What Drives Differences

in Management Practices?

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What Drives Differences in Management Practices?

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Keywords: Management, productivity, competition, learning

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1 Introduction

The interest of economists in management goes at least as far back as *On the Sources of Business Profits* by Francis Walker (1887), the founder of the American Economic Association and the Superintendent of the 1870 and 1880 Censuses.[1] This interest has persisted until today. For example, Syverson's (2011) survey of productivity devotes a section to management as a potential driver, noting that "*no driver of productivity has seen a higher ratio of speculation to research.*" Work evaluating differences in management is often limited to relatively small samples of firms (e.g., Ichniowski, Shaw and Prennushi, 1997), developing countries (e.g., Bloom, Eifert, Mahajan, McKenzie and Roberts, 2013, and Bruhn, Karlan and Schoar, 2016) or particular historical episodes (e.g., Giorcelli, 2016). In addition, although previous work on larger samples has measured differences in management across firms and countries, there is no large-scale work on the variations in management between the plants[2] within a firm.

There are compelling theoretical reasons to expect that management matters for performance. Gibbons and Henderson (2013) argue that management practices are a key reason for persistent performance differences across firms due to relational contracts. Brynjolfsson and Milgrom (2013) emphasize the role of complementarities among management and organizational practices. Halac and Prat (2016) show that "engagement traps" can lead to heterogeneity in the adoption of practices even when firms are *ex ante* identical. By examining the first large sample of plants with this information, this paper provides empirical evidence for the role that management practices play in both firm and plant performance and investigates the causal drivers of why some plants adopt such practices and others do not.

We partnered with the Economic Program Directorate of the U.S. Census Bureau to develop and conduct the Management and Organizational Practices Survey (MOPS).[3] This is the first-ever mandatory government management survey, covering two separate waves of over 35,000 plants in 2010 and 2015, yielding over 70,000 observations.[4] The sample size, panel structure, high

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[1] Walker was also the second president of MIT and the vice president of the National Academy of Sciences. Arguably Adam Smith's discussion of the Pin Factory and the division of labor was an even earlier antecedent.

[2] Because we are focusing on manufacturing, we use the words "plants" and "establishments" interchangeably.

[3] This survey data is available to qualified researchers on approved projects via the Federal Statistical Research Data Center (FSRDC) network and online in tables (https://www2.census.gov/programs-surveys/mops/tables/2015/mops-survey-tables/mops_survey_tables.pdf) and aggregated anonymized http://managementresearch.com/methodology/

[4] See the descriptions of MOPS in Buffington, Foster, Jarmin and Ohlmacher (2016) and Appendix A.

response rate of the survey, its coverage of units within a firm, its links to other Census data, as well as its comprehensive coverage of industries and geographies makes it unique, and enables us to address some of the major gaps in the recent management literature.

We start by examining whether our management measures are linked to performance. We find that plants using more structured management practices have greater productivity, profitability, growth, survival rates and innovation. These relationships are robust to a wide range of controls including industry, education, plant and firm age. The relationship between management practices and performance also holds over time within plants (plants that adopted more of these practices saw improvements in their performance) and across establishments within firms at a point of time (establishments within the same firm with more structured management practices achieve better performance outcomes).

The magnitude of the productivity-management relationship is large. Increasing structured management from the 10th to 90th percentile can account for about 22% of the comparable 90-10 spread in productivity.[5] This is about the same as R&D, more than human capital, and almost twice as much as Information and Communication Technologies (ICT). Of course, all these magnitudes are dependent on a number of other factors, such as the degree of measurement error in each variable, but they do highlight that variation in management practices is likely a key factor accounting for the much-discussed heterogeneity in firm productivity. Technology, human capital and management are interrelated but distinct - when we examine them jointly, we find they account for about 44% of productivity dispersion.

We then turn to examining the variation in management practices across plants, showing three key results. First, there is enormous inter-plant variation in management practices. Although 18% of establishments adopt three-quarters or more of a package of basic structured management practices regarding monitoring, targets and incentives, 27% of establishments adopt less than half of such practices. Second, about 40% of the variation in management practices is across plants *within* the same firm. That is, in multi-plant firms, there is considerable variation in practices across units.[6] The analogy for universities would be that variations in management practices across

[5] We use TFP as shorthand for revenue-based Total Factor Productivity (TFPR). This will contain an element of the mark-up (see Foster, Haltiwanger and Syverson, 2008 and Hsieh and Klenow, 2009) but is likely to be correlated with quantity based TFP (see Bartelsman, Haltiwanger and Scarpetta, 2013).

[6] A literature beginning with Schmalensee (1985) has examined how the variance in *profitability* of business across business divisions decomposes into effects due to company headquarters, industry and other factors. Several papers

departments *within* universities are almost equally large as the variations *across* universities. Third, these variations in management practices are increasing in firm size. That is, larger firms have substantially more variation in management practices. This appears to be largely explained by the greater spread of larger firms across different geographies and industries.

We then examine some "drivers" of management practices. We focus our analysis on two main candidates: the business environment (in particular Right-to-Work laws) and learning spillovers from large plant entry primarily belonging to multinational corporations. We chose these drivers for three reasons. First, we have credible causal identification strategies. Second, they are highly topical with multiple changes in the 2010-2015 time period spanned by our MOPS panel. Third, we show geography plays an important role in shaping variations in management practices. The working paper version of this paper (Bloom et al, 2017) also has analysis of two other drivers – product market competition and education.

On business environment, we exploit two types of quasi-experiments over Right-To-Work (RTW) laws (Holmes, 1998). First, between the two waves of our management panel in 2010 and 2015 two states (Michigan and Indiana) introduced RTW laws in 2012, so this enables us to construct a Difference-In-Difference (DID) design using contiguous states as comparison groups. We find that RTW rules increase structured management practices around pay, promotion and dismissals but seem to have little impact on other practices. To demonstrate that our DID design indeed captures the causal effect of RTW on management, we show that there is no evidence for differential pre-trends for the states switching to RTW compared to control states. Furthermore, we use states that switched post-2015 (i.e. outside our data window) to run a placebo analysis, showing again no evidence for changes in management between 2010 and 2015 for these placebo states. As our second approach, we implement a spatial Regression Discontinuity (RD) Design where we use distance to the border as a running variable and crossing the border as our discontinuity threshold. The results from the RD design are very similar to the ones we find in the DID.

To investigate learning spillovers, we build on Greenstone, Hornbeck and Moretti's (2010)

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have examined productivity differences across sites within a single firm. For example, Chew, Clark, and Bresnahan (1990) looked at 40 operating units in a commercial food division of a large US corporation (the top ranked unit had revenue based Total Factor Productivity twice as high as the bottom ranked); Argote, Beckman and Epple (1990) showed large differences across 16 Liberty shipyards in World War II and Blader, Gartenberg and Pratt (2016) examine productivity differences across sites within a large trucking company. Freeman and Shaw (2009) contains several studies looking at performance differences across the plants of single multinational corporations.

identification strategy using "Million Dollar Plants" (MPDs) – large investments for which both a winning county and a runner-up county are known. Comparing the counties that "won" the large, typically multinational plant versus the county that narrowly "lost," we find a significant positive impact on management practices. Importantly, the positive spillovers only arise if the plant is in an industry where there are frequent flows in managerial labor from the MDP's industry, suggesting that the movement of managers is a mechanism through which learning occurs. We also show positive impacts on jobs and productivity.

The existing management and productivity literature is motivated by a number of different theoretical perspectives (e.g. Penrose, 1959, Syverson, 2011 and Gibbons and Roberts, 2013). One perspective that binds our drivers together follows Walker (1887) and considers some forms of structured management practices to be akin to a productivity-enhancing technology. This naturally raises the question of why all plants do not immediately adopt these practices. One factor is information – not all firms are aware of the practices or believe that they would be beneficial. This motivates our examination of diffusion-based learning and informational spillovers from Million Dollar Plants. Another factor is institutional constraints such as union power - this motivates our examination of regulation, in particular Right-to-Work laws. Of course, there are many other factors that can influence structured management, and we hope that the data we have generated and made available will help future researchers isolate other drivers.

Our paper also builds on a rich empirical literature on the effects of management and organizational practices on performance. One group of papers uses cross-sectional or occasionally panel data on management (or organizational) practices and firm performance. Examples of this would include Black and Lynch (2001, 2004), Bresnahan, Brynjolfsson and Hitt (2002), Brynjolfsson, Hitt and Yang (2002), Capelli and Neumark (2001), Easton and Jarrell (1998), Huselid (1995), Huselid and Becker (1996), Ichniowski and Shaw (1999), and Osterman (1994). These studies tend to find positive associations in the cross sections, but they tend to disappear in the panel (see the survey by Bloom and Van Reenen, 2011). The sample response rates are also usually low (at least compared with the MOPS) and the frames usually tilted towards very large firms. Another group of studies focuses on smaller numbers of firms sometimes even looking across sites in a single firm (labelled "insider econometrics" by Bartel, Ichniowski and Shaw, 2004). Examples would include Bartel, Ichniowski and Shaw (2007); Bandiera et al (2005, 2007), Griffith and Neely (2009); Hamilton et al (2003); Ichniowski, Prennushi and Shaw (1997) and

Lazear (2000). These tend to focus on specific forms of management practice such as incentive pay. Much has been learned from these studies, but because samples are small, it is difficult to generalize across larger swathes of the economy.

The paper is structured as follows. In Section 2, we describe the management survey; in Section 3, we outline the relationship between management and performance; and in Section 4 we detail the variation of management practices across and between firms; in Section 5, we examine potential drivers of management practices. Finally, in Section 6 we conclude and highlight areas for future analysis. Online Appendices go into more detail on Data (A), Theory (B) and a comparison with the World Management Survey (C).

2 Management and Organizational Practices Survey

The Management and Organizational Practices Survey (MOPS) was jointly funded by the Census Bureau, the National Science Foundation, the MIT Initiative on the Digital Economy, the Sloan Foundation and the Kauffman Foundation. It was fielded in 2011 and 2016 as a supplement to the 2010 and 2015 Annual Survey of Manufacturers (ASM), with response mandated by Federal law.[7] The original design was based in part on a survey tool used by the World Bank and adapted to the U.S. through two years of development and cognitive testing by the Census Bureau.[8] It was sent electronically as well as by mail to the ASM respondent for each establishment, which was typically the plant manager, financial controller, CEO, CFO or general manager (see Appendix Table A1 for details). Most respondents (58.4% in 2010 and 80% in 2015) completed the survey electronically, with the remainder completing the survey by paper. Non-respondents were mailed a follow-up letter after six weeks if no response had been received. A second follow-up letter was mailed if no response had been received after 12 weeks. The first follow-up letter included a copy of the MOPS instrument. An administrative error occurred in 2010 when merging Internet and paper collection data that caused some respondents to receive the first follow-up even though they had already responded, and as a result, in some cases there were two different sets of respondents for the same plant. We exploit this accident to deal with measurement error in the management

[7] For more details see Buffington, Foster, Jarmin and Ohlmacher (2016). Note that MOPS surveys for calendar year X are sent in spring of year X+1 to collect retrospective data.

[8] See Buffington, Herrell and Ohlmacher (2016) for more information on the testing and development of the MOPS.

scores in Section 3.

2.1 Measuring Management

The survey in both waves contained 16 management questions in three main sections: monitoring, targets and incentives, based on the World Management Survey (WMS) of Bloom and Van Reenen (2007). This was itself was based in part on the principles of continuous monitoring, evaluation and improvement from Lean manufacturing (e.g., Womack, Jones and Roos, 1990).[9] The survey also contains questions on other organizational practices (such as decentralization) based on work by Bresnahan, Brynjolfsson and Hitt (2002) as well as some background questions on the plant and the respondent.[10]

The monitoring section asked firms about their collection and use of information to monitor and improve the production process. For example, the survey asked, "How frequently were performance indicators tracked at the establishment?" with response options ranging from "*never*" to "*hourly or more frequently*." The targets section asked about the design, integration and realism of production targets. For example, the survey asked, "What was the time-frame of production targets?", with answers ranging from "*no production targets*" to "*combination of short-term and long-term production targets*." Finally, the incentives section asked about non-managerial and managerial bonus, promotion and reassignment/dismissal practices. For example, the survey asked, "How were managers promoted at the establishment?", with answers ranging from "*mainly on factors other than performance and ability, for example tenure or family connections*" to "*solely on performance and ability*." [11]

In our analysis, we aggregate the results from these 16 questions into a single measure which we call "structured management." This management score is the unweighted average of the score for each of the 16 questions, where the responses to each question are first scored to be on a 0-1 scale. Thus, the summary measure is scaled from 0 to 1, with 0 representing an establishment that selected the category which received the lowest score (little structure around performance

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[9] The 16 questions which are the main focus of this paper did not change over the two waves of the MOPS.

