxfordjournals.org/content/suppl/2013/04/02/qjt006.DC1/QJEC12803\\_KLINE\\_online\\_appendix\\_compiled.pdf](http://qje.oxfordjournals.org/content/suppl/2013/04/02/qjt006.DC1/QJEC12803_KLINE_online_appendix_compiled.pdf))

Briefly, the IEB consists of information on employment spells at a given establishment within a calendar-year, the average daily wage (censored at the Social Security maximum earnings level); information on the gender, birth date, education and occupation of the individual and the industry and geographical location of the firm.

We use all full-time males and females age 20-60 working for non-marginal jobs. One observation per person-firm-year is selected (excluding those with a daily wage under 10 Euros). Education is coded into 5 classes.

Roughly 10% of person-year observations for male workers and 1-2% of observations for female workers are top coded. We follow Dustmann et al (2009) and fit a series of Tobit models to log daily wages. We then impute an uncensored value for each censored observation using the estimated parameters of these models and a random draw from the associated (left-censored) distribution. 500 Tobit models are estimated separately by year, education and 10 year age range with the following variables: age, mean log wage in other years, fraction of censored wages, a dummy for individuals only observed one year 1985-2009, and a dummy for one worker firm. Card et al (2013) report various validation exercises for the Tobit specifications.

Estimation of equation (4) proceeded in two steps. First the model is fitted to the sample of movers between firms to recover the vector of establishment fixed effects along with the vector of coefficients on the time varying covariates. Then for each worker who stayed at the same establishment over the sample interval, the estimated person effect is calculated as a residual averaged over the time period the worker stayed at the same workplace.

The main fixed effects we use in this paper rely on the period 1996-2002 (see text) prior to the management surveys. The only exception is the outflow analysis where we use the fixed effects estimated in 2002-09.

### **A3. Merging Firms in WMS with IEB**

As noted in the text, the WMS sampling frame was taken from the BVD ORBIS database for Germany (which is the population of incorporated firms). We selected firms whose primary industry was manufacturing and who reported having between 50 and 5,000 employees. Interviewers were given random lists of names and telephone numbers within this frame and sought to interview a plant manager in the firm. The address of the plant (and name of manager) was collected when a successful interview occurred.

The IEB is an establishment-level database where we also know the address and name of the establishment. Although most firms are single plant, there can be multi-plant establishments and firms. We used a master list maintained by the Federal Employment Agency and merged using a probabilistic record linkage based on firm names and addresses.<sup>39</sup> Data from both sources underwent extensive preprocessing to harmonize spelling and correct typing errors. For the data linkage process we were supported by the German Record Linkage Center and used the probabilistic Jaro algorithm (Jaro, 1989) implemented in the Merge-Tool-Box (Bachteler, 2011).<sup>40</sup> To speed up the linkage process

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<sup>39</sup> The master list is the BA-Betriebedatei 2006 and contains information on approximately 2 million establishments.

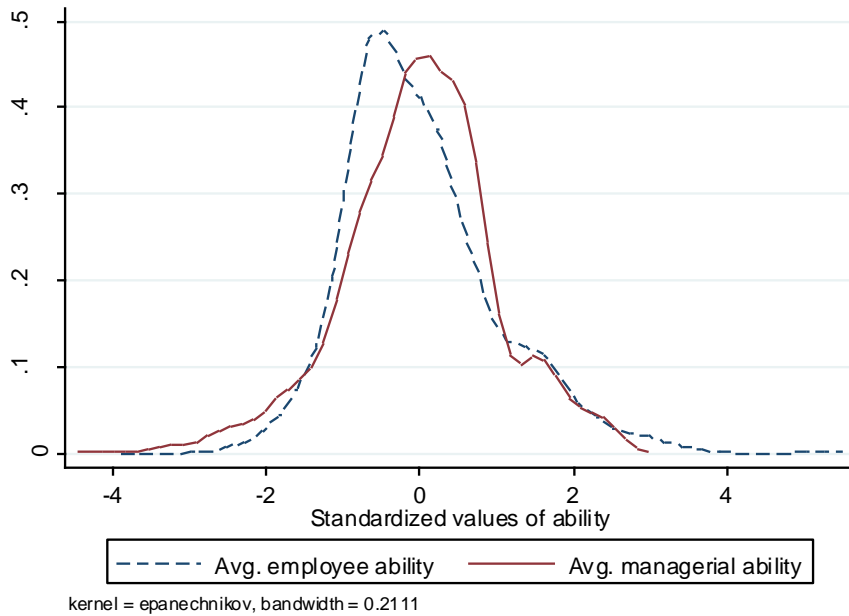
<sup>40</sup> The Merge-Tool-Box is a free Java based record linkage program developed by Rainer Schnell (Schnell et al. 2005).

