OF MANAGERS AND MANAGEMENT: EVIDENCE FROM MATCHED EMPLOYER-EMPLOYEE DATA

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Abstract

Recent evidence suggests that an important fraction of the large productivity dispersion between firms is due to management practices. Are these management practices solely because of the allocation of talent (especially of senior managers)? Or is there an additional role for the way that successful firms combine these units of human capital more efficiently? We address this question by merging our survey data on management practices in the 2000s with near population employer-employee data from Germany between 1975-2011. We find a strong correlation between our management score and the and the ability of employees (as measured by employee fixed effects in wage equations), especially managerial talent. Looking at job inflows and outflows, we find that well managed firms systematically select the more able employees and de-select the less talented. Controlling for observed and unobserved human capital accounts for between one quarter and one half of the firm-level relationship between productivity and management practices. Hence, we argue that the impact of management practices on firm performance is more than simply just the ability of individual managers.

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Keywords: Managerial ability, management practices, productivity, wages

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I. INTRODUCTION

It is widely accepted that there is a huge degree of heterogeneity in firm and establishment performance measures such as productivity that cannot be easily accounted for by measurement error, transitory shocks or conventional factor inputs. For example, the difference in Total Factor Productivity (TFP) between manufacturing plants at the 90th percentile is about double that at the 10th percentile for a typical four digit US industry (Syverson, 2004, 2011). These micro differences appear to matter for aggregate economic performance over time and across countries (e.g. Bailey et al, 1992; Hsieh and Klenow, 2009; Bartelsman, Haltiwanger and Scarpetta, 2013). They are at the heart of many models and theories in macro, IO, trade and labor.

One reason for the dispersion in firm productivity is different management practices. For example, Bloom, Sadun and Van Reenen (2015) argue that about half of the TFP differences between the US and Southern EU countries can be accounted for by their measures of "management capital". At the micro level, Bloom et al (2013) find a large causal role for management practices in their Indian textile field experiment.

If we accept that management practices are an important factor determining productivity, an interesting question arises over whether better management practices are simply due to the quality of individual managers (and/or other employees) or whether firms are more than just "the sum of parts"? If a team of employees of equal human capital were reallocated from firm A to firm B (within the same competitive environment and using the same technologies) would they be equally productive? Or might firm B extract greater productivity from their work efforts if it was better managed?

The classical economic approach to this question is "reductionist", i.e. once we properly measure the inputs of human capital correctly, output should be the same. Lucas (1978) offers a more sophisticated version of this view to account for firm heterogeneity. In his span of control model, it is the talent of the CEO that determines the productivity of the firm. The most talented CEOs are allocated to running the largest firms, so the relationship between management and productivity boils down to the human capital of the CEO. More generally, one might allow for the ability of other managers and workers in the firm to also improve productivity. But the reductionist approach would argue that once we control for all atoms of human capital there is no further role for management practices to affect productivity.

Although the Lucas (1978) model is powerful and parsimonious, we view the focus on CEO-as overly narrow. For example, many iconic firms such as Toyota, GE, IBM and Lincoln Electric remain successful even after their CEO dies and/or all original managers have left the firm. Management scholars refer to this as firm “capabilities” or “corporate culture”. It suggests that there is some intangible managerial capital that is not reducible to the talents of the individuals working there, but is rather to do with how these are combined.[1]

To shed some empirical light on these questions we create a new database which links management practice data that we collected ourselves (the WMS data) using the Bloom and Van Reenen (2007) approach with administrative data on the (near) population of West German workers and the firms that employ them (the IEB data). We proxy (unobserved) managerial and worker ability using the decomposition methods of Abowd, Kramarz and Margolis (1999) and recently extended by Card, Hening and Kline (2013). In these two-way fixed effect models, employee “ability” is proxied by the individual fixed effect in wage equation where we control for time varying observable worker characteristics as well as firm fixed effects.[2]

We match these estimates of individual ability (based on the entire workforce of over 70m observations), to the German firms in the management data. Our results are easily summarized. First, firms with high WMS management practice scores also have highly able employees, in particular they employ highly talented managers. This confirms that other findings of a strong correlation between management practices and observable skills (such as whether an employee attended college) and also holds for unobservable skills. Second, the coefficient on management practices and productivity is reduced by between a quarter and a half when we condition on measures of employee quality. This is consistent with the hypothesis that although managerial talent matters for productivity,

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[1] The idea of corporate culture has recently become popular in economics – see for example Guiso, Sapienza and Zingales (2013, 2015). There is also a huge management literature in this area (e.g. O’Reilly, 1989).

[2] Although there are statistical and economic reasons why the employee fixed effect may not just be ability, we will keep to this convention in the paper and discuss when this might be misleading. It is difficult to think of many other ways to proxy for employee ability in large datasets across many industries and time period.

a large fraction of the impact of management practices on firm performance is not simply the human capital of managers and other employees. Third, better managed firms are able to build up a superior stock of highly able employees through selection (not just on-the job training). They disproportionately hire more able employees and fire less talented employees compared to their less well managed counterparts. We show this by examining the inflows and outflows of the quarter of a million or so workers in the firms we study between 2004 and 2009.

Our paper contributes to many existing literatures. First, as noted above we contribute to the growing literature on firm heterogeneity and economic performance (e.g. de Loecker and Goldberg, 2014). Second, we try to understand the causes of the heterogeneity in management practices and the link to human capital (e.g. Feng and Valero, 2015; Lemos and Scur, 2015; Bloom, Sadun and Van Reenen, 2015). Third, we link to work on corporate culture by economists and management scholars (e.g. Guiso et al, 2013; O'Reilly, 1989). Finally, we contribute to the literature on the importance of managers for firm performance (e.g. Bertrand and Schoar, 2003; Bennesden et al, 2007).

The structure of the paper is as follows. Section II describes the data, Section III gives our empirical framework, and Section IV the results. Some concluding comments are offered in Section V. Online Appendices contain more details about the data.

II. EMPIRICAL MODELS

We begin with the method of estimating individual fixed effects, modelling the ln(daily wage) of individual worker *i* at time *t* to be:

$$y_{it} = \eta_i + \psi_{j\boldsymbol{J}(i,t)} + x'_{it}\beta + r_{it} \qquad (1)$$

Where η_i is the individual worker fixed effect, $\psi_{j\boldsymbol{J}(i,t)}$ is a time-invariant establishment component $x'_{it}\beta$ is a linear index of time varying observable characteristics[3] and r_{it} are random effects. The $\psi_{j\boldsymbol{J}(i,t)}$ has a *t* subscript because the establishment effects are allowed to differ between blocks of time – as noted above we will focus on the estimates for the 1996-2002 period, measuring everything prior

[3] These include education and a cubic in age (interacted with education). We estimate separately for men and women aged between 20 and 60.

to our first management surveys. The random effects are modelled as the sum of a mean zero random match component, a unit root component of individual wages and a mean zero.

We use the total population of the IEB, but following Card et al (2013) restrict the sample for the wage analysis to full time employees ages 20-60 in Western Germany. Separate wage regressions are run for men and women for the following overlapping intervals 1985-1991, 1990-1996, 1996-2002 and 2002-2009. We focus on the decompositions for time intervals between 1996-2002 which cover 86 million person year observations in order that the estimation of the person effects pre-dates the years in which we gather management data (2004-2009). We use the 2002-2009 decompositions as robustness checks in some specifications (this covers 93 million person-year observations).[4]

For each firm we observe the distribution of individual fixed effects η_i, covering 88% of all workers in the matched WMS firms (98% of the relevant population of workers in these firms – e.g. excluding part-timers). All regressions control for the coverage ratio – the proportion of workers in the firm for which we have employee fixed effects.

We are interested in several aspects of how these worker fixed effects relate to the management practice scores and productivity. One part of our analysis examines a classic management augmented production function. Consider modelling output Q_{jt} as proxied by the real sales of firm *j*:

$$\ln Q_{jt} = \alpha_M M_{jt} + \alpha_L \ln L_{jt} + \alpha_K \ln K_{jt} + x'_{jt} \alpha_X + u_{jt} \tag{2}$$

Where *M* is the management practices measure, *L* are labor services, *K* is capital, *x* is a vector of other controls (such as the plant's location within Germany, the number of competitors, firm age, ownership, year and two-digit industry dummies) and *u* is an error term.