[10] The 2015 MOPS survey wave also included questions on two new content areas: "Data and Decision Making" and "Uncertainty." See Buffington, Foster, Jarmin, and Ohlmacher (2016) for more information on the differences in content between survey waves of the MOPS.

[11] The full questionnaire is available on https://www.census.gov/programs-surveys/mops/technical-documentation/questionnaires.html

monitoring, targets and incentives) on all 16 management dimensions and 1 representing an establishment that selected the category that received the highest score (an explicit structured focus on performance monitoring, detailed targets and strong performance incentives) on all 16 dimensions (see more details in the Appendix A and Appendix Table A2).

Figure 1 plots the histogram of plant management scores for the 2010 wave, which displays enormous dispersion.[12] While 18% of establishments have a management score of at least 0.75, meaning they adopt 75% of the most structured management practices, 27% of establishments receive a score of less than 0.5 (that is, they adopt less than half the practices).

Finally, our data collection includes recall questions (in 2015 asking about 2010 and in 2010 asking about 2005). This allows us to construct recall measures for the management score in 2005, and for missing observations in 2010. By comparing the actual management scores in 2010 to the 2010 recall values from the 2015 survey, we can also benchmark the quality of recall responses. Not surprisingly, we find that a key variable that determines the quality of recall management score is the tenure at the establishment of the manager responding to the survey – if the respondent's tenure started at least one year before the period of the recall, response quality is high.[13] As a result of this benchmarking exercise, we only use 2005 and 2010 recall values for the management score when the survey respondent has at least 7 years of tenure at the establishment. We also include a "recall dummy" in regressions to control for the fact that some observations are using recall data.

2.2 Sample and Sample Selection

The sampling frames for the 2010 and 2015 MOPS were the 2010 and 2015 ASM respectively, which were around 50,000 plants in each wave.[14] Overall, about 74,000 responses were successfully returned across both waves, yielding a response rate of around 74%. For most of our analysis, for each wave we further restrict the sample to establishments with at least 10 non-missing responses to management questions that also have positive value added, positive

[12] The average management score over the entire sample is 0.615 (see Appendix Table A4). We test and find that (controlling for recall dummy) management score is marginally (0.013) higher in 2015 compared to 2010.

[13] For 2015 managers answering 2010 questions, if the respondent started at the establishments in 2008 or earlier, the correlation between recall and actual 2010 management scores is 0.48. As discussed below, the correlation between management scores collected from two mangers in the *same* plant at the *same* time is 0.55 – close to the recall correlation for managers with long tenure, suggesting high recall fidelity.

[14] Note that sample counts have been rounded for disclosure reasons throughout the paper.

employment and for cases where we were able to impute a capital measure. Appendix Table A3 shows how our various samples are derived from the universe of establishments.

Appendix Table A4 provides more descriptive statistics. The mean establishment size is 177 employees and the median (fuzzed) is 86. The average establishment in our sample has been in operation for 21 years,[15] 44% of managers and 9.8% of non-managers have college degrees, 12.2% of workers are in unions, 45.1% of plants export, and 67.9% of plants are part of larger multi-plant firms. Finally, Appendix Table A5 reports the results for linear probability models for the different steps in the sampling process for the 2010 MOPS wave. We show that establishments that were mailed and responded to the MOPS survey are somewhat larger and more productive compared to those that did not respond, but these differences are quantitatively small.

2.3 Performance Measures

In addition to our management data, we also use data from other Census and non-Census data sets to create our measures of performance (productivity, profitability, innovation, and growth). We use establishment-level data on sales, value-added and labor inputs from the ASM to create measures of growth and labor productivity. As described in detail in Appendix A, we also combine capital stock data from the Census of Manufactures (CM) with investment data from the ASM and apply the Perpetual Inventory Method to construct capital stock at the establishment level, which we use to create measures of total factor productivity. For innovation, we use firm-level data from the 2010 Business R&D and Innovation Survey (BRDIS) on R&D expenditure and patent applications by the establishment's parent firm.

3 Management and Performance

Given the variations in management practices noted above, an immediate question is whether these practices link to performance outcomes. In this section, we investigate whether these more structured management practices are correlated with five alternative measures of performance (productivity, growth, survival, profitability, and innovation). Although there is good reason to

[15] Measured age is defined as the number of years the establishment has been alive in the Longitudinal Business Database (LBD), starting from its first year in 1976. Hence, age is truncated at 30 years in 2005, and we keep the same truncation for 2010 and 2015 for comparability over years.

think management practices affect performance from both theory and extensive case literature, we do not necessarily attribute a causal interpretation to the results in the section. Instead, it suffices to think about these results as a way to establish whether this management survey is systematically capturing meaningful content rather than just statistical noise.

3.1 Management and Productivity

We start by looking at the relation between labor productivity and management. Suppose that the establishment production function is:

$$Y_{it} = A_{it} K_{it}^{\alpha} L_{it}^{\beta} I_{it}^{\gamma} e^{\delta M_{it}} e^{\mu X_{it}} \tag{1}$$

where Y_{it} is output (shipments deflated by NAICS 6 digit price deflator), A_{it} is (total factor) productivity (excluding management practices), K_{it} denotes the establishment's capital stock at the beginning of the period, L_{it} are labor inputs, I_{it} are intermediate inputs (materials plus energy), X_{it} is a vector of additional factors such as education, and M_{it} is our management score.[16] Management is an inherently multi-dimensional concept, but for this study we focus on a single dimension: the extent to which firms adopt more structured practices.[17]

Dividing by labor and taking logs we can rewrite this in a form to estimate on the data:

$$log\left(\frac{Y_{it}}{L_{it}}\right) = \alpha \log\left(\frac{K_{it}}{L_{it}}\right) + \gamma \log\left(\frac{I_{it}}{L_{it}}\right) + (\alpha + \beta + \gamma - 1)\log\left(L_{it}\right) + \delta M_{it} \\ + \mu X_{it} + f_i + \tau_t + u_{it} \tag{2}$$

where we have substituted the productivity term (A_{it}) for a set of industry (or firm or establishment) fixed effects f_i , time dummies τ_t and a stochastic residual u_{it}. Because we may have multiple establishments per firm, we also cluster our standard errors at the firm level.

In Table 1 column (1), we start by running a basic regression of labor productivity (measured as log(output/employee)) on our management score without any controls other than

[16] We put the management score and X_{it} controls to the exponential simply so that after taking logs we can include them in levels rather than logs.

[17] The individual practices are highly correlated, which may reflect a common underlying driver or complementarities among the practices (Brynjolfsson and Milgrom, 2013). In this exercise, we use the mean of the share of practices adopted, but other measures like the principal factor component or z-score yield very similar results. Indeed, we show in Appendix Table A6 that key results in this section hold when we use every management question individually instead of an overall index.

year and recall dummies. The sample pools responses from 2015 and 2010 and the recall information for 2005 and 2010 (asked in 2010 and 2015 respectively). We find a highly significant coefficient of 1.351, suggesting that every 10 percentage point increase in our management score is associated with a 14.5% (= exp(0.1351) - 1) increase in labor productivity. To get a sense of this magnitude, our management score has a sample mean of 0.615 and a standard deviation of 0.172 (see the sample statistics in Appendix Table A4), so that a one standard-deviation change in management is associated with a 26.2% (= exp(0.172*1.351)) higher level of labor productivity. We provide more detailed analysis of magnitudes in sub-section 3.5. In column (2) of Table 1, we estimate the full specification from equation (1) with capital, intermediates, labor, employee education, and industry dummies on the right hand side. This reduces the coefficient on management to 0.209.

Even after conditioning on many observables, a key question that remains is whether our estimated OLS management coefficient captures a relation between management and productivity, or whether it is just correlated with omitted factors that affect the management score and the productivity measure. To address this, we focus on plants who were in the 2010 and 2015 panel, drop all recall data, and estimate models including plant fixed effects in order to - at least partially - address this concern over omitted factors.[18] As long as the unobserved factors that are correlated with management are fixed over time at the establishment level (corresponding to f_i in equation (2)), we can difference them out by running a fixed effect panel regression. Column (3) reports the results for the 2010-2015 pooled panel regression (including a 2015 time dummy). The coefficient on management, 0.079, remains significant at the 1% level. Of course, this coefficient may still be upwardly biased if management practices are proxies for time-varying unobserved productivity shocks. These could include firm-specific changes in leadership styles, culture or other factors that also happen to be correlated with the management practices that we measure, and our results should be interpreted accordingly. On the other hand, the coefficient on management could also be attenuated towards zero by measurement error, and this downward bias is likely to become much worse in the fixed-effect specification.[19]

[18] The sample is smaller because we drop 2005, and also because it conditions on establishments where we have data on management (and other factors) in both 2010 and 2015. This means we have to drop plants that entered or exited after 2010, and plants that were not part of the ASM rotating panel.

[19] There is certainly evidence of this from the coefficient on capital, which falls dramatically when establishment fixed effects are added, which is a common result in the literature.

The rich structure of our data also allows us to compare firm-level versus establishment-level management practices. In particular, by restricting our analysis to multi-establishment firms, we can check whether there is a correlation between structured management and productivity *within* a firm. Column (4) of Table 1 shows OLS estimates for the sub-sample of multi-establishment firms with firm fixed effects included. The management coefficient of 0.096 is highly significant. In this column, the coefficient on management is identified partially off the variation of management and productivity across plants within each firm in a given year, but also from the time series variation of plants across firms within the panel. To use solely the first source of variation we also include firm by year dummies in column (5) which leads to a management coefficient of 0.074. Hence, even within the very same firm, when management practices differ across establishments, we find large differences in productivity associated with variations in management practices.[20] This is reassuring since we will show in Section 4, that there is a large amount of management variation across plants within the same firm.

How do these estimates compare with earlier results? The easiest way to make the comparison is to consider the association between TFP and a one standard deviation change in the management index. Call this δ_M. Using column (2) of Table 1, we have a coefficient of 0.209 and a standard deviation of the management score of 0.172. Therefore $\delta_M = 0.036$. In the Bloom and Van Reenen (2007) study using WMS data, equivalent estimates from column (4) of their Table 1 is 0.040 which is $\delta_M = 0.040$ (their management measures are already z-scored to be in standard deviation units).[21] So these associations seem broadly comparable between the two datasets. Appendix C gives a detailed comparison of two methods of collecting management data in the MOPS and WMS and show a strong correlation between the two measures where we have overlapping firms.

Firms care more about profits rather than productivity *per se*, so we use the operating profits

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[20] Running regressions in the cross section with firm fixed effects is an even more general model as we (i) allow the coefficients on the factor inputs (and other controls) to be year-specific and (ii) we switch off the time series variation of plant-specific productivity and management within a firm. When running cross section regressions with firm dummies separately in each MOPS wave we obtain significant coefficients on management in each year of a similar magnitude to the pooled estimate in column (5). This shows that the variation from (i) and (ii) are not contributing much to the identification of the management coefficient in column (5).

[21] In the firm-level version of the MOPS data the coefficient on management is 0.307 (from Appendix Table A10) and the standard deviation is 0.16. This implies $\beta_M = 0.307*0.16 = 0.049$, slightly higher than the Bloom and Van Reenen (2007) estimates.

to sales ratio as an alternative measure of firm performance in the next three columns of Table 1. Column (6) has the same specification as column (2) except with profits as the dependent variable and column (7) mimics column (5) including firm by time dummies. We observe a significant management coefficient in both of these specifications. Figure 2 shows that in the raw data we observe a positive correlation with productivity and profits, and also with measures of innovation such as patents and R&D[22], as well as with hourly production wages.

One of the issues of concern is whether plant managers "talk up" their management practices regardless of the underlying reality. If this bias is stable over time then by including plant fixed effects we control for this potential bias. But it could be that the bias changes over time. One way that this would be revealed would be by comparing across different respondents. Were this to be a first order concern, the productivity-management relationship might be different when a different manager answered the survey in 2015 than in 2010 compared to when the same manager answered the survey in both years. The final columns of Table 1 compare results when we look at whether the survey was answered by the same individual respondent (column (8)) or a different respondent (column (9)). The coefficients on management look similar across both samples.