we blocked the data on three-digit postcodes, and limited the matching process to plants/establishments in the same three-digit postcode (with at most one match per plant). We then conducted manual quality checks and editing (including internet research on firm names and addresses) for plants in the WMS that were unmatched, or were matched with relative uncertainty.

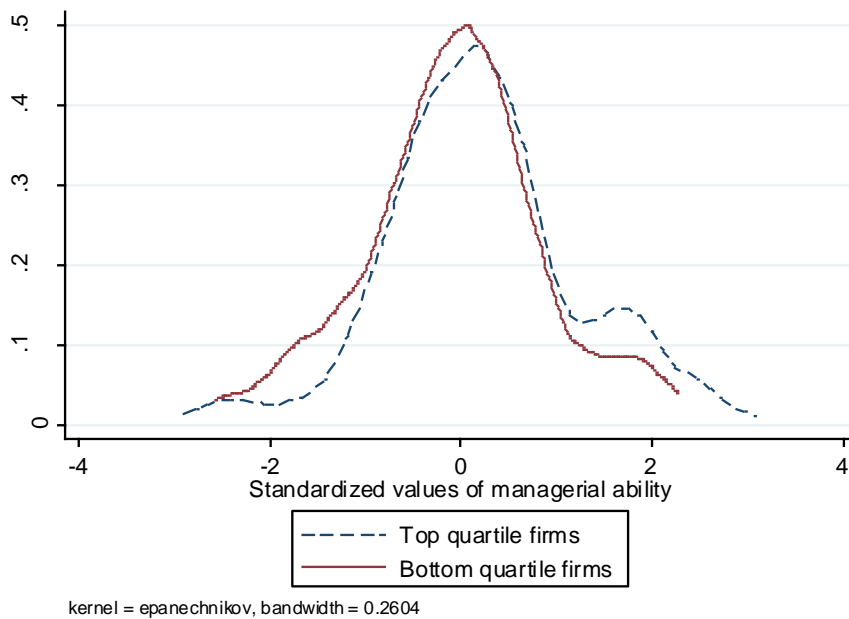
For the majority of the WMS data we can match to IEB straightforwardly on address and name. For some WMS plants belonging to multi-plant companies, we have the issue that IEB name may not correspond easily to the company name. We do, however, have the address from both IEB and WMS which usually resolved any ambiguity. When there still remained any ambiguity (e.g. multiple establishments in a single address, like an industrial park) we could use a combination of the names, whether the plant was a production plant (all WMS plants produce goods, whereas this is not the case in the IEB) and the number of employees at the plant (available in both datasets) to cleanly identify the IEB-WMS matches.

Data at the firm level is at a higher level of aggregation than the establishment. Just as multiple plants can belong to a single establishment, multiple establishments can belong to a single firm. Accounting data on sales, investment and intermediate inputs is only available at the firm level. Hence, when running production functions or TFP equations we should be aware that the accounting measures are only for firm-wide quantities. In the WMS, respondents were encouraged to think of the firm as a whole when answering the questions rather than just their plant. Nevertheless, even if the manager found his plant's practices the most salient in the interview, the management score is still the best predictor of firm-level average practices. In the few cases when we had multiple plants/establishments in the same firm we averaged the responses.

**Figure A1: Employee ability and managerial ability Distribution**  
**Panel A: Overall distribution**



**Panel B: Distribution of managerial ability split by whether the firm has a high or low management practices score**



**Notes:** These are kernel density plots of the average CHK employee fixed effect (“ability) in our firms. Panel A has all employees in dashed blue and just managers (top within firm quartile) in solid red. Panel B plots the density of managerial ability for firms in the top quartile of WMS management score firms (dashed blue) and the lowest quartile (solid red). Better managed firms have a higher mean managerial ability as well as greater dispersion (consistent with Figure 2).