[4] There are many substantive econometric issues involved in consistently estimating equation (1). One threat to identification is "endogenous switching" of workers between firms. Card et al (2013) show that the biases associated with this are unlikely to be large based on (i) the empirical symmetry of wages changes when moving between firms with high and low wage fixed effects and (ii) the small change in R-squared when worker-firm match effects are added to equation (1).

How should one measure labor services, *L*? We observe the number of workers, their average hours and a number of observable aspects of employees such as the proportion with college degrees, their gender composition, experience and so on. However, there are likely to be a large number of *unobservable* factors that are relevant for management and output that we cannot easily control for. Consequently, we consider adding measures of employee ability to equation (2). Our baseline method is to simply use average individual ability ($\overline{\eta}_{jt}$) and a proxy for average managerial ability ($\overline{\eta}_{jt}^{M}$). Note that these have time-varying subscripts because although the individual's ability (by definition of equation (1)) is fixed, the composition of individuals employed by the firm changes over time. Under the plausible assumption that managers are the higher ability individuals we use measures such as the average individual effect for employees in the top quartile of the within-firm ability distribution to proxy managerial ability. We consider alternative measures such as different cut-offs than the top quartile and the average individual effect for workers in "management-related" occupational codes in the firm. We are interested in both the coefficients on employee ability and on how our estimates of α_M change conditional on $\overline{\eta}_j$ and $\overline{\eta}_j^M$. One null hypothesis of interest is whether $\alpha_M = 0$ when we control for worker and managerial ability.

In addition to examining how the productivity-management relationship changes after conditioning on ability, we also examine directly the relationship between the ability distribution and management scores within firms. We first show that firms with high management scores employ people of above average ability, especially high managerial ability. We can decompose the stock of employees into incumbents, joiners and leavers between any two points of time. To what extent is the positive correlation between management practices and stock of highly able employees is due to the well managed firms selecting in more able employees and selecting out less talented employees? We tackle this question by analyzing all individuals who join our companies between 2004 and 2009 (the dates when the management survey took place) and all who leave the company over the same period. Using our pre-2003 estimates of ability in equation (1) we ask whether the better managed firms disproportionately select those of high ability and exit those of low ability. Because some of the component of the management questions relate directly to the removal of under-performers we can even investigate whether the changes in composition are related closely to exactly these particular questions.

III. DATA

This study combines the German part of the World Management Management Survey (WMS, Bloom and Van Reenen, 2007; Bloom al, 2014) with the administrative data of the Institute for Employment Research (IAB) – see Dorner et al. (2010) - to create a new linked WMS employer-employee dataset.

IIIA. Management Practices: WMS

To measure management practices we developed a new "double blind" survey methodology in Bloom and Van Reenen (2007). This uses an interview-based evaluation tool that defines and scores from one ("worst practice") to five ("best practice") across 18 basic management practices on a scoring grid. This evaluation tool was developed by an international consulting firm, and scores these practices in three broad areas.[5] First, *Monitoring*: how well do companies track what goes on inside their firms, and use this for continuous improvement? Second, *Target setting*: do companies set the right targets, track the right outcomes and take appropriate action if the two are inconsistent? Third, *Incentives/people management*[6]: are companies promoting and rewarding employees based on performance, and systematically trying to hire and keep their best employees?

To obtain accurate responses from firms we interview production plant managers using a 'double-blind' technique. One part of this double-blind technique is that managers are not told in advance they are being scored or shown the scoring grid. They are only told they are being "interviewed about management practices for a piece of work".

To run this blind scoring we used open questions. For example, on the first monitoring question we start by asking the open question "tell me how your monitor your production process", rather than closed questions such as "do you monitor your production daily [yes/no]". We continue with open questions focusing on actual practices and examples until the interviewer can make an accurate assessment of the firm's practices. For example, the second question on that performance tracking dimension is "what kinds of measures would you use to track performance?" and the third is "If I

[5] Bertrand and Schoar (2003) focus on another important managerial angle - CEO and CFO management style - which will capture differences in management strategy (say over mergers and acquisitions) rather than practices *per se*.
[6] 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).

walked round your factory could I tell how each person was performing?". The full list of questions for the grid are in Appendix Table B.

The other side of the double-blind technique is that interviewers are not told in advance anything about the firm's performance. They are only provided with the company name, telephone number and industry. Since we randomly sample medium-sized manufacturing firms (employing between 50 to 5,000 workers) who are not usually reported in the business press, the interviewers generally have not heard of these firms before, so should have no preconceptions. By contrast, it would be hard to do this if an interviewer knew they were talking to an employee of Siemens or Daimler-Benz. Focusing on firms over a size threshold is important as the formal management practices we consider will not be so important for smaller firms. We did not focus on smaller firms where more formal management practices may not be necessary. Since we only interviewed one or two plant managers in a firm, we wold only have an inaccurate picture of very large firms.

The survey was targeted at plant managers, who are senior enough to have an overview of management practices but not so senior as to be detached from day-to-day operations. We also collected a series of "noise controls" on the interview process itself – such as the time of day, day of the week, characteristics of the interviewee and the identity of the interviewer. Including these in our regression analysis typically helps to improve our estimation precision by stripping out some of the measurement error.

To ensure high sample response rates and skilled interviewers we hired MBA students to run interviews because they generally had some business experience and training. We also obtained Government endorsements for the surveys in each country covered. Most importantly we positioned it as a "piece of work on Lean manufacturing", never using the word "survey" or "research". We also never ask interviewees for financial data obtaining this from independent sources on company accounts. Finally, the interviewers were encouraged to be persistent – so they ran about two interviews a day lasting 45 minutes each on average, with the rest of the time spent repeatedly contacting managers to schedule interviews. These steps helped to yield a 44% response rate which was uncorrelated with the (independently collected) performance measures.

German firms were interviewed in 2004, 2006, 2009 and 2014. Since the IEB data ends in 2011 (see below) we only use the first three survey waves which cover 365 medium-sized manufacturing firms.

Our main measure of management involves z-scoring each of the 18 individual questions, averaging these z-scores and then z-scoring the average. This gives a management index with mean zero and standard deviation one. We compare this to some of the disaggregated individual scores that we think should be particularly relevant for different outcomes (e.g. firing practices in the exit to unemployment regressions).

IIIB. Manager and Worker ability: IEB

Administrative information from German registry data is available at the IAB. The IAB Integrated Employment Biographies (IEB) include information on people employed subject to social security, marginal part-time workers, benefit recipients and officially registered job-seekers. The employment biographies are available from entry in the labor market from 1975 in West Germany and 1993 in East Germany until 2011. It covers more than 80 million individuals. The data include information on employment status, daily wage, education, occupation, age, industry and sex among others. Information are organized in spells with the possibility that one person can have multiple spells at the same time. Since registry data are used to calculate benefit claims, information on employers, employment duration and wage are precise. However one obstacle is that wages are top coded at the social security threshold (Dorner et al. 2010). We deal with this in the standard way of imputing the wage data from auxilliary regressions (see Dustmann, Ludsteck, and Schonberg, 2009 and Appendix A).

The IEB data have been used by many researchers including Card, Heining, Kline (2013) to estimate the role of workplace heterogeneity in widening wage inequality; by Dustmann and Glitz (2015) for firms' response to changes in local labor supply and Schmieder, von Wachter and Bender (2012) for the effect of extended unemployment insurance on employment.

We combine the IEB with the WMS. To link both data sources we perform a probabilistic record linkage on names and addresses from the survey data and the German establishments in the BA-

Betriebedatei 2006 (establishment data of the federal employment agency). This data set contains German establishments with at least one employee liable to social security, i.e. over 2 million establishments per year. 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). [7] To reduce the size of the output data and speed up the linkage process we blocked the data on 3-digit postcodes. Only observations with the same three -digit postcode from both sources were used for comparison. This on the one hand led to a result file that still had a size that could be handled with regular computers but one the other hand prevented firms with typos in the postcode from being merged. Therefore, to increase match rates we also performed manual quality checks and editing including internet research on firms that we received no or very uncertain matches for. Through this extensive data pre- and post-processing we were able to link 361 out of the 365 surveyed firms to the administrative records. The matched firms correspond to the surveyed firms from the WMS. We did not allow for more than one merge per firm. This limit is due to the post code blocking. Since the WMS firms are medium sized manufacturing entities they have few subsidiaries.