3.2 Cross-industry heterogeneity in the Performance-management relationship

So far, we have established a strong correlation between labor productivity and the adoption of management practices. It is likely that this relation is somewhat contingent on the firm's environment, and that the adoption of particular management practices is more important in some contexts than in others. To investigate this heterogeneity, we estimate the specification in column (2) of Table 1 for the 86 four-digit manufacturing NAICS categories. Figure 3 plots the smoothed histogram of the 86 regression coefficients.[23] To avoid over estimating the dispersion in management coefficients, we apply an Empirical Bayes Shrinkage procedure.[24] The distribution is centered on 0.2, which reassuringly is the coefficient from the pooled regression. All establishments operate in industries with a positive labor productivity-management relation.

Figure 3 demonstrates that there is indeed a lot of heterogeneity between sectors, and an F-

[22] See, for example, Henderson and Cockburn (1994) for a model linking managerial competence and innovation.
[23] To comply with Census disclosure avoidance requirements, we do not report the actual coefficients industry by industry, but a smoothed histogram.
[24] We follow closely Chandra, Finkelstein, Sacarny, and Syverson (2016).

test for the null of no difference across industries is easily rejected (p-value < 0.001). These findings suggest that the importance of structured management varies across environments, as one would expect. We leave a more thorough investigation of the reasons for this heterogeneity for future research, but we did examine whether structured management was less important for productivity in sectors where innovation mattered a lot (e.g. high industry intensities of R&D and/or patenting), as perhaps an over-focus on productive efficiency could dull creativity. Interestingly, we found that the productivity-management relationship was actually *stronger* in these high tech industries, perhaps implying that rigorous management of R&D labs is as important as production plants.

3.3 Measurement error

Estimates in Bloom and Van Reenen (2007) from independent repeat management surveys (at the same point of time) imply that measurement error accounts for about half of the variation in management score, making this an important issue. Including establishment fixed effects controls for measurement error in the management score if it is plant specific and fixed over time. But we can go further in characterizing measurement error by exploiting a valuable feature of the 2010 MOPS survey, which is that approximately 500 plants from our baseline sample have two surveys filled out by different respondents. That is, for this set of plants, two individuals – for example, "John Doe" the plant manager and "Jane Smith" the financial controller – both independently filled out the MOPS survey. This is most likely because a follow-up letter was mailed to a random set of plants in error that included a form and online login information, and an individual other than the original respondent received the letter. We confirm this measurement also turns out to be independent of any firm- or plant-level observable characteristics such as employment, productivity or the number of plants in the firm (see Appendix Table A7), and thus appears to be effectively white noise. These double responses are extremely valuable in enabling an accurate gauge of survey measurement error, because within a three-month window we have two measures of the same plant-level management score provided by two separate respondents.

First, we use these duplicate responses to estimate the degree of measurement error by correlation analysis. Assuming that the two responses have independent measurement error with standard deviation σ_e^2, and defining σ_m^2 as the true management standard deviation, the correlation between the two surveys will be $\sigma_m^2/(\sigma_m^2 + \sigma_e^2)$, and the measurement error share will be $\sigma_e^2/(\sigma_m^2 + \sigma_e^2)$=0.454, where $(\sigma_m^2 + \sigma_e^2)$ is the variance of the observed management score on 500 double score sample and σ_e^2 is half the variance of the difference between the first and second management score. Interestingly, this 45% share of the variation from measurement error is very similar to the 49% value obtained in the World Management Survey from second independent telephone interviews (Bloom and Van Reenen, 2007).

Second, we use these duplicates to instrument one management score with the other to overcome attenuation bias in our OLS performance estimates. We perform this analysis in Table 2, starting by analyzing output in the first row. First, in column (1) we regress log(output) on management for the entire sample. Then in column (2) we re-run this estimate on the 500 duplicates finding a very similar estimation coefficient, suggesting this duplicate sample is similar to the whole sample. Column (3) is the key specification in that we instrument the first management score with its second duplicate score, finding that the point estimate roughly doubles from 4.465 to 9.174. In column (4) we compare these OLS and IV coefficients to estimate that measurement error accounts for about 51% of the management variation. We repeat this exercise for log(employment) in the second row, for log(output/employee) in the third row (replicating column (1) of Table 1), and for industry normalized log(output/employee) in the fourth row. These produce qualitatively similar results to the first row: (i) the 500 establishment duplicate sample yields a similar coefficient on management to the whole sample; and (ii) the IV estimates are roughly twice the OLS estimates (similar to the 45% estimate of measurement error from the two management score variances and covariance noted above). These results imply that about half the variation in the management data is measurement error.

3.4 Management Practices, Survival and Growth

In Table 3, we focus on two other important outcomes: exit (Panel A) and employment growth (Panel B). Because the Census tracks the survival and employment of all plants in the Longitudinal Business Database (LBD) we have up to 5 years of data on the MOPS 2010 cohort (2015 is the last year where we have reliable data at time of writing).[25] In column (1) we examine whether firms have exited the economy by the end of December 2011. Since MOPS was conducted in the

[25] As additional years of the Longitudinal Business Database (LBD) become available we can examine increasingly long-run relationships between management practices, employment and survival.

middle of 2011, this is a very short window, so we widen the window in subsequent columns to exit by the end of 2012 in column (2), end of 2013 in column (3) and so on. The coefficients become monotonically more negative (by about 3 to 4 percentage points per year) as we move across the columns. Since establishment death is an absorbing state this is what we would expect. Column (5) shows that by 2015 the coefficient is large and highly significant (-0.180). This indicates that a one standard deviation increase in the management score (0.172) is associated with a 3.1 percentage point reduction in the probability of establishment death, which is 26% of the mean death rate of 11.8%. In column (6) we run the most exacting specification to test if the 2010 management score can predict the exit rates five year later between 2014 and 2015, and find it can. This highlights how the management score has highly significant predictive power for longer-run as well as shorter-run plant performance.

In column (7) of Table 3 we include firm effects in the "exit by 2015" equation of column (5). We still observe a negative and significant coefficient, showing that even within the same firm, a plant with a relatively poor management score is relatively more likely to be closed down. Interestingly, this coefficient is even larger than in column (5). A possible interpretation is that for a single plant firm, it is the market signal of negative profits that should induce exit. By contrast, for a multi-plant firm, the headquarters is deciding which plants to shut down and this might be easier to accomplish (e.g. by moving assets and employment from one plant to another). Hence, such creative destruction may be more easily implemented within firms than between them.[26]

In column (8) of Table 3 we include 2010 labor productivity (value added per worker) into the specification of column (5) and then add firm by year fixed effects in column (9). Less productive plants are more likely to exit, but the coefficient on management practices is robust to this and remains significant. Since management practices and productivity are correlated, the coefficient on management practices falls. For example, in column (8) it is -0.153 compared to -0.180 in column (5). Strikingly, the contribution of management practices in accounting for exit is *larger* than productivity (a marginal R^2 of 0.005 for management practices compared to 0.003 for productivity in column (8)).

[26] See Davis, Handley, Haltiwanger, Jarmin, Lerner and Miranda (2014) for related evidence on this issue. They show that firms taken over by private equity downsize inefficient plants and expand efficient plants much more aggressively than other firms. As we show in Section 4, there is substantial plant heterogeneity in management within the same firm, suggesting that changing management on the intensive margin may be hard to achieve easily.

In Panel B of Table 3 we repeat the specifications of Panel A using employment growth as the outcome.[27] The findings here mirror the exit analysis with firms who had higher management scores in 2010 being significantly more likely to grow over the next 5 years. Using the results from column (5), a one standard deviation increase in management practices is associated with 7 percent faster growth.

One interesting extension we ran on Table 3 is to examine if the association between management practices and plant performance varied with plant age. In short (details in Appendix Table A8) the management score was much more strongly related to growth and survival for younger plants – for example, the exit relationship was twice as strong for plants aged 5 years or less compared to those older than 20 years. This is consistent with many standard models of market selection (e.g. Jovanovic, 1982; Hopenhayn, 1992; Melitz, 2003; Bartelsman, Haltiwanger and Scarpetta, 2013) where plants have a heterogeneous managerial capability when they are born, but there follows a rapid selection process where the weaker establishments exit the market. When incumbent plants have matured to their steady state size, there is less of a relationship between growth and management practices (random management shocks will lead to some relationship).[28]

We also ran a series of other robustness tests on Tables 1 and 3, such as using standardized z-scores (rather than the 0-1 management scores), dropping individual questions that might be output-related and using ASM sampling weights, and found very similar results. We also looked at a non-parametric analysis of the management-size relationship (Appendix Figure A1), finding a continuous positive relationship with establishment and firm size from 10 employees until about 5,000 employees where it flattens out. This is also quantitatively large: a firm with 10 employees has an average management score of 0.5 (the 20th percentile) compared to 0.7 (the 70th percentile) for one with 1,000 employees. Finally, we examined whether management could simply be proxying for other unobserved cultural or organizational features of the establishment (e.g. Gibbons and Henderson, 2013). These are by nature hard to observe but in Appendix Table A9 we look at decentralization (a measure of the distribution of power between the plant manager and corporate headquarters) and data-driven decision making. While these are informative in terms of

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27 Growth between years s and t is calculated as $2*(L_t - L_s)/(L_t + L_s)$ following Davis and Haltiwanger (1992).

28 Note that it is not obvious why TFP should be any more strongly related to management for young firms under these class of models. Indeed, in Appendix Table A8 we do not find any systematic relationship in the TFP-management relationship by plant age.

productivity, our management indicator remains robust to including these as additional controls.

3.5 Magnitudes of the Management and Productivity Relationship

To get a better sense of the magnitudes of the relationship between management practices and productivity, we compare management practices to other factors that are commonly considered important drivers of productivity: R&D (Research and Development spending), Information and Communication Technologies (ICT) and human capital. We focus on these three because they are leading factors in driving productivity differences (e.g., discussed in detail in the survey on the determinants of productivity in Syverson, 2011), and because we can measure them well using the same sample of firms used for the analysis of the management practices-productivity link. In particular, we ask how much of the productivity spread can be accounted for by the spread of management practices, R&D expenditure per worker, ICT investment per worker (spending on information and communication technology hardware and software), and human capital (measured as the share of employees with a college degree). We do this analysis at the firm level as establishment-level R&D is not the appropriate level for multi-plant firms.

Columns (1)-(4) of Table 4 report the results from firm-level regressions of log labor productivity (value added per worker) on those four factors individually. All of these factors are positively and significantly related to productivity. To obtain an aggregate firm-level labor productivity measure, the dependent variable is calculated as the weighted (by the plant shipment share of firm shipments) industry-demeaned plant-level labor productivity.[29] This is then regressed on the firm-level value of the management score in column (1). The bottom row of column (1) shows that the 90-10 spread in management practices accounts for about 22% of the spread in labor productivity. In columns (2) to (4) we examine R&D, ICT and skills and find these measures account for 22%, 12% and 16% of the 90-10 productivity gap, respectively. Column (5) shows that the role of management practices remains large in the presence of the other factors, and that jointly these can account for about 44% of the 90-10 productivity spread in productivity. Similar conclusions come from other ways of accounting for productivity dispersion. For example, the contribution of each factor to the standard deviation of firm log(value added per worker) is 19.3%

[29] To obtain the firm-level measure of the right hand side variables, we weight the right-hand variables by their plant's share of total shipments (exactly as we do for the dependent variable). Results are robust to using the non-demeaned measure or other weighting schemes.

(management), 22% (R&D), 13.5% (ICT) and 14.2% (skills). The results in Table 4 highlight that our measure of management practices can account for a relatively large share of firm-level productivity.

There are several alternative approaches to looking at magnitudes. First, we used TFP[30] instead of labor productivity even though this is problematic as we are now summing across plants in industries with heterogeneous technologies when aggregating to the firm level. Nevertheless, the contribution of each factor to the 90-10 spread is similar to Table 4: 18.1% (management practices), 16.9% (R&D), 7.5% (ICT), 11.1% (skills) and 32.5% (all four).[31] Second, we can simply run the analogous production functions of Table 1, but at the firm level instead of plant level. Appendix Table A10 does this. Although the absolute level of the contribution of management practices (and the other factors) falls compared to Table 4, the relative contribution of management practices continues to remain as large as that of R&D and larger than that of ICT or skills.