**Table A1: Description and source of variables**

<b>Variable</b>	<b>Source</b>	<b>Description</b>
<i>Average employee ability</i>	IAB	Firm average of employee ability measured for the period 1996 to 2002 from wage regressions (see text). For cross section this is an annual value on June 30 <sup>th</sup> and for pooled data this is the average over the observation period (2003-2009) The cross section is used for the correlation and the production function. Flows are based on the pooled data.
<i>Coverage</i>	IAB-WMS match	Share of workers in a firm that is covered by the estimated employee effects
<i>Average Managerial Ability</i>	IAB	Average of estimated employee fixed effect for those in the top quartile of the ability distribution
<i>Inflow above the 75<sup>th</sup> percentile of ability</i>	IAB	Fraction of total inflows in the sample above the 75 <sup>th</sup> percentile of the ability distribution (in the sample as a whole) to a particular firm. Ability measured 1996 to 2002. Other percentiles defined analogously. Inflow pool is specific to flows from one of the three labor market states (unemployment, other jobs and non-employment)
<i>Ability of the outflows</i>	IAB	This averages the ability of the outflows (ability measure 2002 to 2009). Calculated for all outflow destinations separately to the three labor market states (unemployment, other jobs and non-employment)
<i>Female share</i>	IAB	Share of female workers in the firm



<i>College share</i>	IAB	Share of workers with college or university degree in the firm, or among the inflows/outflows
<i>Age of inflows/outflows</i>	IAB	Avg. age of the individuals entering or leaving the firm
<i>East Germany</i>	IAB	Firm is located in East Germany
<i>Firm Age</i>	WMS	How many years firm has existed
<i>Labour</i>	IAB	Number of employees
<i>Capital</i>	WMS/BVD	Historical value of fixed asses
<i>Materials</i>	WMS/BVD	Cost of all intermediate inputs
<i>Competition</i>	WMS	Categorical, 1: no competitors, 2: less than 5 competitors, 3: 5 or more competitors
<i>Ownership</i>	WMS	Six types: Family; Founder; Institution; Manager; Other; Private

**Table A2: Correlations of Management with Individual Ability, additional controls for tenure and experience**

<b>Dependent Variable:</b>	(1) <b>Management z-Score</b>	(2) <b>Management z-Score</b>	(3) <b>Management z-Score</b>	(4) <b>Management z-Score</b>	(5) <b>Management z-Score</b>
Mean employee ability	-0.093 (0.112)	-0.111 (0.109)	-0.075 (0.106)	-0.084 (0.105)	-0.110 (0.108)
Mean managerial ability	0.258*** (0.095)	0.248*** (0.094)	0.246*** (0.090)	0.243*** (0.093)	0.239** (0.093)
Ln(Number of Employees)	0.263*** (0.050)	0.276*** (0.051)	0.263*** (0.050)	0.253*** (0.051)	0.263*** (0.053)
% Employees with college	1.022** (0.452)	1.070** (0.453)	0.943** (0.476)	1.033** (0.459)	1.129** (0.532)
Ln(labor market exp.)			-0.306 (0.316)		0.201 (0.669)
Ln(Tenure with firm)		-0.114 (0.0742)			-0.098 (0.083)
Ln(Employee age)				-0.0242 (0.0157)	-0.029 (0.032)
Observations	588	588	588	588	588

**Notes:** \*\*\* indicates significance at the 1% level, \*\* at the 5% level and \* at the 10% level. All standard errors clustered by firm (in parentheses under coefficients estimated by OLS). WMS Management score, employee and managerial ability are all standardized to have mean zero and standard deviation one. All columns include a dummy for East German firms, the share of female workers, ownership dummies, the numbers of competitors, firm age, a cubic in the coverage rate, industry dummies and time dummies. Mean Employee ability is mean level of individual fixed effect (measured over 1996-2002 period). Mean Managerial ability is employee ability in the top quartile of the within firm distribution.