We sampled all employees in the IEB data who have worked in one of the WMS firms for at least one day between 2002 and 2009. We observe 251,872 employees in the 361 matched firms. For correlation analysis and the extended production function we use a panel version of the data from 2002 to 2009[8] on June 30th.

For the inflow and outflow analysis we pool the data between 2003 and 2009, i.e. we have one observation per firm. All entries and exits that fall in this period are counted for our sample. We calculate entries to the firms from the following sources. Firstly we define job-to-job transitions as entries of people from other employers. Job-to-job switchers are allowed to have a gap of no longer than two month between two employment spells with no longer than 30 days of unemployment. With this more relaxed definition of job-to-job movers we account for frictions between jobs. Employees might already have a new job offer but have to wait for the new contract to start or want to take some

[7] The Merge-Tool-Box is a free Java based record linkage program developed by Rainer Schnell (Schnell et al. 2005).
[8] To be more precise, we have built up a panel on June 30th for every year between 2002 and 2009.

time off before starting a new job. We cannot differentiate between voluntary and involuntary separations. Recalls into the same firm are not classified as job-to-job movers unless there is at least one other employment spell in between.

Secondly inflows from unemployment, all person observations are taken into account that have an unemployment spell longer than one month before entering a new firm. For the definition of unemployment we follow Eberle et al (2013) as suggested in their guidelines for data preparation of the Sample of Integrated Labour Market Biographies for Stata. Prior to unemployment these person have to have an employment spell within at least two month before registering as unemployed. People that have gaps that are longer than two month before entering our surveyed firms are classified as inflows from other sources. This group "other sources" is quiet heterogeneous. It includes people that might have never worked before, people that might have been self-employed or civil servants[9] as well as people on maternity leave or that worked in foreign countries before. Because we have German administrative data we are not able to distinguish these different inflows. As our analysis is not focusing on these specific inflow reasons not distinguish them will suffice our purpose. We defined outflows out of our firms using the same criteria as for inflows. One person is allowed to move in and out of a firm more than once in the observation period. Table two gives an overview of the in- and outflows into our firms. The majority of transitions are job-to-job moves. For inflows the second largest group is inflows from non-employment whereas outflows are directed rather more to unemployment.

The third dataset we use is on individual level to analyze wage growth in our firms. We use only fulltime employees to have comparable daily wages. For wages above the social security threshold we use the imputed wages from Card et al. (2013). We do wage regressions only on inflows after the first year of firm entry.

Our main regressions are at the firm-year rather than individual level, so we typically average employee ability (or quantiles of ability) across the firm for a given year.

III.C Matched WMS and IEB Dataset

[9] Both groups are not covered by the IEB.

Panel A of Table 1 gives an overview on key firm indicators with exact definitions in Table A1. The firms are spread across 15 out of 16 German Federal states, with 13% in East Germany and thus giving a good regional coverage. Our firms are on average 64 years old, employ 440 workers and pay a daily wage of just over 100 Euros. To make interpretation easier we standardize the management survey scores and ability measures.[10] We have employee ability measures for just under four-fifths of the average firm's employees, mainly because of the age and full year restrictions.[11] We control for a third order polynomial in this "coverage ratio" in all our analyses.

Panel B of Table 1 shows the number of observations we have on inflows and outflows to different labor market states. There are over 132,000 individuals who leave our firms and 122,000 who join the firms. Most outflows and inflows are job-to-job, but there are substantial numbers from (over 19,000) and to (over 40,000) unemployment. We focus on these unemployment transitions as this is where the firm management policies we observe are most likely to show up (we do not know the management practices in most firms on the other side of the job to job transition). But we also present results with flows from other labor market states (i.e. job to job transitions and those to and from non-participation).

IV. RESULTS

IV.A Management Practices and Employee quality

Figure 1 plots out the average ability of workers as measured by the person effects estimated over the 1996 to 2002 period (the full distribution is in Table A1). There is a positive relationship between the two variables, especially after controlling for firm size (Figure 2). Table 2 investigates these relationships in a regression format where the dependent variable is the management z-score. We also control for firm size as previous work has shown that there is a strong positive relationship between size and management (e.g. Bloom et al, 2014). Column (1) shows that mean employee quality is strongly positively associated with this management score as Figures 1 and 2 suggested. Moving a

[10] Note that in the regressions to avoid losing observations on control variables we set missing values to the sample mean and include a dummy when we do this missing variable dummy. This is just a handful of observations except for capital where 92 firms had missing data.

[11] 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.

firm's mean employee ability by one standard deviation is associated with a 0.215 increase in the management score. Column (2) looks at a measure of managerial ability, which assumes managers are in the top quartile of the employee ability distribution. The coefficient on "managerial ability" is larger than on overall ability. Column (3) enters both measures of ability in the same regression and shows that it is managerial ability that matters – the coefficient on average employee ability is insignificant conditional on managerial ability. This result is robust to controlling for an observable measure of human capital (college share) in column (4).

Overall Table 2 suggests that the management practice scores and human capital (especially unobserved managerial ability) are complementary, in the sense that they co-vary together.

IV.B Production Functions

We now turn to examining firm productivity. Figure 3 shows the non-parametric relationship between labor productivity as measured by ln(sales per worker) and the WMS management score. As is well known there is a positive relationship between the two even after controlling for size. Figure 4 shows an analogous scatterplot for productivity and the average employee fixed effect in the firm. There is also a clear positive relationship motivating our question of whether management practices just reflects employee talent. Interestingly the relationship is quite convex, suggesting that it is top talent that matters most, hinting at a greater role for managers as discussed above.

We turn to some regression analysis of the production functions in Table 3. In column (1) we regress ln(sales) on the management score, ln(employment) and the basic controls. The management variable has a highly significant coefficient of 0.264. This implies that increases of 0.1 standard deviation of the management score is associated with 2.6% higher labor productivity. This is similar to the coefficient in the overall WMS sample covering 34 countries (Bloom, Sadun and Van Reenen, 2015). In column (2) we introduce the average employee ability (proxied by the mean of the individual employee effects as in Table 2) which attracts a positive and significant coefficient of 0.815. This implies a 0.1 standard deviation increase in mean employee ability is associated with a 8% increase in labor productivity. In this specification the coefficient on management falls to 0.199. Column (3) includes our measure of managerial ability (defined as in Table 2 to be to be those in the top quartile of the distribution of person effects). Managerial ability appears to be important for productivity over and above the average ability of all employees (managers and non-managers). Taken literally, this implies that increasing mean employee ability by extending the top tail of managers has a larger effect on productivity than raising the ability in the bottom part of the distribution. Comparing the change in the management coefficient in column (3) to column (1) there is a fall of 0.119 (= 0.264 - 0.145). Taken literally, this implies that human capital accounts for almost 45% of the relationship between productivity and management practices. Column (4) includes the proportion of employees with college degrees as a conventional human capital control. This is also positive and significant and reduces the coefficients on employee ability and management practice, although they all remain significant at the 5% level.[12] The three human capital measures together reduce the management coefficient by half compared to column (1). Column (5) of Table 3 introduces the capital stock, which unsurprisingly is positive and significant and large - German manufacturing firms are well known to be capital intensive (e.g. Bond, Harhoff and Van Reenen, 2004). The coefficients on management and ability can now be interpreted as associations with (two factor) TFP and remains positive and significant, although smaller in magnitude.

In column (6) of Table 3 we look at sub-sample where we have data on materials inputs, reducing the number of observations from 560 to 378 due to missing values. The significant coefficient on management of 0.0421 is its association with "three factor TFP". Column (7) includes the two ability measures which are both significant at the 10% level and reduces the management-TFP relationship to 0.0332. In the final column we also include the share of college educated. The management coefficient is now 0.316 and significant at only the 10% level (compared to column (6) it has fallen in magnitude by about a quarter). The three human capital variables are positive but are all individually insignificant. This is because of collinearity - the three human capital variables are jointly significant at the 1% level.[13]

Recall that we simply used an overall index of management by z-scoring each of the 18 questions, averaging this and then z-scoring the average. The results are robust to other ways of defining management such as using principal components or looking at the sub-elements of the management

[12] In this column a standard deviation increase in management is associated with an 12% increase in productivity which is similar to the findings of the Indian RCTs and non-experimental regressions across all countries (Bloom et al, 2014).
[13] F-test = 7.90. The joint significance of the unobserved two ability measures is 5.87 with a p-value of 0.003.

score, such as only the people management questions. For example (see Table A7), using the first principal component for Management (with all 18 management questions loading positively on this) in a Table 3 column (3) specification generates a coefficient (standard error) on management of 0.0592 (0.0166).