One obvious caveat throughout this management practices and performance analysis is causality, which is hard to address with this dataset. In related work, Bloom et al. (2013) run a randomized control trial varying management practices for a sample of Indian manufacturing establishments with a mean employment size of 132 (similar to our MOPS sample average of 167). They find evidence of a large causal impact of management practices towards increasing productivity, profitability and firm employment. Other well-identified estimates of the causal impact of management practices – such as the RCT evidence from Mexico discussed in Bruhn, Karlan and Schoar (2016) and the management assistance natural experiment from the Marshall plan discussed in Giorcelli (2016) – find similarly large impacts of management practices on firm productivity.

Given the evidence of the strong relationship between establishment performance and management, after briefly examining variation in management practices within firms we then turn to looking at two drivers of structured management practices where we believe we have credible

[30] We use a "two factor" estimate of TFP in these calculations to be consistent with Table 4 which uses value added as the dependent variable.

[31] About 50% of firm-level TFP appears to be measurement error according to Collard-Wexler (2013) and Bloom, Floetotto, Jaimovich, Saporta-Eksten and Terry (2018). Under the assumption that this measurement error is uncorrelated with the factors in Table 4 this implies these four factors can potentially account for about two-thirds of the true (non-measurement error) variation in TFP.

causal identification.

4 Management Practices across Plants and Firms

One important question is: to what extent do these variations in management practices across plant occur *within* rather than *between* firms? The results in Tables 1 and 3 suggest that there is enough within firm (across plant) variation even in the cross section to uncover a relationship between plant productivity and plant management. The voluminous case-study literature on management practices[32] often highlights the importance of variations both within and between organizations, but until now it has been challenging to measure these separately due to the lack of large samples with both firm and plant variation.

The benefit of the MOPS sample in addressing this question is twofold. First, the large sample means we have thousands of firms with multiple plants. Second, thanks to 500 double plant surveys we can control for measurement error, which would otherwise inflate the within firm cross-plant variation. Armed with the earlier estimate that 45% of the variation accounted for by measurement error, we can now decompose the remaining variation in the management score into the part accounted for by the firm and the part accounted for by the plant. To do this, we keep the sample of 16,500 plants (out of ~32,000 plants) that are in firms with two or more plants in the MOPS survey in 2010. Although this sample only contains 44% of the overall number of observations in the sample, these are larger plants and account for 74% of output in the MOPS sample.

The first series in Figure 4 (blue diamonds) plots the share of the plant-level variation in the management score accounted for by the parent firm in firms with two or more plants after scaling by (0.546=1-0.454) to account for measurement error. To understand this graph, first note that the top left point is for firms with exactly two plants. For this sample, firm fixed effects account for 90.4% of the adjusted R-squared in management variation across plants,[33] with the other 9.6%

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32 For example Brynjolfsson and Milgrom (2013) cite 11 case studies about variations in management practices and performance including Berg and Fast (1975), Barley (1986), Brynjolfsson, Renshaw and Van Alstyne (1997), and Autor, Levy and Murnane (2002).

33 It is essential for this part of the analysis that the adjusted R^2 on the firm fixed effects is not mechanically decreasing in the number of establishments in the firm. To alleviate any such concern, we simulated management scores for establishments linked to firms with the same sample characteristics as our real sample (in terms of number of firms and number of establishments in a firm), but assuming *no firm fixed effects*. We then verified that indeed for this sample, the adjusted R^2 is zero and does not show any pattern over the number of establishments in a firm.

accounted for by variation across plants within the same firm. So, in smaller two-plant firm samples, most of the variation in management practices is due to differences across firms.

Moving rightwards along the x-axis in Figure 4, we see that the share of management variation attributable to the parent firm declines as firm size rises.[34] For example, in firms with 50-74 plants, the parent firm accounts for about 40% of the observed management variation, and in firms with 150 or more plants, the parent firm accounts for about 35% of the variation. Hence, in samples of plants from larger firms, there is relatively more within-firm variation and relatively less cross-firm variation in management practices. The horizontal solid red line plotted shows the average share of variation in management scores across plants accounted for by the parent firm in our sample, which is 58%.

At least two important results arise from Figure 4. First, both plant-level and firm-level factors are important for explaining differences in management practices across plants, with the average share of management variation accounted for by firms being 58% (so 42% is across plants within the same firm). Second, the share of management practice variation accounted for by the parent firm is declining in the overall size of the firm, as measured by the number of establishments.

What explains the large fraction of within-firm variation in management practices? One likely explanation is that within a firm, different establishments operate in different environments – for example, different industries or locations. To evaluate this explanation, the second series in Figure 4 (green dots) repeats the analysis with one change: when we run the regressions of management on firm fixed effects (used to recover the adjusted R^2), we control for the part of the management score that is explained by within firm/across plant industry and MSA variation.[35] This essentially removes the within-firm share of variation in management that is explained by industry and geographical variation. There are two points to highlight from this exercise. First, by construction, the overall within-firm management variation is smaller, going down from 42% on average to 19%. Second, the relation between size and within-firm variation is flatter. Although we see a clear downward slope for firms with under 10 plants, we cannot reject the null that the

[34] The number of establishments on the x-axis is calculated using the LBD, counting all manufacturing establishments associated with the parent firm.

[35] Specifically, the R^2 regressions include now the linear projection of management from a regression of management on full sets of NAICS and MSA dummies (where for plants in areas without an MSA, the state is used), where the regression also includes firm fixed effects. The sample for this regression is identical to both series in Figure 4.

within-firm variation is similar for all firms with 10 or more plants. This is consistent with larger firms (those with more than 10 plants) operating across more industries and geographical regions, which accounts for their greater within firm spread in management practices.

We further explore these points in Table 5, reporting results from a regression of the within-firm standard deviation of the management score on firm level characteristics. Consistent with the first series in Figure 4 (blue diamonds), columns (1) and (2) demonstrate that the standard deviation of management within a firm is increasing with the number of establishments in the firm, and that this relation is stronger for firms with 10 establishments or less. Column (3) shows that operating in more industries and over more locations are both correlated with a larger within-firm spread of management. Columns (4) and (5) are consistent with the results in the second series in Figure 4 (green dots): controlling for the number of within-firm industries and locations, the relationship between management spread and size weakens and becomes insignificant for firms with more than 10 manufacturing establishments. Columns (6)-(11) show that the within-firm spread of management is correlated with other factors in an intuitive way. Although we do not find a correlation between the spread of management and the spread of establishment age within the firm (column (6)), we find that the spread of management is larger for firms with a larger size spread across plants (column (7)). We also find a larger spread for firms with more ownership changes over the past one, two and three years (columns (8) to (10)), suggesting it takes at least three years after a firm acquires a new plant to significantly change its management practices.[36]

The importance of geographical location stands out in Table 5, being significant across all columns. This motivate us to consider geographical factors that may help explain the wide variation of management practices across plants.

5 Drivers of Management Practices

The previous literature on management has pointed to a wide variety of potential factors driving management practices. We focus on two –business environment and learning spillovers – for which we have credible identification strategies and significant spatial variation. Online Appendix B describes a simple model to help interpret the coefficients of the effect of these drivers

[36] We have also checked for the correlation with 4- and 5-year ownership changes, finding decreasing point estimates (with neither statistically significant at the 5% level).

on management (and other outcomes like measured TFP).

5.1 Business Environment

The business environment in which plants operate is often thought to be a major factor for understanding the variation in management across plants. As a measure of the business environment, we use “Right-to-Work” (RTW) laws, which are state-level laws prohibiting agreements between employers and labor unions that require employees’ membership, payment of union dues, or fees as a condition of employment, either before or after hiring. They now cover 28 states, and have been growing in coverage. We use two identification strategies to examine the causal impact of RTW on management. First, we use a Difference-in-Differences (DID) approach exploiting the introduction of RTW in two states in 2012. Second, in the spirit of Holmes (1998) we use a spatial RD Design around state boundaries.

Difference in Differences (DID)

In 2012 two US states – Michigan and Indiana – introduced RTW laws. Since we have waves of the management survey in 2010 and 2015 we can run a DID analysis of management changes between 2010 and 2015 comparing these states to their neighbors. The treatment states are compared to their contiguous neighbors – Ohio, Illinois, and Kentucky.[37] We do not use the neighboring state of Wisconsin as it introduced Right-to-Work laws right at the end of our panel (in 2015). Three other states – West Virginia (2016), Kentucky (2017), and Missouri (introduced 2017, currently postponed) introduced Right-to-Work laws after our sample period. This enables us to run a placebo test on these three states to examine whether other events triggering a successful RTW vote could be influencing management rather the RTW laws themselves.

Our empirical analysis relies on a standard DID specification:

$$M_{it}^{m} = \theta_1(RTW_s * POST_t) + \theta_2 X_{i,t} + \omega_s + \tau_t + \epsilon_{it}.$$

Where M_i^m indicates the management practice score of plant *i* - the superscript *m* indicates whether we are considering subsets of the management score such as incentives practices, RTW_s is a dummy for the two RTW states, $POST_t$ is a dummy for the years after the introduction of RTW in

[37] The large sample size (35,000 plants) for each MOPS wave, plus the high density of manufacturing plants in these states, means we have 15,000 observations across both waves for this DID regression analysis.

2012 (i.e. a dummy for 2015), $X_{i,t}$ are other observable controls (such as recall and NAICS6 dummies), ω_s are state dummies, τ_t are time dummies and ϵ_{it} is an error term.

Table 6 contains the results for our baseline specification in Panel A. Column (1) reports a positive and weakly significant coefficient on the treatment variable. RTW is likely to primarily effect "incentives practices" over human resources such as tying pay, firing, and promotion to employees' ability and performance. Unions frequently oppose these practices which they believe give too much discretion to employers, so if unions are weakened by RTW then these incentives practices will likely become more structured. Consequently, column (2) looks specifically at these incentive practices as an outcome (questions 9 through 16 in the MOPs questionnaire).[38] The treatment effect is larger and more significant in this specification. In column (3) we examine non-incentive management practices (the other 8 MOPS questions on monitoring and targets, which are much less directly related to RTW laws), and find a positive coefficient but one which is small in magnitude and statistically insignificant.

In column (4) of Table 6 we examine unionization directly as the most likely mechanism through which the RTW effect might operate. In the MOPS survey union density is in bins so we create a dummy indicating very strong labor unions: where 80% or more of workers are union members. RTW has a negative and significant effect on the prevalence of these highly unionized plants. This is as expected since the introduction of RTW eliminates the need for all employees to be a union member. Columns (5) and (6) look at performance related outcomes. Column (5) shows that RTW has a positive and significant effect on size of establishments as measured by employment, and column (6) shows a small, but insignificant positive effect of about 1.5% on TFP, measured in log deviations from the 6 digit NAICS industry mean. The absence of a RTW effect on measured TFP may seem surprising given the positive effects on management, but one potential explanation is the greater entry of plants in RTW states increases demand for scare inputs and so drives up relative input prices (such as land and local materials prices).[39] These "congestion effects" will tend to bias measured TFP downwards and in principle, a driver could even appear to have a negative effect. This is a more general concern with TFP and we discuss this issue in more

[38] We verify that the results are not sensitive to questions more likely to be output-related. For example, repeating the specification in Panel A, Column 2 removing MOPS questions 9-12, we get an estimate of 0.015 (0.0085), very similar to the estimate using all the incentives related questions.

[39] If this entry also increased local product market competition this would also generate a downward bias to our revenue based measure TFP measure as mark-ups would shrink.

detail below in relation to MDPs (see Appendix B for a formal discussion).

An obvious concern with the DID strategy is that there may be pre-policy trends, so that incentives management, employment and productivity might have increased even in the absence of the RTW policy change. To assess this we can use the 2005 and 2010 data and run a pseudo-experiment as if a RTW vote was passed between these years. Replicating the specifications of Panel A in Panel B of Table 6 we find that there is no significant effect in any column, which is consistent with the hypothesis of no pre-policy trends contaminating the treatment effects. Panel C includes a full set of NAICS6 industry dummies in the Appendix A specification to see if the differences we observe are due to industry mix. The results are very similar. In Panel D we use the LBD to trace year of birth and location for each establishment in our 2015 sample. We then focus on plants who were alive in 2010 and are recorded in 2015 at the same state as they are in 2010, so dropping entrants and movers between 2010 and 2015. The similarity of the results with Panel A shows that our results are driven by changes in incumbents rather than new plants attracted to the state due to the RTW policy.