**Table A3: Inflows from Employment**

Dependent Variable:	(1)	(2)	(3)	(4)	(5)
Percentile	10%	25%	50%	75%	90%
<b>Panel A. No Size Control</b>					
Management Score	0.002 (0.002)	0.004 (0.004)	0.010* (0.005)	0.019*** (0.007)	0.020*** (0.007)
% college	0.103*** (0.018)	0.213*** (0.033)	0.207*** (0.0517)	-0.032 (0.065)	0.028 (0.063)
<b>Panel B. Including Size Control</b>					
Management Score	0.002 (0.003)	0.005 (0.004)	0.008 (0.005)	0.009 (0.007)	0.011 (0.007)
% college	0.002 (0.002)	-0.003 (0.004)	0.006 (0.005)	0.030*** (0.007)	0.028*** (0.008)
Firm Size: Ln(labor)	0.107*** (0.019)	0.209*** (0.033)	0.217*** (0.051)	0.015 (0.067)	0.073 (0.066)
Observations	353	353	353	353	353

**Notes:** This is the equivalent of Table 6 except using inflows from just employment as the dependent variable. \*\*\* indicates significance at the 1% level, \*\* at the 5% level and \* at the 10% level. All standard errors clustered by firm in parentheses under coefficients estimates by OLS. The management score is standardized. Panel A controls for an East Germany firm dummy, competition, ownership, ln(firm age), female share and industry dummies. Panel B has additional controls for age of inflows.

**Table A4: Inflows from unemployment**

Dependent Variable:	(1)	(2)	(3)	(4)	(5)
Percentile	10%	25%	50%	75%	90%
<b>Percentile of the ability of different quantiles of the inflow distribution</b>					
<b>Panel A. No Size Control</b>					
Management Score	0.002 (0.002)	0.004 (0.005)	-0.001 (0.007)	0.023*** (0.009)	0.022*** (0.008)
% college	0.031* (0.016)	0.110*** (0.030)	0.288*** (0.055)	0.090 (0.067)	0.096 (0.074)
<b>Panel B. Including Size Control</b>					
Management Score	0.002 (0.002)	0.003 (0.005)	0.000 (0.009)	0.012 (0.009)	0.013 (0.010)
% college	0.030 (0.018)	0.109*** (0.032)	0.283*** (0.052)	0.148** (0.074)	0.142* (0.080)
Firm Size: Ln(labor)	-0.000 (0.003)	0.001 (0.005)	-0.003 (0.011)	0.032*** (0.011)	0.025** (0.010)
Observations	344	344	344	344	344

**Notes:** This is the equivalent of Table 6 except using inflows from just unemployment as the dependent variable. \*\*\* indicates significance at the 1% level, \*\* at the 5% level and \* at the 10% level. All standard errors clustered by firm in parentheses under coefficients estimates by OLS based on 32,763 inflows from unemployment in these firms. The management score is standardized. Panel A controls for an East Germany firm dummy, competition, ownership, ln(firm age), female share and industry dummies. Panel B has additional controls for age of inflows and college share of inflows.

**Table A5: Annual average wage growth for entries from employment and unemployment combined**

<b>Dependent variable:</b>	(1) <b>wage growth</b>	(2) <b>wage growth</b>	(3) <b>wage growth</b>	(4) <b>wage growth</b>	(5) <b>wage growth</b>
Management	-0.001 (0.002)		-0.001 (0.002)	-0.001 (0.002)	
Promoting high performers					0.001 (0.005)
Employee ability		-0.007*** (0.002)	-0.007*** (0.002)	-0.007*** (0.002)	-0.007*** (0.002)
Management * Employee ability				-0.001 (0.001)	-0.000 (0.001)
Observations	37,499	37,499	37,499	37,499	37,499
No of firms	357	357	357	357	357

**Notes:** \*\*\* indicates significance at the 1% level, \*\* at the 5% level and \* at the 10% level. All standard errors clustered by firm in parentheses under coefficients estimated by OLS. Management, individual ability, management score and individual ability are standardized. All columns include industry dummies, a cubic in coverage, whether individual is female, whether they have a college degree, a quadratic in individual age, the firm's share of women, ln(firm age), ln(firm size), a dummy for being located in East Germany, competition and ownership. Column (4) also includes interactions between promotion management (“promoting high performers”) and both college and age.