We have focused on the individual employee effects but it is also of interest to consider the unobserved firm fixed effect in wages, , $\psi_{j\boldsymbol{J}(i,t)}$ from equation (1). We regard this as part of the firm's performance, so it is unclear that we want to treat this differentially from management practices. Nevertheless, it is interesting to observe whether these firm effects in wages (which are intrinsically hard to theoretically explain) correlate with our management practices measure.[14]

Table A8 contains results of a regression where the dependent variable is the standardized firm fixed effect. In column (1) we include management on the right hand side with no controls and observe a strongly significant correlation of 0.213. Column (2) includes the basic controls and column (3) also adds size. The correlation falls to 0.134 but remains significant. We then add the share of college workers (strongly associated with the firm effect) and our measures of unobserved worker and managerial ability. The coefficients suggest that the high human capital workers and managers are matched to the high paying firms. Our measure of management practices remains positive and significant at the 10% level.[15]

IVC. Inflows and Outflows

We have shown that firms with a larger stock of high ability employees, especially highly talented managers tend to have better management practices and higher productivity. We now investigate in more detail how firms come to have higher ability employees by looking at the inflows and outflows of workers to our firms.

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[14] Estimating firm effects in the presence of endogenous sorting is more problematic than the individual effects (whose true value will still be positively and monotonically increasing in the estimating employee fixed effects). Better managers may actually be more productive in turning around "failing firms" for example, so there may be negative sorting.

[15] We also ran estimates with the firm effect on the right hand side of a production function. If we substitute the firm effect for employee ability in column (1) of Table 3, it has a coefficient (standard error) of 0.167(0.061). When all employee and firm effects are entered together, the average employee effect dominates the average firm effect. For example in a the specification of column (4) the coefficient on managerial ability is 0.277(0.0826) whereas the coefficient on the firm effect is 0.089(0.053).

We consider all employees who came to work in our matched IEB-WMS firms between 2003 and 2009 (the period over which we also gathered management data) and stayed for at least one year (Table 1 showed that there are just over 122,471 individuals in this sub-sample). We focus first on those who switched from unemployment to jobs under the assumption that firm policies are more salient here - for job to job transitions we would like to know the management practices in the firms that the individuals left which is generally unobserved.[16] There are 19,026 unemployment to job transitions in our matched WMS-IAB data.

The dependent variable in Table 4 is the proportion of the 19,026 inflowing individuals whose ability was greater that a specified percentile in the overall distribution. We look at the 10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th} percentiles in each of the five columns. In column (5) for example, the dependent variable is the proportion of workers who were in the top decile of the ability distribution. It is clear that well managed firms are hiring people from higher up the ability distribution. The coefficient on management is positive at every percentile, but particularly strong for workers un the top quartile of the distribution (at the 75^{th} and 90^{th} percentile the coefficient is highly significant and large whereas at the median and below it is smaller in magnitude and insignificant). F-tests reject the hypothesis that the management coefficient is the same at the 10^{th} percentile as it is at the 75^{th} (p-value = 0.044) and the 90^{th} (p-value=0.042). [17] A concern with this result is that larger firms will mechanically get more workers at all points of the distribution so Panel B repeats the exercise but controls also for firm size with broadly similar results.

Appendix Tables A2 and A3 repeat the analysis for inflows from "non-participation"[18] and job to job transitions. The results are weaker for these alternative dependent variables, although the pattern of coefficients is similar. This is likely because inflows from unemployment are more a function of the firm management practices we focus on. For job-to job transfers we do not observe the management of the firms people leave from and for non-participants, these flows are more likely to be completely voluntary (assuming that a reasonable fraction of unemployment is involuntary).

[16] 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.

[17] A possible reason for the coefficients not being larger at the 90^{th} compared to the 75^{th} is that as noted in the Data Section, the IEB wage data is censored at the top end due to social security cut-offs. As in Card et al (2013) we deal with this through predicting wages above the threshold, but this is likely to be imperfect.

[18] As noted in the data section this is a very heterogeneous group.

We next turn to looking at worker outflows from our firms in Table 5. Symmetrically with the inflow analysis we look at all employees who *left* the firms in our dataset between 2003 and 2009. We again focus on the outflows to unemployment as these are more likely to be determined by the policies of the firm rather than choices of workers or management practices in other firms in job to job transitions. There are 40,098 workers in this category (compared to 132,726 total outflows – see Table 1). The dependent variable in column (1) is the average value of the person effect of the outflow to unemployment (normalized on the average ability of firm's lagged incumbent stock to reflect the fact that better managed firms have higher ability employees). Firms with better management practices appear significantly less likely to lose their relatively high ability workers. This correlation remains robust in column (2) to more general controls for firm size, being in East Germany, college and female share of employees, firm age, competition and ownership. A concern with the result is that the unobserved ability of the individuals who outflow may be correlated with some other covariate. Consequently we also experimented with conditioning on some of the observable characteristics of the outflows such as age (in column (3)) and whether the individual was college educated (column (4)). Although these are significant, the coefficient on management is little changed.

Some of the questions in the management grid are likely to be more related to outflows than others. In particular, one of the questions is over whether the firm has systematic policies for dealing with under-performing employees (Question 15 in Appendix Table B1). This indicator of "tough firing practices" (see column (5)) is more strongly related to exiting low ability workers than most of the other management practice questions).[19] We were concerned to make sure that the results is driven by the numerator and not just the denominator (average worker ability) of the dependent variable. Consequently, we implemented an alternative specification where the absolute outflow is the dependent variable (numerator of previous columns) and the average employee ability is brought onto the right hand side (denominator in previous columns). The results are robust, although the point estimate is smaller in column (6).

[19] We estimated this equation 18 times substituting the z-score of individual management question. Of the other 17 questions 12 were smaller in magnitude than the tough firing practices question and only 5 were larger.

We again repeated these specifications looking at other outflows to jobs and to non-employment (see Appendix Tables A4 and A5). 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 transitions to and from unemployment.

IVD. Other analysis and Discussion

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 (Table A6). We did find that better managed firms had faster wage growth, although the coefficient was insignificant. High ability workers entering the firm appeared to have slower wage growth however, possibly because of mean reversion (e.g. if they had unexpectedly high wages in a previous job they might have slower wage in their new job). Interacting management and ability together in the wage growth equation we did find that better managed firms seemed to promote high ability workers more quickly. But this positive coefficient was insignificant.

Our findings suggest that management and human capital are complementary in the sense that firms who are (observed and unobserved) skill-intensive have also higher management scores. One interpretation in a full information world is that the employee effects we use may be unobservable to the econometrician, but they are fully observable to the market so better skilled workers match to better managed firms (similar to Garicano and Rossi-Hansberg, 2006). An interesting question is whether the firms who are better managed on the WMS scores are also able to "cherry pick" workers who are under-valued by the market. The success of Billy Beane and the Oakland A's is attributed to this in "Moneyball" (Lewis, 2003). This would imply that not all firms are able to identify worker fixed effects (e.g. if the full IEB employment history is not known to the firm as it cannot be credibly signaled by the worker). Since our measure of ability is market based, the wage that the worker is earning, it is difficult to directly test this hypothesis. We would need some additional measure of worker productivity to assess whether or not well managed firms had a greater ability to do this than other firms. This would be an interesting avenue for future work.

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) are simply due to the higher ability of employees, especially managers, in these firm. We merge the near-population administrative data matched worker-firms in Germany (the IEB) with the WMS management data. We estimate unobserved ability using the employee fixed effects from wage equations in the manner of Abowd et al (1999) following Card et al (2013) on data prior to 2004, i.e. a period prior to our management surveys.

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 skills). When we estimate production functions we find that firms with higher worker and managerial talent have higher productivity. However, the WMS management scores remain significant in production functions even after conditioning on all measures of observed and unobserved employee ability. Including human capital reduces the association of productivity with management by between one quarter to one half. 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 in firm performance regressions is striking.

Delving further into the management-ability relationship, we show that well managed firms have a higher stock of high (unobserved ability) employees. They 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 ability 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.