Finally, as noted above, West Virginia, Kentucky and Missouri introduced Right-to-Work laws, but after 2015, the last year of our panel. This enables us to run a placebo test on the voting for (but not the introduction of) RTW legislation. This is to address the concern that there may be unobservables correlated with the holding of a RTW vote which could confound our treatment effects. Again we use contiguous states as controls.[40] Panel E of Table 6 contains these placebo results and shows that there is no significant treatment effect on any of the outcomes.

Regression Discontinuity (RD) Design

At the time of the 2010 MOPS survey, 22 states had RTW laws in place, mostly in the South, West and Midwest. In Table 7, we compare plants in counties that are within 100 miles of state borders that divide states with different RTW rules. We estimate the following equation

$$M_i^m = \theta_1 D_i + \theta_2 X_i + \varphi_B(DISTANCE_i) + B_{s,s'} + e_i,$$

where D_i is a dummy variable for whether the firm is located in a state with a RTW law, X_i are

[40] These states are Virginia, Maryland, Pennsylvania, Tennessee, Illinois, Ohio, Arkansas, Oklahoma, Kansas, Nebraska, and Iowa.

other observable controls, $\varphi_B(DISTANCE_i)$ is a polynomial function of a plant's distance to a state border (which we allow to take a different shape on either side of the border as indicated by the "B" subscript), and $B_{s,s'}$ are 74 border dummies, specific to every pair of states with a different RTW regime. Since we have multiple years we define variables specific to the year and add time dummies (and a recall dummy) to the regression.[41] We have 39 states who are either RTW states or their neighbors and cluster the standard errors at the state level.

Unlike a classic RD Design, the location of the plant across the discontinuity (border) *can* be manipulated by agents. So the treatment effect we identify is a combination of any effects on existing plants plus the selection of plants with more structured incentive management into RTW states. Furthermore, recall that θ_1 will reflect the effect entire bundle of state specific policies on either side of the border, not just RTW laws (the DID analysis is more specific in this respect). The key identification assumption is that as we shrink distance to zero, the non-state policy related factors (e.g. economic and geographical) become identical on either side of the border.

Figure 5 shows the RD Design visually. Panel A looks at average non-incentive management practices for various distances away from the border. There is no apparent discontinuity in the adoption of non-incentive practices around RTW border in the data. In Panel B when we look specifically at incentive management practices and observe a clear discontinuity in incentives management at the state boundary. This is consistent with a causal effect. Interestingly, the incentive management scores look broadly stable as we move away from the border. If there were very local selection effects so that the impact of state policies was to switch only a few highly structured management plants across the border, we might expect to see some bunching (a sudden increase in average management scores as we approach the border), which we do not observe.[42]

Table 7 reports similar outcomes to the ones reported in the DID estimates of Table 6 but for estimates from the RD Design, allowing for different trends in distance on two sides of the border. In columns (1) - (3) of Table 7, the regression sample includes all plants in bordering pairs within 100 miles of a state-border between two states with different RTW laws. In Panel A, we see that the plants on the RTW side of the border have significantly higher incentive management

[41] Results are almost identical when we generalize the model to include border pair interacted by time dummies.
[42] Note that we do see more plants on the RTW side of the border, i.e. there is a bigger mass on the RTW side of the border, though this is not driven by bunching at the border.

scores, but there are no significant effects on other types of management practices. The magnitude of the effect is very similar to the magnitude from the DID analysis. For example, the treatment effect in column (2) is 0.017, almost identical to the same estimate in column (2) of Table 6. Given that these are from different identification strategies, this similarity is reassuring. RTW reduces union density according to column (4). We also find significant positive effects on employment in column (5), but again no significant effects on TFP.

Panel B of Table 7 includes NAICS6 dummies and shows robust effects of RTW. As noted above, the RD coefficient reflects both pure treatment effects on incumbents and the fact that plants with more incentive management practices will likely sort onto the RTW side of the border. From a state policy perspective, these sorting effects are of interest, but if all of the effect is selection through cross border switching then this may mean the equilibrium impact of the policy is zero. Furthermore, even from a purely local perspective, the effect is over-estimated because some of the impact is may be coming from lower structured management scores in the non-RTW states due to the movement of plants with more structured practices to the RTW side of the border. So in Panel C we look at plants in the least-tradable quartile of industries – industries like cement, wood pallet construction or bakeries, defined in terms of being in the bottom quartile of geographic concentration – that are the least likely to select on location because of high transport costs.[43] Again, we find RTW states have significantly higher structured management scores within this sample of relatively non-tradable products for which selecting production location based on "business-friendly" conditions is harder. This, coupled with the similarity of the effect for plants further from the border and the DID effects on incumbents, suggests that the management effects of RTW are not primarily due to cross border switching. The last two panels of Table 7 report technical robustness tests for the RD estimates. In Panel D we replace the linear trends in distance from border with quadratic trends, and in Panel E we weight observations using the Epanechnikov Kernel applied to (absolute distance of) distance from border. As these panels show, the results are not sensitives to the econometric details of the RD Design specification.

5.2 Learning Spillovers: Million Dollar Plants

Do structured management practices "spill over" from one establishment to another? We would

[43] Our industry geographic concentration indexes are calculated following Ellison and Glaeser (1997) using the 2007 Census of Manufacturers.

expect this to happen if there is learning behavior, making management qualitatively from other factor inputs. To get closer to a causal effect, we study how management practices in particular counties in the US change when a new, large and typically multinational establishment (likely to have higher management scores) is opened in the county.[44] A key challenge, of course, is that such counties are not selected at random. It is in fact very likely that counties that "won" such large multinational establishments are very different than a typical county in the U.S. To overcome this issue, we compare counties that "won" the establishment with the "runner-up" counties that competed for the new establishment. This approach is inspired by Greenstone, Hornbeck and Moretti (2010), who study the effect of agglomeration spillovers by looking at productivity of winners and runner-up counties for Million Dollar Plants (MDPs). We used *Site Selection* magazine to find "Million Dollar Plants" as described by Greenstone, Hornbeck and Moretti (2010), extending the list by web searching for MDP counties and runner-ups (see Appendix A for more details about data construction), with our full MDP data available online.[45]

Following our data structure of a 5-year panel, we estimate the following equation

$$\Delta M_{icst} = \theta_1 \Delta MDP_{ct} + \theta_2 X_{icst} + P_{c,c'} + f_s + e_{it},$$

where ΔM_{ict} is change in the management score for establishment i in county c, state s between year $t-5$ and year t, ΔMDP_{ct} is a dummy that equals one if the county had an MDP opening between years $t-5$ and t, X are other observable controls, and $P_{c,c'}$ are 45 dummies, specific to every pair of winning and losing counties, and f_s are state fixed effects. The MDP opening year for the regression is set to be the first year the MDP shows up in the LBD in cases where the establishment is new (rather than an expansion) and was successfully matched to the LBD. Otherwise we use the announcement year +1. We use 2005-2008 MPD openings for the 2005-2010 changes, and 2010-2013 openings for the 2010-2015 changes to allow one or two years before any meaningful managerial occur.

Before looking at the results, we check that the observable characteristics for winners and runner-up counties are balanced (see Table A11). We look at all MDPs pooled in column (1) and

44 Note that we *do not* choose these plant openings using Census data, but using public data only (see more details in the Appendix A). In fact, to ensure the confidentiality of plants in our sample, we do not report whether these plants even appear in our data or not.

45 See https://people.stanford.edu/nbloom/research. We are grateful to Hyunseob Kim for sharing an updated list of million dollar plants and discussing search strategies from his work Kim (2013).

then separately for establishments with high and low worker flow between the establishment and the MDP industry codes in the next two columns. Of the 33 coefficients, only five are statistically significant. Importantly, there are no significant differences in $t-10$ to $t-5$ *trends* in employment, productivity, value added and county characteristics between winners and runner-ups.

Table 8 contains the spillover results with the baseline results in Panel A. Column (1) suggests a positive and significant effect of MDPs on management. Unlike in the RTW case there are significant effects on both incentives and non-incentives management.[46] This is unsurprising, as there are no *ex ante* reasons to believe the effects of MDPs should be larger on incentives management. Column (2) shows that the results are in fact somewhat larger and more significant controlling for 6 digit NAICS industry dummies. Columns (3) and (4) show a positive but statistically insignificant effects on TFP. As with the RTW case, this may be because of plant entry driving up land and input prices in MDP counties, downward biasing measured TFP.[47] Columns (5) and (6) uses employment growth as a dependent variable and show positive and significant effects.

Some plants are more likely to benefit from MDPs than others. In particular, if the MDP effect is really due to learning spillovers we would expect the benefits to be particularly strong if there are likely to be larger flows of managers between the MDP and local firms. To examine this we pooled the Current Population Surveys (CPS) from 2003 to 2015 and examined the flows of managers between different three digit NAICS industries. For every MDP we can observe its industry code and whether a plant in the treatment (or control) county is in an industry that is more likely to benefit from a managerial flow. We then split plants into above vs. below median management flows for based on the plant and the MDP industry codes using the bilateral matrix for employees in managerial occupations from the CPS.[48] Panel B of Table 8 shows that the MDP

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[46] If anything we found somewhat stronger effects for non-incentives management practices. Without controls, the coefficient (standard error) on non-incentive management is 0.018 (0.005) whereas the coefficient on incentives management is 0.009 (0.010). Controlling for industry fixed effects, the coefficients are of similar size at 0.019 (0.007) for non-incentives and 0.020 (0.011) for incentives management.

[47] Indeed, the original Greenstone, Hornbeck and Moretti (2010) reported the impact of MDPs on land prices and wages, so that not only land but any local land or labor intensive inputs would see higher prices.

[48] We use employees in occupation classification "Executive, Administrative, and Managerial Occupations", corresponding to occupation codes 003 to 037 in the IPUMS harmonized occ1990 variable.

effect is only statistically significant for plants in those industries that are more likely to receive a larger managerial flow from the MDP industry.[49] Consistent with this, we find that these "more exposed" plants also benefit from significantly higher TFP and jobs growth. Note that the spillover may occur in more subtle ways than simply the movement of managers from the MDP to local firm. Using national inter-industry managerial labor flows as a "distance metric" may also reflect that there will be greater interactions between MDP managers and those of local firms in professional and social situations.

There are many other ways to build up a distance metric between the MDP and the incumbent plants. Panel C uses the goods input-output matrix. We do not find much evidence of larger management to TFP spillovers associated with higher trade links, but we do find some larger employment effects. This is consistent with incumbent plants benefitting from a demand effect if an MDP is in a buyer-seller relationship, but not learning spillovers. Panel D looks at the product market dimension dividing MDPs into manufacturing vs. non-manufacturing MDPs. Consistent with the idea that our manufacturing plants are more likely to benefit from manufacturing MDPs, only manufacturing MDPs are statistically significant. However, the coefficients on the two types of MDPs are not significantly different from each other.

We conclude that MDPs do appear to have significant effects on management, but only if plants are closely connected as revealed through managerial labor markets (rather than just being in an input-output or product market relationship). These improvements in management also feed through into jobs and productivity gains.

5.3 Discussion

Through the lens of the simple model in Appendix B there are at least two mechanisms through which the reduced-form evidence of our drivers could influence management practices. First, by reducing the effective "price" of adopting structured management practices RTW and MDP could increase management scores. This could then improve productivity as suggested by Table 1. However, an alternative story would be that RTW and MDP increased productivity through some

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[49] We also find a similar pattern using the bilateral flow matrix for all employees, but the results are weaker than just using managerial flows. Whereas the p-test of the significance between the two types of industries for managerial flows is significant at the 5 or 10% levels as shown in Table 8, a similar test for all employee flows has p-values of 0.23 to 0.26.

non-management mechanism (e.g. the adoption of new technologies) and that this increase in productivity caused the firm to grow and therefore increase all factor inputs including managerial capital.

We cannot directly rule out this second mechanism with our data, but several pieces of evidence suggest that it is not the whole story. First, the RTW effect is not on all managerial practices, but specifically over those related to incentives, which is exactly where we would expect the regulation to have its largest effect. One might believe that incentives are easier to adjust than other types of management (although one could make the opposite case that pay and promotions are actually very sensitive organizational issues and are often the most difficult practices to change). However, we can directly look at this by disaggregating the management score in the MDP analysis. As discussed above, here we find that if anything the MDP effects look stronger on the non-incentive aspects of management, such as lean manufacturing and monitoring. This is plausible as these aspects may be the harder ones to understand and implement in the absence of demonstration by another firm. Second, we can condition on employment growth to absorb the overall effects on size. These regressions must be interpreted with caution as we have an endogenous variable on the right hand side, but it is striking that the coefficient on our treatment variable does not fall by much in these "conditional management-capital demand" equations.[50] Thirdly, it is worth noting that the effects of these drivers is generally stronger on management than it is on TFP.