**Table A6: Production function (Principal Component version of Management Score)**

<b>Dependent Variable:</b>	(1) <b>Ln(sales)</b>	(2) <b>Ln(sales)</b>	(3) <b>Ln(sales)</b>	(4) <b>Ln(sales)</b>	(5) <b>Ln(sales)</b>	(6) <b>Ln(sales)</b>	(7) <b>Ln(sales)</b>	(8) <b>Ln(sales)</b>
<b>Management Score</b>	0.108*** (0.021)	0.082*** (0.018)	0.062*** (0.017)	0.054*** (0.017)	0.031** (0.015)	0.017** (0.008)	0.014* (0.007)	0.0126* (0.007)
<b>Mean Employee Ability</b>		0.819*** (0.143)	0.597*** (0.101)	0.375*** (0.105)	0.250** (0.098)		0.110* (0.060)	0.082 (0.073)
<b>Mean Managerial ability</b>			0.361*** (0.107)	0.327*** (0.100)	0.183* (0.100)		0.082* (0.048)	0.082* (0.049)
<b>% Employees with College degree</b>				1.871*** (0.641)	1.308*** (0.464)			0.194 (0.232)
<b>Ln(Labor)</b>	0.313*** (0.070)	0.444*** (0.067)	0.587*** (0.071)	0.589*** (0.071)	0.389*** (0.062)	0.055*** (0.019)	0.129*** (0.030)	0.130*** (0.029)
<b>Ln(Capital)</b>					0.431*** (0.048)	0.204*** (0.023)	0.181*** (0.022)	0.182*** (0.023)
<b>Ln(Materials)</b>						0.696*** (0.036)	0.666*** (0.032)	0.663*** (0.035)
<b>Observations</b>	560	560	560	560	560	378	378	378

**Notes:** \*\*\* indicates significance at the 1% level, \*\* at the 5% level and \* at the 10% level. All standard errors are clustered by 333 firms in parentheses under coefficients that are estimated by OLS. Management score uses first principal component of the 18 questions and employee ability is standardized. All columns include a dummy for East German firms, the share of female workers, ownership dummies, the numbers of competitors, firm age, a quadratic in the coverage rate, industry dummies and time dummies. Mean Employee ability is mean level of individual fixed effect measured (over 1996-2002 period). Mean Managerial ability is employee ability in the top quartile of the within firm distribution.

**Table A7: Correlation of Firm Fixed effect in wages with the WMS management score**

<b>Dependent Variable:</b>	(1) <b>Firm effect</b>	(2) <b>Firm effect</b>	(3) <b>Firm effect</b>	(4) <b>Firm effect</b>	(5) <b>Firm effect</b>	(6) <b>Firm effect</b>
<b>Management Score</b>	0.201*** (0.045)	0.140*** (0.037)	0.124*** (0.040)	0.102*** (0.039)	0.101*** (0.039)	0.081** (0.041)
<b>Ln(Labor)</b>			0.061 (0.044)	0.087* (0.047)	0.097 (0.059)	0.089 (0.054)
<b>% Employees with College degree</b>				1.012*** (0.348)	0.655 (0.594)	0.530 (0.477)
<b>Mean Employee Ability</b>					0.121 (0.225)	-0.055 (0.241)
<b>Mean Managerial ability</b>						0.291** (0.139)
<b>General Controls</b>	No	Yes	Yes	Yes	Yes	Yes
<b>Observations</b>	588	588	588	588	588	588

**Notes:** \*\*\* indicates significance at the 1% level, \*\* at the 5% level and \* at the 10% level. All standard errors clustered by 354 firms in parentheses under coefficients estimated by OLS. The firm effect, WMS management score and employee ability measures are standardized. All columns include a dummy for a firm located in East Germany, the share of female workers, ownership dummies, the number of competitors, firm age, a quadratic in the coverage rate, industry dummies and time dummies. Mean Employee ability is mean level of individual fixed effect (measured over the 1996-2002 period). Mean Managerial ability is employee ability in the top quartile of the within firm distribution.

**Table A8: TFP equations with average wages on right hand side**

	(1)	(2)	(3)	(4)	(5)	(6)
<b>Dependent variable:</b>	<b>Ln(TFP)</b>	<b>Ln(TFP)</b>	<b>Ln(TFP)</b>	<b>Ln(TFP)</b>	<b>Ln(TFP)</b>	<b>Ln(TFP)</b>
<b>Ln(average accounting wage)</b>		0.204* (0.104)		0.074 (0.100)		
<b>Average individual ln(wage)</b>					0.596*** (0.072)	0.454*** (0.101)
<b>Mean employee ability</b>			0.103*** (0.033)	0.104*** (0.033)		0.068* (0.037)
<b>Mean managerial ability</b>			0.059* (0.034)	0.057* (0.033)		0.059* (0.033)
<b>Firm fixed effect in wages</b>			0.070*** (0.018)	0.064*** (0.020)		0.007 (0.022)
<b>Management Score</b>	0.081*** (0.021)	0.074*** (0.020)	0.044** (0.018)	0.043** (0.018)	0.038** (0.015)	0.028* (0.015)
<b>Observations</b>	378	378	378	378	378	378
<b>R-squared</b>	0.561	0.575	0.685	0.687	0.679	0.725