This is a fascinating research path to pursue as it links economics with other areas of social science. However, it may be that we are still not properly measuring all aspects of human capital in the firm. The censoring of the wage distribution may mean, for example, we underestimate the talent of senior managers. Combining the data we have here with richer information on the talent of top managers would be an important extension of our work (e.g. Bandiera et al, 2011).

Bibliography

Abowd, John, Francis Kramarz, and David Margolis (1999) "High Wage Workers and High Wage Firms" *Econometrica* 67(2): 251-333.

Bachteler, Tobias (2012) *Merge ToolBox*, Version 0.74, German Record Linkage Center

Baily, Martin, Charles Hulten and David Campbell "Productivity Dynamics in Manufacturing Plants" (1992), *Brookings Papers on Economic Activity: Microeconomics*, 187-267

Bandiera, Oriana, Luigi Guiso, Andrea Prat, and Raffaella Sadun (2011). "What Do CEOs Do?" Harvard Business School Working Paper, No. 11-081

Bartelsman, Erik, Haltiwanger, John and Scarpetta, Stefano (2013) "Cross Country Differences in Productivity: The Role of Allocation and Selection" *American Economic Review*, 103(1) 305-334

Bauer, Thomas K, Alexandra Schmucker, Matthias Vorell (2008) KMU und Arbeitsplatzdynamik: Eine Analyse auf Basis der Beschäftigten-Historik. In: Zeitschrift für ArbeitsmarktForschung, Jg. 41, H. 2/3, S. 199-221.

Bennesden et al, (2007)

Bertrand, Marianne and Antoinette Schoar (2003), "Managing with Style: The Effect of Managers on Firm Policies", *Quarterly Journal of Economics*, CXVIII (4), 1169-1208

Black, Sandra and Lisa Lynch (2001) 'How to Compete: The Impact of Workplace Practices and Information Technology on Productivity', *Review of Economics and Statistics*, 83(3), 434–445.

Bloom, Nicholas, and John Van Reenen (2007) "Measuring and Explaining Management Practices across Firms and Countries", *Quarterly Journal of Economics*, 122(4), 1341-1408.

Bloom, Nicholas, Eifert, Ben, Mahajan, Abarjit, McKenzie, David and John Roberts (2013) "Does management matter? Evidence from India" *Quarterly Journal of Economics* 128 (1) 1-51

Bloom, Nicholas, Erik Brynjolfsson, Lucia Foster, Ron Jarmin, Itay Saporta-Eksten and John Van Reenen (2013) "Management in America" Census Bureau Working Paper 13-1

Bloom, Nicholas, Renata Lemos, Raffaella Sadun, Daniella Scur and John Van Reenen (2014), "The new empirical economics of management" *Journal of the European Economic Association* 12: 835–76,

Bond, Stephen, Dietmar Harhoff and John Van Reenen (2005) "Investment, R&D and Financial Constraints in Britain and Germany" *Annales d'Economie et de Statistique* 79/80, 435-462

Card, David, Jörg Heining and Patrick Kline (2012) "Workplace Heterogeneity and the Rise of. West German Wage Inequality" *Quarterly Journal of Economics*

De Loecker, Jan and Pinelopi Goldberg (2014) "Firm Performance in a Global Market" *Annual Review of Economics*, 6(1), 201-227

Dorner, Matthias ,Jörg Heining, Peter Jacobebbinghaus, and Stefan Seth (2010) "The Sample of Integrated Labour Market Biographies" *Schmollers Jahrbuch* 130, 599-608.

Dustmann, Christian, Johannes Ludsteck, and Uta Schonberg (2009) "Revisiting the German Wage Structure" *Quarterly Journal of Economics* 124(2): 843-881

Dustmann, Christian and Albrecht Glitz (2015) "How do Industries and Firms Respond to Changes in Local Labor Supply?" *Journal of Labor Economics*, forthcoming

Eberle, Johanna; Schmucker, Alexandra and Seth, Stefan (2013) "Example programs for data preparation of the sample of integrated labour market biographies for Stata creating cross-sectional data and biographical variables" *FDZ-Methodenreport*, 04/2013, Nürnberg.

Feng, Andy and Anna Valero (2015) "Management, skills and universities", LSE mimeo

Garicano, Luis and Esteban Rossi-Hansberg (2006) "Organization and Inequality in a Knowledge Economy" *Quarterly Journal of Economics* 121(4), 1383-1435

Garicano, Luis, Claire Lelarge and John Van Reenen (2013) "Firm Size Distortions and the Productivity Distribution: Evidence from France" NBER Working Paper No. 18841

Gibbons, Robert and John Roberts (2013) *The Handbook of Organizational Economics*, Princeton: Princeton University Press

Guiso, Luigi, Paola Sapienza, and Luigi Zingales (2013) "The Value of Corporate Culture" NBER Working Paper No. w19557

Guiso, Luigi, Paola Sapienza and Luigi Zingales (2015) "Corporate Culture, Societal Culture, and Institutions" *American Economic Review*, 105(5), 336-39

Haltiwanger, Hyatt and McEntarfer (2015) "Cyclical Reallocation of Workers across Employers by Firm size and Firm Wage", University of Maryland mimeo

Hsieh, Chiang-Tai and Pete Klenow (2009), "Misallocation and Manufacturing TFP in China and India", *Quarterly Journal of Economics*, 124(4), 1403-1448

Ichniowski, Casey, Kathryn Shaw, and Giovanna Prennushi (1997) "The Effects of Human Resource Management Practices on Productivity: A Study of Steel Finishing Lines", *American Economic Review*, 87(3), 291-313.

Jaro, M. (1989) "Advances in record-linkage methodology as applied to matching the 1985 Census of Tampa, Florida" *Journal of the American Statistical Association* 84(406) 414–420.

Lemos, Renata and Daniela Scur (2015) "Management Practices and human capital" Cambridge/Oxford mimeo

Lewis, Michael (2003) *Moneyball*, New York: Norton

Lucas, Robert. (1978) "On the Size Distribution of Business Firms", *Bell Journal of Economics*, 9: 508-523.

Melitz, Marc (2003) "The impact of trade on intra-industry reallocations and aggregate productivity growth" *Econometrica*, 71, 1695-1725

O'Reilly, C. A. (1989) "Corporations, culture and commitment: Motivation and social control in organizations" *California Management Review*, 31 (4): 9-25.

Schmieder, Johannes, Til von Wachter and Stefan Bender (2012) "The Long-Term Effects of UI Extensions on Employment" *American Economic Review*, 102(3), 514-519.

Schnell, R., Bachteler, T., and Reiher, J. (2005). "MTB: Ein Record-Linkage-Programm für die empirische Sozialforschung" *ZA-Information* 56 93–103.

Syverson, Chad (2004) "Product Substitutability and Productivity Dispersion" *Review of Economics and Statistics*, 86(2) 534-550

Syverson, Chad (2011) "What determines productivity?" *Journal of Economic Literature*, 49(2) 326–365

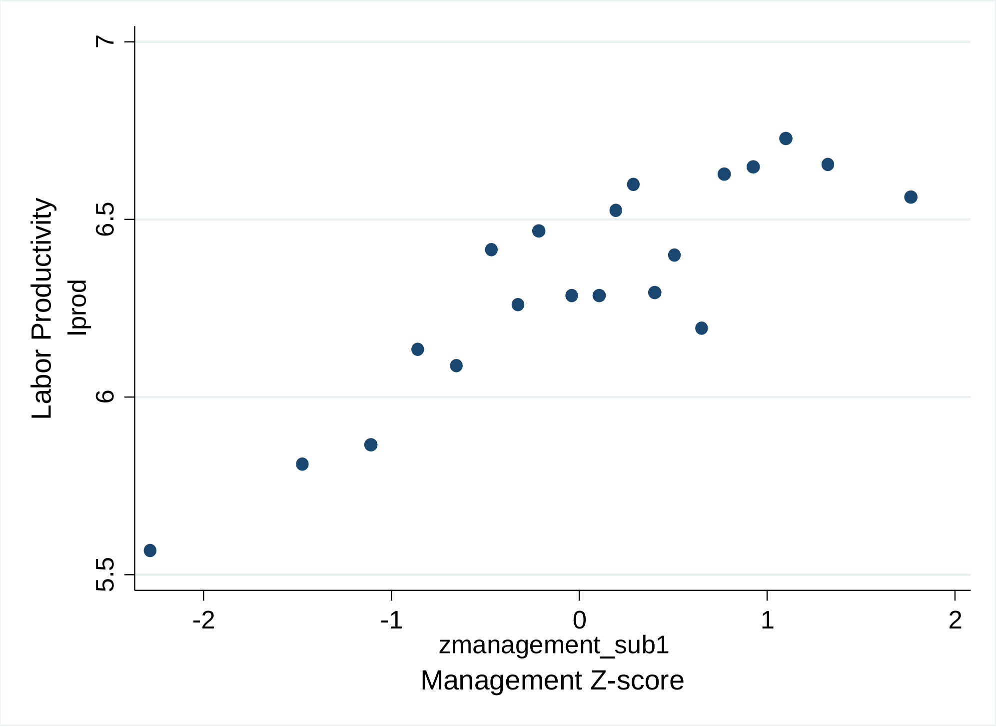
Figure 1: Correlation of Management Score and employee ability

Notes: Management is the z-score of the average of the z-score of the 18 management practices from the WMS survey. Employee ability is the z-score of the firm-level average person effect estimated from wage equations in the 1996-2002 period in the entire IEB sample. We group ability into vingtiles and calculate mean management score.