5.4 Other Drivers

We have focused on two important drivers of management – business environment and learning spillovers. But there are many other potential factors. In the Working Paper version of this paper (Bloom et al, 2017) we also focus on two additional factors - education and competition. We find robust evidence that higher levels of human capital and competition are both positively associated with higher levels of the management scores.[51]

[50] For MDP the coefficient changes from 0.18 in column (2) of Table 8 Panel A to 0.17 (0.006); for the RD Design RTW in column (2) of Table 7 it falls from 0.017 to 0.012 (0.005) and in the DID RTW of column (2) of Table 6 it falls from 0.017 to 0.009 (0.006).

[51] To generate some exogenous sources of variation we used trade shocks as an IV for competition (Bertrand, 2004) and the location of land grant colleges as an IV for the supply of educated workers (Moretti, 2004). The correlations were robust to these IV strategies.

6 Conclusions and Future Research

This paper analyzes a recent Census Bureau survey of structured management practices in 2010 and 2015 for about 35,000 plants in each wave across the U.S. Analyzing these data reveals three major findings. First, there is a large variation in management practices across plants, with about 40% of this variation being across plants *within* the same firm. This within-firm across-plant variation in management cannot easily be explained by many classes of theories that focus on characteristics of the CEO, corporate governance or ownership (e.g., by family firms or multinationals) because these would tend to affect management across the firm as a whole.

Second, we find that these management practices are tightly linked to several measures of performance, and they account for about a fifth of the cross-firm productivity spread, a fraction that is as large as or larger than technological factors such as R&D or IT. Furthermore, management practices are very predictive of firm survival rates, in fact, more so than TFP.

Third, we find causal evidence that two drivers are very important in improving management practices. Regulation of the business environment (as measured by the Right-to-Work laws) increases the adoption of structured incentives management practices. Learning spillovers as measured by the arrival of large new entrants in the county ("Million Dollar Plants") increases the management scores of incumbents.

Although both of these drivers are qualitatively important across geographical regions, they cannot explain the large variation of management practices within the same region, much of which is within the same firm. This is not obviously due to firm wide factors such as CEO identity or corporate governance. It is suggestive of the importance of frictions to within firm changes in management and organization as discussed by Gibbons and Henderson (2013) and Milgrom and Roberts (1990) among others. This leaves ample room for new theory, data and designs to help understand one of the oldest questions in economics and business: why is there such large heterogeneity in management practices?

Bibliography

Argote, Linda, Sara Beckman and Dennis Epple (1990) “The Persistence and Transfer of Learning in Industrial Settings” *Management Science*, 36(2) 140-154

Autor, David H., Frank Levy, and Richard J. Murnane. 2002. “Upstairs, Downstairs: Computers and Skills on Two Floors of a Large Bank.” *Industrial and Labor Relations Review* 55: 432–447.

Bandiera, Oriana, Iwan Barankay and Imran Rasul (2005) “Social Preferences and the Response to incentives: Evidence from Personnel Data”, *Quarterly Journal of Economics*, 120(3), 917-962.

Bandiera, Oriana, Iwan Barankay, and Imran Rasul (2007) “Incentives for Managers and Inequality among Workers: Evidence from a Firm-Level Experiment,” *Quarterly Journal of Economics*

Barley, Steven R. (1986) “Technology as an Occasion for Structuring: Evidence from Observations of CT Scanners and the Social Order of Radiology Departments.” *Administrative Science Quarterly* 31: 78–108.

Bartel, Ann, Casey Ichniowski and Kathryn Shaw (2004) “Using "Insider Econometrics" to Study Productivity” *American Economic Review*, 94 (2): 217-223.

Bartel, Ann, Casey Ichniowski and Kathryn Shaw (2007) “How Does Information Technology Really Affect Productivity? Plant-Level Comparisons of Product Innovation, Process Improvement and Worker Skills”, *Quarterly Journal of Economics*, 122(4), 1721-1758

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

Berg, Norman A., and Norman D. Fast. (1975) “The Lincoln Electric Company.” Harvard Business School Case 376-028. Cambridge, MA: Harvard Business School.

Bertrand, Marianne, (2004), “From the Invisible Handshake to the Invisible Hand? How Import Competition Changes the Employment Relationship," *Journal of Labor Economics*, 22(4), 723-765.

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.

Black, Sandra and Lisa Lynch (2004) “What's Driving the New Economy? The Benefits of Workplace Innovation”, *Economic Journal*, 114(493), 97-116.

Blader, Steve, Claudine Gartenberg and Andrea Pratt (2016) “The Contingent Effect of Management Practices” CEPR Discussion Paper 11057

Bloom, Nicholas, Erik Brynjolfsson, Lucia Foster, Ron Jarmin, Itay Saporta-Eksten, and John Van Reenen, (2017) “A Detailed Analysis of What Drives Differences in Management Practices” NBER Working Paper No. 23300

Bloom, Nicholas, Benn Eifert, Aprajit Mahajan, David McKenzie, and John Roberts, (2013b), “Does Management Matter? Evidence from India”, *Quarterly Journal of Economics*, 128(1), 1-51.

Bloom, Nicholas, Max Floetotto, Nir Jaimovich, Itay Saporta-Eksten and Stephen Terry, (2018), “Really Uncertain Business Cycles,” forthcoming *Econometrica.*

Bloom, Nicholas, Raffaella Sadun and John Van Reenen, (2016), “Management as a Technology,” NBER Working Paper No. 22327

Bloom, Nicholas and John Van Reenen, (2007), "Measuring and Explaining Management Practices Across Firms and Countries," *Quarterly Journal of Economics* 122(4), 1351–1408

Bloom, Nicholas and John Van Reenen. (2011). "Human Resource Management and Productivity" in *Handbook of Labor Economics Volume 4B*, Orley Ashenfelter and David Card editors.

Bresnahan, Timothy F., Erik Brynjolfsson, and Lorin M. Hitt. "Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence." *Quarterly Journal of Economics* 117(1) (2002): 339-376.

Bruhn, Miriam, Dean Karlan and Antoinette Schoar (2016), "The Impact of Consulting Services on Small and Medium Enterprises: Evidence from a Randomized Trial in Mexico," forthcoming, *Journal of Political Economy.*

Brynjolfsson, Erik, Hitt, Lorin M. and Shinkyu Yang (2002) "Intangible Assets: Computers and Organizational Capital," *Brookings Papers on Economic Activity*: Macroeconomics (1): 137-199.

Brynjolfsson, Erik, and Paul Milgrom (2013) "Complementarity in Organizations" in Robert Gibbons and John Roberts (eds) *Handbook of Organizational Economics*, 11-55Princeton: Princeton University Press.

Brynjolfsson, Erik, Amy Austin Renshaw, and Marshall van Alstyne. 1997. "The Matrix of Change." *Sloan Management Review* 38(2): 37–54.

Buffington, Catherine, Lucia Foster, Ron Jarmin and Scott Ohlmacher (2016), "The Management and Organizational Practices Survey (MOPS): An Overview," Census Bureau Center for Economic Studies Working Paper No. 16-28.

Buffington, Catherine, Kenny Herrell and Scott Ohlmacher (2016), "The Management and Organizational Practices Survey (MOPS): Cognitive Testing," Census Bureau Center for Economic Studies Working Paper No. 16-53.

Capelli, Peter and David Neumark (2001) "Do High-Performance Work Practices Improve Establishment-Level Outcomes?", *Industrial and Labor Relations Review*, 54(4), 737-775.

Chandra, A, Amy Finkelstein, Adam Sacarny, and Chad Syverson (2016), "Health Care Exceptionalism? Performance and Allocation in the US Health Care Sector", *The American Economic Review*, 106(8) 2110-2144

Chew, W., Kim Clark, and Tim Bresnahan (1990), "Measurement, Coordination and Learning in a Multi-plant Network" in Robert Kaplan. *Measures for Manufacturing Excellence*, Boston: Harvard Business School Press

Collard-Wexler, Allan, (2013), "Demand Fluctuations in the Ready-Mix Concrete Industry" *Econometrica*," 81(3) 1003–1037

Davis, Steven, John Haltiwanger, Kyle Handley, Ron Jarmin, Josh Lerner and Javier Miranda (2014) "Private Equity, Jobs, and Productivity" *American Economic Review*, 104(12), 3956-90

Davis, Steven and John Haltiwanger (1992) "Gross Job Creation, Gross Job Destruction and Employment Reallocation" *Quarterly Journal of Economics* 107(3) 819-863

Easton, George and Sherry Jarrell (1998) "The Effects of Total Quality Management on Corporate Performance: An Empirical Investigation", *Journal of Business* 71(2), 253–307.

Ellison, Glenn and Edward L. Glaeser, (1997), "Geographic Concentration in U.S. Manufacturing

Industries: A Dartboard Approach," *Journal of Political Economy*, 105(5).

Foster, Lucia, John Haltiwanger and C.J. Krizan, (2001), "Aggregate Productivity Growth: Lessons from Microeconomic Evidence," *New Developments in Productivity Analysis*, NBER, University of Chicago Press.

Foster, Lucia, John Haltiwanger, and Chad Syverson. (2008). "Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?" *American Economic Review,* 98 (1): 394-425.

Freeman, Richard and Katheryn Shaw (2009) *International Differnces in the Business Practices and Productivity of Firms*, Chicago: Chicago University Press.

Gibbons, Robert, and Rebecca Henderson. (2013), "What Do Managers Do? Exploring Persistent Performance Differences among Seemingly Similar Enterprises." in Robert Gibbons and John Roberts (eds) *Handbook of Organizational Economics*, 680–731, Princeton: Princeton University Press.

Giorcelli, Michela, (2016), "The Long-Term Effects of Management and Technology Transfer: Evidence from the US Productivity Program," UCLA mimeo.

Greenstone, Michael, Richard Hornbeck and Enrico Moretti, (2010), "Identifying Agglomeration Spillovers: Evidence from Winners and Losers of Large Plant Openings," *Journal of Political Economy* 118(3): 536-598.

Griffith, Rachel and Andrew Neely (2009) "Incentives and Managerial Experience in Multi-task Teams: Evidence from Within a Firm", *Journal of Labor Economics*, 27(1), 49-82.

Halac, Marina and Andrea Prat, (2016) "Managerial Attention and Worker Engagement," *American Economic Review*, 106(10): 3104–3132

Henderson, Rebecca and Iain Cockburn (1994) "Measuring Competence? Exploring Firm Effects in Pharmaceutical Research," *Strategic Management Journal*, 15(S1) 63-84

Hamilton, Barton H., Jack A. Nickerson, and Hideo Owan (2003) "Team Incentives and Worker Heterogeneity: An Empirical Analysis of the Impact of Teams on Productivity and Participation", *Journal of Political Economy*, 111(3), 465-497.

Hopenhayn, Hugo (1992,) "Entry, Exit, and Firm Dynamics in Long-Run Equilibrium," *Econometrica*. 1127–1150.

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

Holmes, Thomas J., (1998), "The Effect of State Policies on the Location of Manufacturing: Evidence from State Borders," *Journal of Political Economy* 106(4): 667-705.

Huselid, Mark (1995) "The Impact of Human Resource Management Practices on Turnover, Productivity and Corporate Financial Performance", *Academy of Management Journal*, 38, 635-672.

Huselid, Mark and Brian Becker (1996) "Methodological Issues in Cross-sectional and Panel Estimates of the Human Resource-firm Performance link", *Industrial Relations*, 35, 400-422.

Ichniowski, Casey and Kathryn Shaw (1999), "The Effects of Human Resource Management Systems on Economic Performance: An International Comparison of U.S. and Japanese Plants" *Management Science,* 45(5) 704 - 721

Ichniowski, Casey, Kathryn Shaw, and Giovanna Prennushi. "The effects of human resource management practices on productivity: A study of steel finishing lines." *American Economic Review* (1997): 291-313.

Jovanovic, Boyan (1982) "Selection and Evolution of Industry." *Econometrica* 50(3) 649-670

Lazear, Edward (2000) "Performance Pay and Productivity", *American Economic Review* 90(5), 1346- 1361.