**Notes:** \*\*\* indicates significance at the 1% level, \*\* at the 5% level and \* at the 10% level. All standard errors clustered by firm (in parentheses under coefficients estimated by OLS). The Management score, managerial ability and employee ability are standardized. All columns include industry dummies, a quadratic in the coverage rate, year dummies and firm size. Mean Employee ability is mean level of individual fixed effect (measured over 1996-2002 period). Mean Managerial ability is employee ability in the top quartile of the within firm distribution.



## APPENDIX B1: MANAGEMENT PRACTICES QUESTIONNAIRE

Any score from 1 to 5 can be given, but the scoring guide and examples are only provided for scores of 1, 3 and 5. The survey also includes a set of Questions that are asked to score each dimension, which are included in Bloom and Van Reenen (2007).

<b>(1) Modern manufacturing, introduction</b>			
	<b>Score 1</b>	<b>Score 3</b>	<b>Score 5</b>
<b>Scoring grid:</b>	Other than Just-In-Time (JIT) delivery from suppliers few modern manufacturing techniques have been introduced, (or have been introduced in an ad-hoc manner)	Some aspects of modern manufacturing techniques have been introduced, through informal/isolated change programs	All major aspects of modern manufacturing have been introduced (Just-In-Time, automation, flexible manpower, support systems, attitudes and behaviour) in a formal way
<b>(2) Modern manufacturing, rationale</b>			
	<b>Score 1</b>	<b>Score 3</b>	<b>Score 5</b>
<b>Scoring grid:</b>	Modern manufacturing techniques were introduced because others were using them.	Modern manufacturing techniques were introduced to reduce costs	Modern manufacturing techniques were introduced to enable us to meet our business objectives (including costs)
<b>(3) Process problem documentation</b>			
	<b>Score 1</b>	<b>Score 3</b>	<b>Score 5</b>
<b>Scoring grid:</b>	No, process improvements are made when problems occur.	Improvements are made in one week workshops involving all staff, to improve performance in their area of the plant	Exposing problems in a structured way is integral to individuals' responsibilities and resolution occurs as a part of normal business processes rather than by extraordinary effort/teams
<b>(4) Performance tracking</b>			
	<b>Score 1</b>	<b>Score 3</b>	<b>Score 5</b>
<b>Scoring grid:</b>	Measures tracked do not indicate directly if overall business objectives are being met. Tracking is an ad-hoc process (certain processes aren't tracked at all)	Most key performance indicators are tracked formally. Tracking is overseen by senior management.	Performance is continuously tracked and communicated, both formally and informally, to all staff using a range of visual management tools.
<b>(5) Performance review</b>			
	<b>Score 1</b>	<b>Score 3</b>	<b>Score 5</b>
<b>Scoring grid:</b>	Performance is reviewed infrequently or in an un-meaningful way, e.g. only success or failure is noted.	Performance is reviewed periodically with successes and failures identified. Results are communicated to senior management. No clear follow-up plan is adopted.	Performance is continually reviewed, based on indicators tracked. All aspects are followed up ensure continuous improvement. Results are communicated to all staff