Figure 2: Correlation of Management Score and employee ability controlling for size

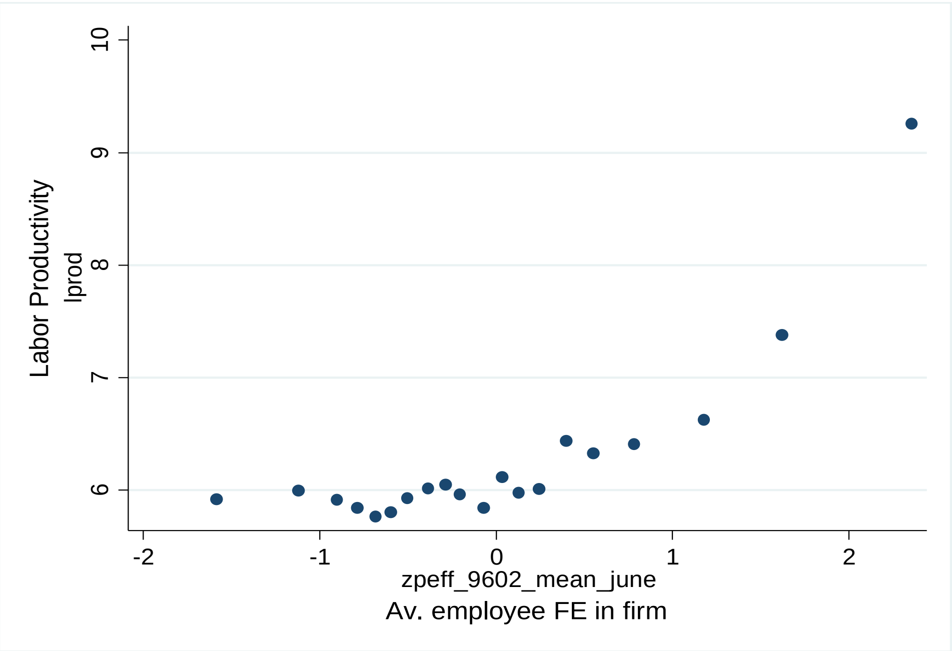
Notes: Management is the z-score of the average of the z-score of the 18 management practices from the WMS survey. Employee ability is the z-score firm-level average person effect estimated from wage equations in the 1996-2002 period in the entire IEB sample. We residualize both measures by regressing against firm size as measured by the number of employees. We group residual ability into vingtiles and calculate mean residual management score.

Figure 3: Positive Correlation of Ln(Labor Productivity) and WMS Management scores



Notes: This is a binscatter of ln(sales per worker) and the WMS management zscore. These are both residualized off firm size (as measured by ln(labor)).

Figure 4: Productivity is increasing in employee ability, especially for high levels of ability



Notes: This is a binscatter of ln(sales per worker) and the average employee effect in the firm (zscore)

<u>Table 1: Descriptive Statistics for matched WMS-IAB Data</u>

Panel A: Firms

	Mean	Median	Minimum	Maximum	SD
Firm located in East Germany	0.13	0.00	0.00	1.00	0.34
Firm age	64.34	42.50	1	489.67	62.79
Number of workers	440.02	238	1	6971	642.87
Proportion Female	0.27	0.22	0	0.89	0.17
% Employees with college degree share	0.12	0.08	0	0.80	0.13
Median daily wage	101.58	99.51	37.21	172.60	28.46
ln(capital)	9.89	10.18	2.71	13.82	1.69
ln(materials)	11.29	11.78	8.44	14.47	1.07
Coverage (% employees with fixed effects)	0.79	0.87	0.01	1.00	0.25
Management Score	0	0.055	-3.253	2.679	1
Average employee ability (fixed effect)	0	-0.177	-5.585	3.429	1
% with 5 or more competitors	0.586				
% family owned	0.229				
% non-family private owned	0.223				
% institutional owned	0.127				

Notes: 361 Firms from WMS data matched to IEB in 2004, 2006 and 2009 (590 firm-year surveys across all three waves).

Panel B: Individuals

Variables	Inflows to our firms from the specified labor market state	Outflows from our firms to the specified labor market state
Unemployment	19,026	40,098
Jobs	70,682	75,028
Non-participation	32,763	17,600
Total	122,471	132,726

Notes: These are all individuals who left the matched WMS-IEB firms between 2004 and 2009

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

Dependent Variable:	(1) Management z-Score	(2) Management z-Score	(3) Management z-Score	(4) Management z-Score
Mean employee quality	0.215***		0.0135	-0.0985
	(0.0772)		(0.0900)	(0.112)
Mean managerial quality		0.298***	0.290***	0.268***
		(0.0675)	(0.0859)	(0.0891)
Ln(Number of Employees)	0.237***	0.273***	0.274***	0.274***
	(0.0486)	(0.0483)	(0.0494)	(0.0498)
% Employees with college				0.971**
				(0.452)
Firms	354	354	354	354
Observations	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. Dependent variables and employee quality measures are z-scored. All columns include a dummy for firm located in East Germany, the share of female workers, ownership dummies (family, founder, private, institution, manager and other), the number of competitors, firm age, three digit industry dummies and time dummies. Employee quality is mean level of individual fixed effect measured over 1996-2002 period. Managerial quality is mean employee quality in the top quartile of the within firm distribution.

Table 3: Production Functions

Dependent Variable:	(1) Ln(sales)	(2) Ln(sales)	(3) Ln(sales)	(4) Ln(sales)	(5) Ln(sales)	(6) Ln(sales)	(7) Ln(sales)	(8) Ln(sales)
Management Score	0.264***	0.199***	0.145***	0.125***	0.0708*	0.0421**	0.0332**	0.0316*
	(0.0519)	(0.0457)	(0.0422)	(0.0426)	(0.0379)	(0.0191)	(0.0168)	(0.0169)
Mean Employee Quality		0.815***	0.601***	0.384***	0.249***		0.103*	0.0839
		(0.143)	(0.107)	(0.108)	(0.0941)		(0.0590)	(0.0724)
Mean Managerial quality			0.337***	0.296***	0.168*		0.0809*	0.0797
			(0.107)	(0.0983)	(0.0926)		(0.0488)	(0.0487)
% Employees with College degree				1.894***	1.305***			0.141
				(0.642)	(0.465)			(0.223)
Ln(Labor)	0.315***	0.446***	0.588***	0.591***	0.388***	0.0538***	0.128***	0.129***
	(0.0697)	(0.0672)	(0.0701)	(0.0703)	(0.0607)	(0.0175)	(0.0257)	(0.0267)
Ln(Capital)					0.435***	0.200***	0.177***	0.178***
					(0.0472)	(0.0222)	(0.0214)	(0.0219)
Ln(Materials)						0.691***	0.663***	0.660***
						(0.0341)	(0.0310)	(0.0330)
Observations	560	560	560	560	560	378	378	378
Firms	333	333	333	333	333	229	229	229

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 quadratic in the coverage rate, industry dummies and time dummies. Mean Employee quality is mean level of individual fixed effect measured over 1996-2002 period. Mean Managerial quality is employee quality in the top quartile of the within firm distribution.