Meagher, K. and Strachan, R. (2016) "Evidence on the Non-Linear Impact of Management" Australian National University mimeo

Melitz, Marc J., (2003) "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity," *Econometrica*, 71 (6), 1695–1725.

Milgrom, Paul and John Roberts (1990) "The Economics of Modern Manufacturing: Technology, Strategy, and Organization", *American Economic Review*, 80(3), 511–28.

Moretti, Enrico, (2004), "Estimating the Social Return to Higher Education: Evidence from Longitudinal and Repeated Cross-Sectional Data," *Journal of Econometrics*, 121, 1–2: 175-212

Nevins, Allan, (1962) *The State Universities and Democracy*, University of Illinois Press, Urbana, IL.

Osterman, Paul (1994) "How Common Is Workplace Transformation and Who Adopts It?" *Industrial and Labor Relations Review*, 47(2), 173-188

Penrose, Edith (1959), *The Theory of Growth of the Firm*, New York: Wiley Publishers

Schmalensee, Richard (1985), "Do Markets Differ Much" *American Economic Review* 75(3), 341-351

Syverson, Chad, (2011), "What Determines Productivity?" *Journal of Economic Literature*, 49(2), 326-365.

Walker, Francis (1887) "The Source of Business Profits." *Quarterly Journal of Economics.* 1(3): 265-288.

Womack, James, Daniel Jones and Daniel Roos, (1991), *The Machine that Changed the World*, Simon and Schuster Inc: New York.

Table 1: Plant Management Scores and Performance

Dependent Variable	Log(Output/Employment)					Profit/Sales		Log(Output/Emp)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Management	1.351***	0.209***	0.079***	0.096***	0.074***	0.095***	0.051***	0.105**	0.071*
	(0.039)	(0.013)	(0.030)	(0.025)	(0.025)	(0.005)	(0.010)	(0.045)	(0.037)
Log(Capital/Emp)		0.100***	0.012	0.096***	0.096***	0.026***	0.023***	0.004	0.016
		(0.003)	(0.010)	(0.005)	(0.005)	(0.001)	(0.002)	(0.017)	(0.012)
Log(Material/Emp)		0.495***	0.333***	0.525***	0.534***	-0.068***	-0.069***	0.309***	0.342***
		(0.004)	(0.016)	(0.008)	(0.009)	(0.001)	(0.003)	(0.030)	(0.018)
Log(Employment)		-0.027***	-0.192***	-0.054***	-0.053***	-0.002	-0.009***	-0.217***	-0.183***
		(0.002)	(0.019)	(0.005)	(0.005)	(0.001)	(0.002)	(0.034)	(0.023)
Share employees w. a college degree		0.223***	0.013	0.180***	0.179***	0.023***	0.025**	0.064	-0.001
		(0.015)	(0.031)	(0.024)	(0.024)	(0.007)	(0.011)	(0.066)	(0.035)
Observations	~82,500	~82,500	~33,000	~43,000	~43,000	~82,500	~43,000	~10,000	~23,000
Num. establishments	~52,500	~52,500	~16,500	~26,500	~26,500	~52,500	~26,500	~5,000	~11,500
Num. firms (clusters)	~32,500	~32,500	~9,800	~5,100	~5,100	~32,500	~5,100	~4,200	~6,800
Sample	All	All	Panel	Multi-plant firm		All	Multi-plant	Panel-Same responder	Panel-Different responder
Fixed Effects	None	Industry	Establish.	Firm	Firm*Year	Industry	Firm*Year	Establish.	Establish.

Notes: ***Significant at 1% level, **5% level, *10% level. OLS coefficients with standard errors in parentheses (clustered at the firm level). The management score is the unweighted average of the score for each of the 16 questions, where each question is first normalized to be on a 0-1 scale. The sample in columns 1,2, and 6 is all MOPS observations with at least 10 non-missing responses to management questions and a successful match to ASM, which were also included in ASM tabulations, have positive value added, positive employment and positive imputed capital in the ASM. Recalls are used for respondents with at least 7 years of tenure at the establishment. Sample in column (3) includes only establishments with 2 observations (in 2010 and 2015 excluding recalls). Sample in columns (4), (5), and (7) includes establishments that have at least one sibling (i.e. from the same parents firm) in MOPS within the year. Columns (8) and (9) split the sample from column (3) to establishment with same respondent for 2010 and 2015 (8) and different respondent over the two years (9). In columns (1) through (5), (8), and (9) the dependent variable is log(real output over total employment). In column (6) to (7) profits are measured by value added minus wages and salaries over total value of shipments. All regressions include year fixed effect and recall dummy.

Table 2: Management and Performance, Accounting for Measurement Error

Sample	Baseline	Duplicates sample	Duplicates sample	Implied share Measurement Error
Methodology	OLS	OLS	IV	
	(1)	(2)	(3)	(4)
Log(Output)	4.264*** (0.057)	4.465*** (0.398)	9.174*** (1.073)	0.513
Log(Employment)	2.913*** (0.044)	3.401*** (0.348)	6.949*** (0.890)	0.511
Log(Output/Employment)	1.351*** (0.039)	1.094*** (0.266)	2.344*** (0.563)	0.533
Log(Output/Employment) Deviations from industry mean	0.535*** (0.02)	0.549*** (0.201)	1.104*** (0.389)	0.503
Observations	~82,500	~500	~500	

Notes: ***Significant at 1% level, **5% level, *10% level. Each row report the results from regressions on a different dependent variable listed in the left column. Columns (1) to (3) report regression coefficients with standard errors in parentheses (clustered at the firm level) for regressions ran on three different specifications. Columns (1) reports results from OLS regressions for the baseline sample (as in columns (1) and (2) of Table 1). Columns (2) and (3) report results from OLS and IV regressions for the sample with duplicates reports. In column (3) each management score is instrumented using the duplicate report. Regressions in columns 1 include year fixed effect and recall dummy.

Table 3: Management, Exit and Growth

Time Window	2010 to 2011 (1)	2010 to 2012 (2)	2010 to 2013 (3)	2010 to 2014 (4)	2010 to 2015 (5)	2014 to 2015 (6)	2010 to 2015 (7)	2010 to 2015 (8)	2010 to 2015 (9)
Panel A: Dependent variable: Exit									
Management	-0.046***	-0.086***	-0.131***	-0.153***	-0.180***	-0.035***	-0.286***	-0.153***	-0.280***
	(0.007)	(0.01)	(0.012)	(0.013)	(0.014)	(0.007)	(0.033)	(0.014)	(0.033)
Log(Value Added/Emp)								-0.025***	-0.039***
								(0.003)	(0.006)
Marginal R^2 for Management (*100)								0.506	0.665
Marginal R^2 for Log(Value Added/Emp) (*100)								0.308	0.482
Panel B: Dependent variable: Employment Growth									
Management	0.130***	0.227***	0.324***	0.350***	0.412***	0.088***	0.629***	0.326***	0.609***
	(0.019)	(0.023)	(0.028)	(0.03)	(0.033)	(0.018)	(0.075)	(0.035)	(0.075)
Log(Value Added/Emp)								0.078***	0.131***
								(0.007)	(0.013)
Marginal R^2 for Management (*100)								0.394	0.535
Marginal R^2 for Log(Value Added/Emp) (*100)								0.525	0.915
Firm Fixed Effects	No	No	No	No	No	No	Yes	No	Yes
Observations	~32,000	~32,000	~32,000	~32,000	~32,000	~29,000	~17,000	~32,000	~17,000

Notes: ***Significant at 1% level, **5% level, *10% level. OLS coefficients with standard errors in parentheses (clustered at the firm level). The management score is the unweighted average of the score for each of the 16 questions, where each question is first normalized to be on a 0-1 scale. The sample in columns (1) to (5) and (8) is all MOPS observations with valid management score in 2010 and a successful match to ASM, which were also included in ASM tabulations, have positive value added, positive employment and positive imputed capital in the ASM. In column (6) we further conditions on survival up to 2014, and in columns (7) and (9) we use the 2010 sample conditioning on the establishment having a sibling in the sample (i.e. same parent firm). In Panel A the dependent variable is a dummy that takes the value of 1 for exit between the two years listed in the Time Window row. In Panel B, the dependent variable is employment growth between the two years specified in the Time Window row. Growth between years s and t is calculated as $0.5*(e_t - e_s)/(e_t + e_s)$.

Table 4: Drivers of Productivity Variation

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:			**Firm Level Log(Labor Productivity)**		
Management score	0.864***				0.612***
	(0.043)				(0.043)
R&D		0.133***			0.095***
		(0.010)			(0.010)
ICT/worker			0.062***		0.047***
			(0.006)		(0.006)
Skills (% employees with college degree)				0.800***	0.208***
				(0.064)	(0.060)
Observations	~18,000	~18,000	~18,000	~18,000	~18,000
Share of 90-10 explained	0.216	0.216	0.120	0.159	0.441
Share of S.D explained	0.193	0.219	0.134	0.142	0.282

Notes: OLS coefficients with standard errors in parentheses (clustered at the firm level). Dependent variable is firm level Log(Value Added over Employment) built from industry de-meaned plant-level Log(Value Added over Employment) weighted up by plant's shipments. Right-hand side variables are management score, R&D from BRDIS measured as log(1+R&D intensity) where R&D intensity is the total domestic R&D expenditure divided by total domestic employment, ICT investment per worker (1000* spending on information and communication technology hardware and software per employee), skill measured by the share of employees (managers and non-managers) with a college degree. All these variables are also weighted up to the firm level using plant's total value of shipments. Missing values have been replaced by zero for R&D and by means for the other variables. Industry demeaning is at NAICS 6 level. All regressions are weighted by the number of establishments in the firm. "Share of 90-10 explained" is calculated by multiplying the coefficient on the key driver variable (e.g., management in column 1) by its 90-10 spread and dividing this by the 90-10 spread of TFP. Share of S.D. explained corresponds to the square root of the R^2 in the regression.

Table 5: Within Firm (and across plant) Variation in Management

Dependent Variable: Standard Deviation (Std Dev) of Management Spread within Firm

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Number of Manufacturing	0.959***			0.202							
Establishments (in logs)	(0.091)			(0.176)							
Number of Manufacturing Est.		1.37***			0.56**	0.562**	0.473*	0.593**	0.607**	0.594**	0.517*
X (10 establishments or smaller)		(0.231)			(0.284)	(0.284)	(0.287)	(0.283)	(0.283)	(0.283)	(0.286)
Number of Manufacturing Est.		0.679***			0.133	0.133	0.1	0.112	0.134	0.15	0.0828
X (larger than 10 establishments)		(0.204)			(0.231)	(0.231)	(0.232)	(0.23)	(0.23)	(0.23)	(0.231)
Number of Manufacturing			0.378**	0.285*	0.29*	0.29*	0.254	0.269	0.265	0.261	0.234
Industries (in logs)			(0.147)	(0.171)	(0.171)	(0.171)	(0.172)	(0.171)	(0.171)	(0.171)	(0.172)
Number of Manufacturing			1.04***	0.908***	0.883***	0.882***	0.925***	0.872***	0.868***	0.872***	0.912***
States (in logs)			(0.14)	(0.182)	(0.186)	(0.186)	(0.186)	(0.186)	(0.186)	(0.186)	(0.186)
Std Dev of Age of Manufacturing						-0.0131					-0.132
Establishments						(0.29)					(0.294)
Std Dev of Emp. in Manufacturing							0.449**				0.465**
Establishments							(0.227)				(0.231)
Share of MOPS est. with Ownership								1.65**			1.63**
Change in the Prior Year								(0.808)			(0.804)
Share of MOPS est. with Ownership									1.07**		
Change in the Prior 2 Years									(0.532)		
Share of MOPS est. with Ownership										0.75*	
Change in the Prior 3 Years										(0.416)	
Number of Firms	~3,100	~3,100	~3,100	~3,100	~3,100	~3,100	~3,100	~3,100	~3,100	~3,100	~3,100

Notes: ***Significant at 1% level, **5% level, *10% level. A firm-level regression with the standard deviation of management scores across establishments within the firm as the dependent variable. The regression sample is all firms with 2+ establishment responses in the MOPS 2010 survey. The total number of establishments, the number of establishments within manufacturing, the number of different industries, the different number of states these establishments span, and the Standard Deviation of age and employment are all calculated from the Longitudinal Business Database (LBD). Change of ownership is defined as share of MOPS establishments with a different FIRMID as compared to a base year's LBD (e.g., LBD 2009 for 09-10). In all columns, we control for a 5 degree polynomial of average management score at the firm. Robust standard errors are reported in parentheses. Establishment size and age is in logs (note age is censored in 1976 as it is when the LBD begins). For scaling purposes all coefficients and standard errors have been multiplied by 100.