<b>(6) Performance dialogue</b>			
<b>Scoring grid:</b>	<b>Score 1</b> The right data or information for a constructive discussion is often not present or conversations overly focus on data that is not meaningful. Clear agenda is not known and purpose is not stated explicitly	<b>Score 3</b> Review conversations are held with the appropriate data and information present. Objectives of meetings are clear to all participating and a clear agenda is present. Conversations do not, as a matter of course, drive to the root causes of the problems.	<b>Score 5</b> Regular review/performance conversations focus on problem solving and addressing root causes. Purpose, agenda and follow-up steps are clear to all. Meetings are an opportunity for constructive feedback and coaching.
<b>(7) Consequence management</b>			
<b>Scoring grid:</b>	<b>Score 1</b> Failure to achieve agreed objectives does not carry any consequences	<b>Score 3</b> Failure to achieve agreed results is tolerated for a period before action is taken.	<b>Score 5</b> A failure to achieve agreed targets drives retraining in identified areas of weakness or moving individuals to where their skills are appropriate
<b>(8) Target balance</b>			
<b>Scoring grid:</b>	<b>Score 1</b> Goals are exclusively financial or operational	<b>Score 3</b> Goals include non-financial targets, which form part of the performance appraisal of top management only (they are not reinforced throughout the rest of organization)	<b>Score 5</b> Goals are a balance of financial and non-financial targets. Senior managers believe the non-financial targets are often more inspiring and challenging than financials alone.
<b>(9) Target interconnection</b>			
<b>Scoring grid:</b>	<b>Score 1</b> Goals are based purely on accounting figures (with no clear connection to shareholder value)	<b>Score 3</b> Corporate goals are based on shareholder value but are not clearly communicated down to individuals	<b>Score 5</b> Corporate goals focus on shareholder value. They increase in specificity as they cascade through business units ultimately defining individual performance expectations.
<b>(10) Target time horizon</b>			
<b>Scoring grid:</b>	<b>Score 1</b> Top management's main focus is on short term targets	<b>Score 3</b> There are short and long-term goals for all levels of the organization. As they are set independently, they are not necessarily linked to each other	<b>Score 5</b> Long term goals are translated into specific short term targets so that short term targets become a "staircase" to reach long term goals
<b>(11) Targets are stretching</b>			
<b>Scoring grid:</b>	<b>Score 1</b> Goals are either too easy or impossible to achieve; managers provide low estimates to ensure easy goals	<b>Score 3</b> In most areas, top management pushes for aggressive goals based on solid economic rationale. There are a few "sacred cows" that are not held to the same rigorous standard	<b>Score 5</b> Goals are genuinely demanding for all divisions. They are grounded in solid, solid economic rationale

<b>(12) Performance clarity</b>			
<b>Scoring grid:</b>	<b>Score 1</b> Performance measures are complex and not clearly understood. Individual performance is not made public	<b>Score 3</b> Performance measures are well defined and communicated; performance is public in all levels but comparisons are discouraged	<b>Score 5</b> Performance measures are well defined, strongly communicated and reinforced at all reviews; performance and rankings are made public to induce competition
<b>(13) Managing human capital</b>			
<b>Scoring grid:</b>	<b>Score 1</b> Senior management <b>do not</b> communicate that attracting, retaining and developing talent throughout the organization is a top priority	<b>Score 3</b> Senior management believe and communicate that having top talent throughout the organization is a key way to win	<b>Score 5</b> Senior managers are evaluated and held accountable on the strength of the talent pool they actively build
<b>(14) Rewarding high-performance</b>			
<b>Scoring grid:</b>	<b>Score 1</b> People within our firm are rewarded equally irrespective of performance level	<b>Score 3</b> Our company has an evaluation system for the awarding of performance related rewards	<b>Score 5</b> We strive to outperform the competitors by providing ambitious stretch targets with clear performance related accountability and rewards
<b>(15) Removing poor performers</b>			
<b>Scoring grid:</b>	<b>Score 1</b> Poor performers are rarely removed from their positions	<b>Score 3</b> Suspected poor performers stay in a position for a few years before action is taken	<b>Score 5</b> We move poor performers out of the company or to less critical roles as soon as a weakness is identified
<b>(16) Promoting high performers</b>			
<b>Scoring grid:</b>	<b>Score 1</b> People are promoted primarily upon the basis of tenure	<b>Score 3</b> People are promoted upon the basis of performance	<b>Score 5</b> We actively identify, develop and promote our top performers
<b>(17) Attracting human capital</b>			
<b>Scoring grid:</b>	<b>Score 1</b> Our competitors offer stronger reasons for talented people to join their companies	<b>Score 3</b> Our value proposition to those joining our company is comparable to those offered by others in the sector.	<b>Score 5</b> We provide a unique value proposition to encourage talented people join our company above our competitors
<b>(18) Retaining human capital</b>			
<b>Scoring grid:</b>	<b>Score 1</b> We do little to try to keep our top talent.	<b>Score 3</b> We usually work hard to keep our top talent.	<b>Score 5</b> We do whatever it takes to retain our top talent.

Source: Bloom and Van Reenen (2007)

## **Bibliography Online Appendix**

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