Table 4: Inflows from Unemployment

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	**Proportion of workers above different percentiles of the inflow distribution**				
Percentile	**10%**	**25%**	**50%**	**75%**	**90%**
Panel A. No Size Control					
Management Score	0.00165	0.00200	0.000827	0.0201**	0.0227**
	(0.00249)	(0.00465)	(0.00750)	(0.00891)	(0.00909)
% college	0.0400***	0.117***	0.254***	0.162**	0.0198
	(0.0155)	(0.0293)	(0.0597)	(0.0802)	(0.0985)
Panel B. Including Size Control					
Management Score	0.00235	0.00267	0.00229	0.0188**	0.0157*
	(0.00238)	(0.00470)	(0.00833)	(0.00908)	(0.00897)
% college	0.0183	0.0305	0.150	0.174	0.0756
	(0.0222)	(0.0369)	(0.100)	(0.113)	(0.0917)
Firm Size: Ln(labor)	-0.00230	0.000244	-0.0120	0.0143	0.00717
	(0.00279)	(0.00565)	(0.0110)	(0.0124)	(0.0118)
Firms	352	352	352	352	352

Notes: *** indicates significance at the 1% level, ** at the 5% level and * at the 10% level. The dependent variable is the proportion of the inflow above a threshold of employee ability that go to a particular firm. All standard errors clustered by firm in parentheses under coefficients estimates by OLS based on 19,026 inflows from unemployment in these firms. The management score is standardized. Panel A controls for east dummy, competition, ownership, log(firm age), female share, industry. Panel B has additional controls for age of inflows and college share of inflows.

<u>Table 5: Outflows to Unemployment</u>

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:		**Average ability of outflow/Average ability of incumbents**				**Average ability of outflow**
Management Score	-0.0912*	-0.116**	-0.107*	-0.135**		
	(0.0527)	(0.0580)	(0.0592)	(0.0571)		
Stringent firing/fixing Practices					-0.0993*	-0.0469*
					(0.0508)	(0.0290)
Average incumbent ability						0.518***
						(0.0992)
Average age of outflows			0.0468***	0.0411***	0.0434***	0.0177
			(0.0160)	(0.0150)	(0.0149)	(0.0148)
% college of outflows				4.915***	4.877***	4.202***
				(0.873)	(0.881)	(0.561)
General Controls	No	Yes	Yes	Yes	Yes	Yes
Firms	347	347	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 40098 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.

APPENDIX A: DATA

A1. Management 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 (2015). More information 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) Amadeus dataset. This provided sufficient information on companies to conduct a stratified telephone survey (company name, address and a size indicator). BVD has accounting information on employment, sales and capital. Apart from size, we did not insist on having accounting information to form the sampling population, however.

In every country the sampling frame for the management survey was all firms with a manufacturing primary industry code with between 50 and 5,000 employees on average over the most recent three years of data 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 resurveyed 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, with a manufacturing primary industry code and 50 to 10,000 employees (on average between 2000 and 2003). This sample was drawn from the Amadeus dataset. In 2009 we also resurveyed all firms interviewed in 2006.

The accounting databases are used to generate our management survey. 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.[20] Despite these potential differences, the broad picture is that the sample matches up reasonably with the population

[20] 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. This was particularly a problem for Indian and Japanese firms, so for these countries we imputed the missing employment numbers based in a sales regression.

of medium sized manufacturing firms. This suggests our sampling frame covers near to the population of all firms for most countries

Of the firms we contacted 58.6% took part in the survey: a high success rate given the voluntary nature of participation. 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.[21]

The ratio of successful interviews to rejections (ignoring "scheduling in progress") is above 1. Hence, managers typically agreed to the survey proposition when interviewers were able to connect with them. In Bloom et al (2015) 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 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, return on capital and listed status are all uncorrelated with response rates.

We have firm accounting data on sales, employment, capital, 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 aboard 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* (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.

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[21] The reason for this high share of 'scheduling in progress' firms was the need for interviewers to keep a portfolio of firms who they cycle though when trying to contact managers. Since interviewers only ran an average of 2.8 interviews a day the majority of their time was spent trying to contact managers to schedule future interviews. For scheduling it was efficient for interviewers to keep a stock of between 100 to 300 firms to cycle through.

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)

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 a 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, dummy for one worker firm. Card et al (2013) report various validation exercises for the Tobit specifications.

Estimation of equation (1) 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.

<u>Figure A1: Employee ability and managerial ability Distribution</u>

Panel A: Overall distribution

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

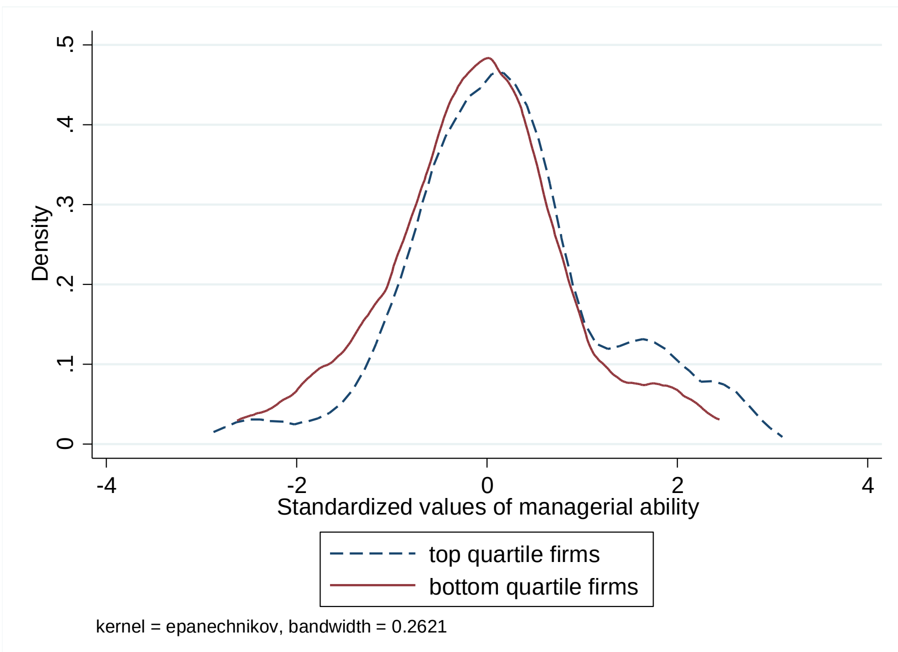

Table A1: Description and source of variables

Variable	Source	Description
Average employee ability	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 30th 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.
Coverage	IAB-WMS match	Share of workers in a firm that is covered by the estimated employee effects
Average Managerial Ability	IAB	Average of estimated employee fixed effect for those in the top quartile of the ability distribution
Inflow above the 75th percentile of ability	IAB	Fraction of total inflows in the sample above the 75th 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 an d non-employment)
Ability of the outflows	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 an d non-employment)
Female share	IAB	Share of female workers in the firm

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

Table A2: Inflows from other jobs

	(1) 10%	(2) 25%	(3) 50%	(4) 75%	(5) 90%
Panel A. No Size Control					
Management Score	0.00248	0.00446	0.0103*	0.0196***	0.0197***
	(0.00247)	(0.00420)	(0.00534)	(0.00739)	(0.00674)
% college	0.103***	0.215***	0.218***	0.0342	0.132
	(0.0166)	(0.0329)	(0.0615)	(0.0940)	(0.0936)
Panel B. Including Size Control					
Management Score	0.00212	0.00546	0.00860	0.0108	0.0112*
	(0.00256)	(0.00434)	(0.00562)	(0.00658)	(0.00641)
% college	0.0572**	0.0727	0.0583	0.162	0.190
	(0.0264)	(0.0540)	(0.0952)	(0.122)	(0.123)
Ln(labor)	-0.000472	-0.00461	-0.000598	0.0143	0.0106
	(0.00284)	(0.00458)	(0.00603)	(0.00873)	(0.00865)
Observations	357	357	357	357	357

Notes: This is the equivalent of Table 4 except using inflows from other jobs (instead of 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 70,682 inflows from unemployment in these firms. The management score is standardized. Panel A controls for east dummy, competition, ownership, log(firm age), female share, and industry dummies. Panel B has additional controls for age of inflows and college share of inflows,.

Table A3: Inflows from outside labour market

	(1) 10%	(2) 25%	(3) 50%	(4) 75%	(5) 90%
Panel A. No Size Control					
Management Score	0.00523*	0.00937**	0.0101*	0.00791	0.00932
	(0.00271)	(0.00393)	(0.00536)	(0.00679)	(0.00702)
% college	0.0162	0.0513	0.0607	-0.0326	-0.0579
	(0.0248)	(0.0340)	(0.0443)	(0.0886)	(0.0760)
Panel B. Including Size Control					
Management Score	0.00286	0.00568	0.00441	0.00676	0.00675
	(0.00212)	(0.00386)	(0.00524)	(0.00648)	(0.00656)
% college	0.0545	0.0955*	0.162***	0.230***	0.213***
	(0.0389)	(0.0486)	(0.0600)	(0.0688)	(0.0543)
Ln(labor)	0.00516	0.0103**	0.0173**	0.0126*	0.0181**
	(0.00372)	(0.00481)	(0.00682)	(0.00754)	(0.00771)
Observations	356	356	356	356	356

Notes: This is the equivalent of Table 4 except using inflows from non-participation (instead of 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 east dummy, competition, ownership, log(firm age), female share, industry. Panel B has additional controls for age of inflows and college share of inflows.

Table A4: Outflows to other-jobs

	(1)	(2)	(3)	(4)	(5)	(6)
	Average ability of outflow/Average ability of incumbents					**Average ability of outflow**
Management Score	0.00269	-0.0586	-0.0562	-0.0847		
	(0.0562)	(0.0596)	(0.0613)	(0.0617)		
Stringent firing/fixing					-0.0554	-0.0345
Practices					(0.0439)	(0.0280)
Average incumbent ability						0.478***
						(0.0890)
Average age of outflows			0.0115	0.0161	0.0181	0.0270*
			(0.0147)	(0.0144)	(0.0144)	(0.0137)
% college of outflows				4.313***	4.334***	3.192***
				(0.741)	(0.749)	(0.395)
Observations	347	347	347	347	347	347

Notes: Equivalent to the Table 5 except using outflows to other-jobs (rather than unemployment). *** 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 40098 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 A5: Outflows to non-participation

	(1)	(2)	(3)	(4)	(5)	(6)
	Average ability of outflow/Average ability of incumbents					**Average ability of outflow**
Management Score	-0.0159	-0.0110	0.00787	-0.00293		
	(0.0556)	(0.0722)	(0.0684)	(0.0662)		
Stringent firing/fixing Practices					-0.0321	-0.0440
					(0.0531)	(0.0531)
Average incumbent ability						0.265*
						(0.143)
Average age of outflows			0.0420***	0.0336***	0.0336***	0.0475***
			(0.0103)	(0.00949)	(0.00950)	(0.0162)
% college of outflows				4.126***	4.170***	3.845***
				(0.689)	(0.701)	(0.670)
Observations	339	339	339	339	339	339

Notes: Equivalent to the Table 5 except using outflows to non-participation (rather than unemployment). *** 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 40098 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 A6: Annual average wage growth for entries from unemployment

	(1)	(2)	(3)	(4)
Dependent variable:	**wage growth**	**wage growth**	**wage growth**	**wage growth**
Management	0.00183		0.00229	0.00517
	(0.0024)		(0.0024)	(0.0062)
Promoting high performers				
Employee ability		-0.0107**	-0.0110**	-0.0108**
		(0.0050)	(0.0049)	(0.0050)
Management * Employee ability				0.00141
				(0.0011)
Observation	7,730	7,730	7,730	7,730
No of firms	342	342	342	342

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/ has a college degree a quadratic in individual age², firm's share of women, ln(firm age), ln(firm size), and dummies for being located in East Germany, and controls for competition and ownership; column (4) additionally includes interactions between management (promoting high performers) and college respectively age.

Table A7: : Production function (Principal Component Analysis)

Dependent Variable:	(1) Ln(sales)	(2) Ln(sales)	(3) Ln(sales)	(4) Ln(sales)	(5) Ln(sales)	(6) Ln(sales)	(7) Ln(sales)	(8) Ln(sales)
Management Score	0.107***	0.0811***	0.0592***	0.0518***	0.0292*	0.0163**	0.0127*	0.0121*
	(0.0204)	(0.0179)	(0.0166)	(0.0169)	(0.0150)	(0.00764)	(0.00680)	(0.00681)
Mean Employee Quality		0.813***	0.601***	0.384***	0.249***		0.103*	0.0838
		(0.142)	(0.107)	(0.108)	(0.0942)		(0.0589)	(0.0723)
Mean Managerial quality			0.335***	0.294***	0.167*		0.0809*	0.0797
			(0.107)	(0.0985)	(0.0928)		(0.0488)	(0.0487)
% Employees with College degree				1.892***	1.305***			0.143
				(0.641)	(0.464)			(0.223)
Ln(Labor)	0.313***	0.444***	0.585***	0.588***	0.387***	0.0539***	0.128***	0.129***
	(0.0694)	(0.0670)	(0.0701)	(0.0703)	(0.0606)	(0.0175)	(0.0257)	(0.0268)
Ln(Capital)					0.434***	0.200***	0.177***	0.178***
					(0.0472)	(0.0222)	(0.0214)	(0.0220)
Ln(Materials)						0.691***	0.663***	0.660***
						(0.0343)	(0.0310)	(0.0331)
Observations	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 clustered by 333 firms in parentheses under coefficients estimates by OLS. Management score uses first principal component 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 quadratic in the coverage rate, industry dummies and time dummies. Mean Employee quality is mean level of individual fixed effect measured over 1996-2002 period. Mean Managerial quality is employee quality in the top quartile of the within firm distribution.

Table A8: Correlation of Firm Fixed effect in wages with management

Dependent Variable:	(1) Firm effect	(2) Firm effect	(3) Firm effect	(4) Firm effect	(5) Firm effect	(6) Firm effect
Management Score	0.215***	0.150***	0.134***	0.110***	0.108***	0.0853*
	(0.0482)	(0.0396)	(0.0424)	(0.0414)	(0.0414)	(0.0438)
Ln(Labor)			0.0646	0.0922*	0.102	0.101*
			(0.0470)	(0.0503)	(0.0632)	(0.0577)
% Employees with				1.077***	0.678	0.510
College degree				(0.370)	(0.632)	(0.511)
Mean Employee Quality					0.134	-0.0418
					(0.238)	(0.252)
Mean Managerial quality						0.293**
						(0.136)
General Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	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. Dependent variable, management score and employee ability measures are z-scored. All columns include a dummy for firm located in East Germany, the share of female workers, ownership dummies (family, founder, private, institution, manager and other), the number of competitors, firm age, three digit industry dummies and time dummies. Mean Employee quality is mean level of individual fixed effect measured over 1996-2002 period. Mean Managerial quality is employee quality 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).

(1) Modern manufacturing, introduction

	Score 1	Score 3	Score 5
Scoring grid:	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, autonomation, flexible manpower, support systems, attitudes and behaviour) in a formal way

(2) Modern manufacturing, rationale

	Score 1	Score 3	Score 5
Scoring grid:	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)

(3) Process problem documentation

	Score 1	Score 3	Score 5
Scoring grid:	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

(4) Performance tracking

	Score 1	Score 3	Score 5
Scoring grid:	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.

(5) Performance review

	Score 1	Score 3	Score 5
Scoring grid:	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

		Score 1	Score 3	Score 5
(6) Performance dialogue	**Scoring grid:**	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	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.	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.
(7) Consequence management	**Scoring grid:**	Failure to achieve agreed objectives does not carry any consequences	Failure to achieve agreed results is tolerated for a period before action is taken.	A failure to achieve agreed targets drives retraining in identified areas of weakness or moving individuals to where their skills are appropriate
(8) Target balance	**Scoring grid:**	Goals are exclusively financial or operational	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)	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.
(9) Target interconnection	**Scoring grid:**	Goals are based purely on accounting figures (with no clear connection to shareholder value)	Corporate goals are based on shareholder value but are not clearly communicated down to individuals	Corporate goals focus on shareholder value. They increase in specificity as they cascade through business units ultimately defining individual performance expectations.
(10) Target time horizon	**Scoring grid:**	Top management's main focus is on short term targets	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	Long term goals are translated into specific short term targets so that short term targets become a "staircase" to reach long term goals
(11) Targets are stretching	**Scoring grid:**	Goals are either too easy or impossible to achieve; managers provide low estimates to ensure easy goals	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	Goals are genuinely demanding for all divisions. They are grounded in solid, solid economic rationale

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

Source: Bloom and Van Reenen (2007)