Table 6: Difference-in-Difference Estimates for the Effect of RTW

Dependent variable:	Management score	Incentive Management	Non-incentive Management	High Union (Density >80%)	Log(Emp)	3 Factor Log(TFP)
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: DID estimates for the effect of RTW						
PostXTreat	0.009*	0.017***	0.003	-0.017**	0.158***	0.015
	(0.005)	(0.007)	(0.006)	(0.007)	(0.031)	(0.013)
Obs	~15,000	~15,000	~15,000	~15,000	~15,000	~15,000
Panel B: Pre-trends						
PreXTreat	0.005	0.002	0.008	0.001	0.017	0.006
	(0.006)	(0.008)	(0.007)	(0.010)	(0.039)	(0.017)
Obs	~9,900	~9,900	~9,900	~9,900	~9,900	~9,900
Panel C: DID estimates controlling for 6-digit NAICS						
PostXTreat	0.007	0.014**	0.002	-0.020***	0.131***	0.019
	(0.005)	(0.006)	(0.005)	(0.007)	(0.027)	(0.013)
Obs	~15,000	~15,000	~15,000	~15,000	~15,000	~15,000
Panel D: DID estimates on 2010 incumbent plants						
PostXTreat	0.008	0.014**	0.004	-0.017**	0.155***	0.017
	(0.005)	(0.007)	(0.006)	(0.007)	(0.031)	(0.013)
Obs	~14,000	~14,000	~14,000	~14,000	~14,000	~14,000
Panel E: Placebo using West Virginia, Kentucky and Missouri						
PostXTreat	-0.0002	0.003	-0.001	-0.008	-0.025	-0.005
	(0.005)	(0.007)	(0.006)	(0.008)	(0.033)	(0.016)
Obs	~23,000	~23,000	~23,000	~23,000	~23,000	~23,000

Notes: ***Significant at 1% level, **5% level, *10% level. OLS coefficients with standard errors in parentheses (clustered at the establishment level). The dependent variable is the management score in column (1). In columns (2) and (3) the score is calculated as the unweighted average of the incentives related practices (MOPS questions 9-16) and non-incentives related practices (MOPS questions 1-8) respectively. The dependent variable in column (4) is calculated using the categories in MOPS question 36 (2010 numbering). The dependent variable in column (5) is log of employment at the establishment, and in column (6) the log of Total Factor Productivity, calculated using a factor share of 3 factors (capital, labor and material). The sample in Panels A and C is all MOPS observations with at least 10 non-missing responses to management questions and a successful match to ASM, which were also included in ASM tabulations, have positive value added, positive employment and positive imputed capital in the ASM from treated and neighboring states for the years 2010 and 2015. Recalls are used for respondents with at least 7 years of tenure at the establishment. Sample in Panel B is defined similarly to Panel A, for 2005 and 2010. Sample in Panel D further restricts the Panel A sample to establishments which existed and were in the same state in 2010 as in 2015. The sample in Panel E is defined similarly to the Panel A sample, but for the placebo states and their neighboring states. All regressions include year and state fixed effects and a recall dummy.

Table 7: RD Design Estimates for the Effect of RTW

Dependent variable:	Management score (1)	Incentive Management (2)	Non-incentive Management (3)	High Union (Density >80%) (4)	Log(Emp) (5)	3 Factor Log(TFP) (6)
Panel A: RD design estimates						
RTW side of the border	0.008	0.017***	0.002	-0.042***	0.110**	-0.012
	(0.006)	(0.006)	(0.007)	(0.006)	(0.054)	(0.012)
Obs	~39,000	~39,000	~39,000	~39,000	~39,000	~39,000
Panel B: RD design estimates controlling for 6-digit NAICS						
RTW side of the border	0.007	0.014***	0.002	-0.038***	0.034	-0.008
	(0.0045)	(0.005)	(0.005)	(0.007)	(0.034)	(0.012)
Obs	~39,000	~39,000	~39,000	~39,000	~39,000	~39,000
Panel C: RD design estimates for non-tradables (25% lowest HHI in sample)						
RTW side of the border	0.017**	0.023**	0.015*	-0.033***	0.165***	-0.052**
	(0.007)	(0.009)	(0.008)	(0.009)	(0.058)	(0.024)
Obs	~9,200	~9,200	~9,200	~9,200	~9,200	~9,200
Panel D: RD design estimates allowing quadratic distance functions						
RTW side of the border	0.009	0.015*	0.006	-0.053***	0.092	-0.022*
	(0.007)	(0.007)	(0.008)	(0.012)	(0.059)	(0.011)
Obs	~39,000	~39,000	~39,000	~39,000	~39,000	~39,000
Panel E: RD design estimates with Epanechnikov weights for distance from border						
RTW side of the border	0.009	0.018***	0.004	-0.043***	0.095*	-0.015
	(0.006)	(0.006)	(0.007)	(0.007)	(0.055)	(0.011)
Obs	~39,000	~39,000	~39,000	~39,000	~39,000	~39,000

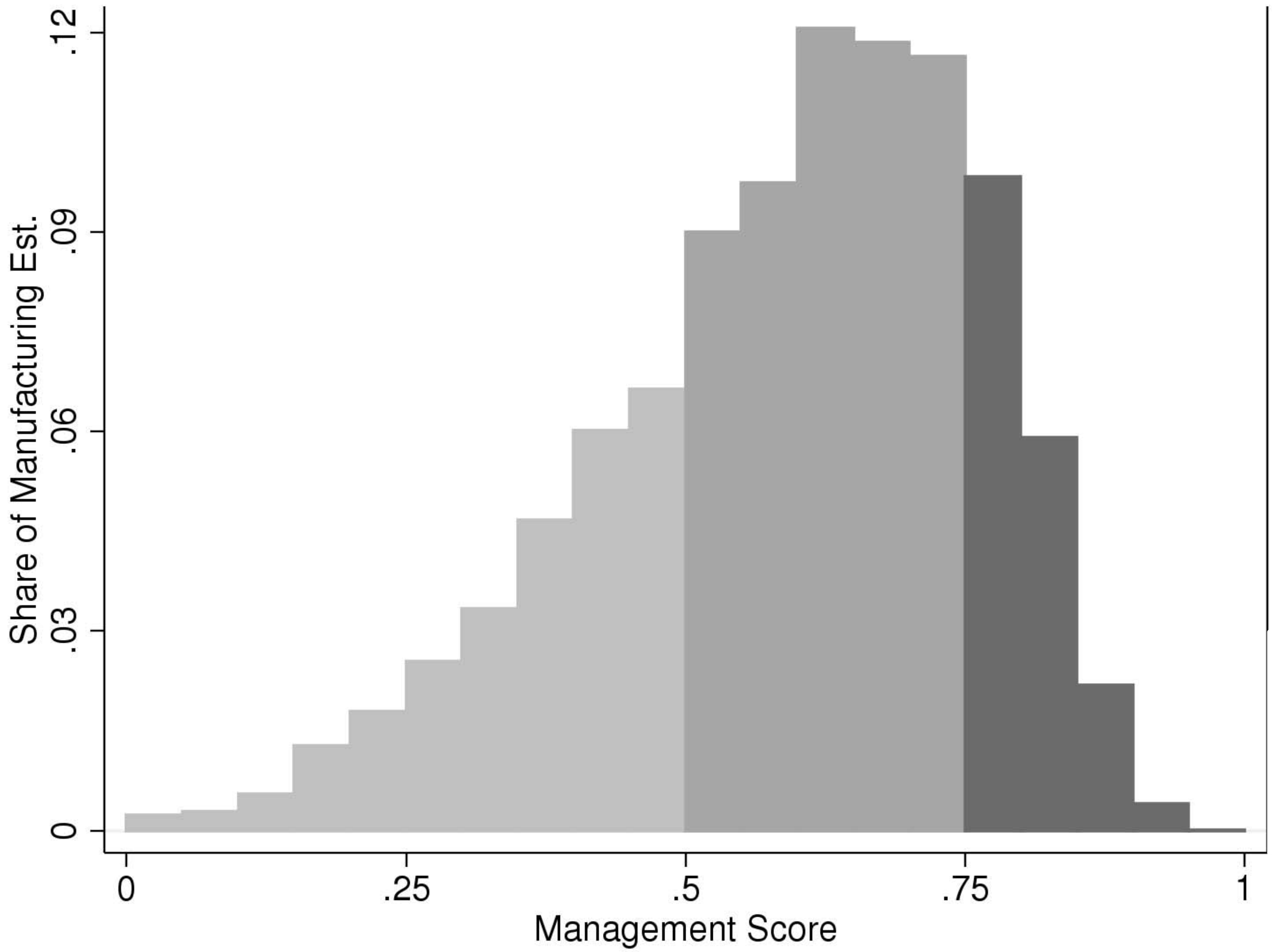
Notes: ***Significant at 1% level, **5% level, *10% level. OLS coefficients with standard errors in parentheses (clustered at the establishment level). The dependent variable is the management score in column (1). In columns (2) and (3) the score is calculated as the unweighted average of the incentives related practices (MOPS questions 9-16) and non-incentives related practices (MOPS questions 1-8) respectively. The dependent variable in column (4) is calculated using the categories in MOPS question 36 (2010 numbering). The dependent variable in column (5) is log of employment at the establishment, and in column (6) the log of Total Factor Productivity, calculated using a factor share of 3 factors (capital, labor and material). The sample in Panels A, B, D and E is all MOPS observations with at least 10 non-missing responses to management questions and a successful match to ASM, which were also included in ASM tabulations, have positive value added, positive employment and positive imputed capital in the ASM from RTW states or states with a RTW border. Recalls are used for respondents with at least 7 years of tenure at the establishment. Sample in Panel C is defined similarly to Panel A, but restricted to the 25% of the sample from most tradable industries, where non-tradables are defined as industries with low regional concentration level calculated following Ellison and Glaeser (1997) using data from the 2007 census. All regressions include year and border fixed effects and a recall dummy. Panels A, B, C and E allow for different linear trend on each side of the border, while Panel D allows for different quadratic trend. Panel E applies Epanechnikov kernel for weighting observations according to distance from the border.

Table 8: Management Knowledge Spillovers

Dependent variable:	Change in Management		Change in Log(TFP)		Employment Growth	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All industries pooled						
MDP Opens	0.012**	0.018***	0.022	0.024	0.011**	0.014***
	(0.005)	(0.007)	(0.016)	(0.017)	(0.004)	(0.005)
Panel B: Split high/low manager flow						
MDP Opens×High	0.023***	0.031***	0.074***	0.069***	0.013**	0.017***
	(0.008)	(0.008)	(0.027)	(0.019)	(0.006)	(0.006)
MDP Opens×Low	-0.005	-0.005	-0.059	-0.050	0.007	0.009
	(0.010)	(0.011)	(0.040)	(0.034)	(0.009)	(0.01)
P-value for equality	0.056	0.007	0.026	0.004	0.606	0.495
Panel C: Split high/low trade (demand spillovers)						
MDP Opens×High	0.010	0.012	0.012	0.041	0.021**	0.029***
	(0.008)	(0.011)	(0.037)	(0.033)	(0.009)	(0.010)
MDP Opens×Low	0.015**	0.023***	0.030	0.004	0.002	0.001
	(0.007)	(0.009)	(0.031)	(0.032)	(0.007)	(0.008)
P-value for equality	0.681	0.439	0.765	0.509	0.133	0.037
Panel D: Manufacturing MDPs Split Out						
MDP Opens×Manuf.	0.010**	0.016**	0.036***	0.040**	0.011**	0.011*
	(0.004)	(0.007)	(0.014)	(0.016)	(0.005)	(0.006)
MDP Opens×non-Manuf.	0.018	0.022	-0.016	-0.016	0.011	0.022***
	(0.014)	(0.015)	(0.033)	(0.038)	(0.009)	(0.008)
P-value for equality	0.603	0.734	0.126	0.175	0.998	0.297
Industry F.E.:	No	Yes	No	Yes	No	Yes
Observations	~2,500	~2,500	~2,500	~2,500	~2,500	~2,500

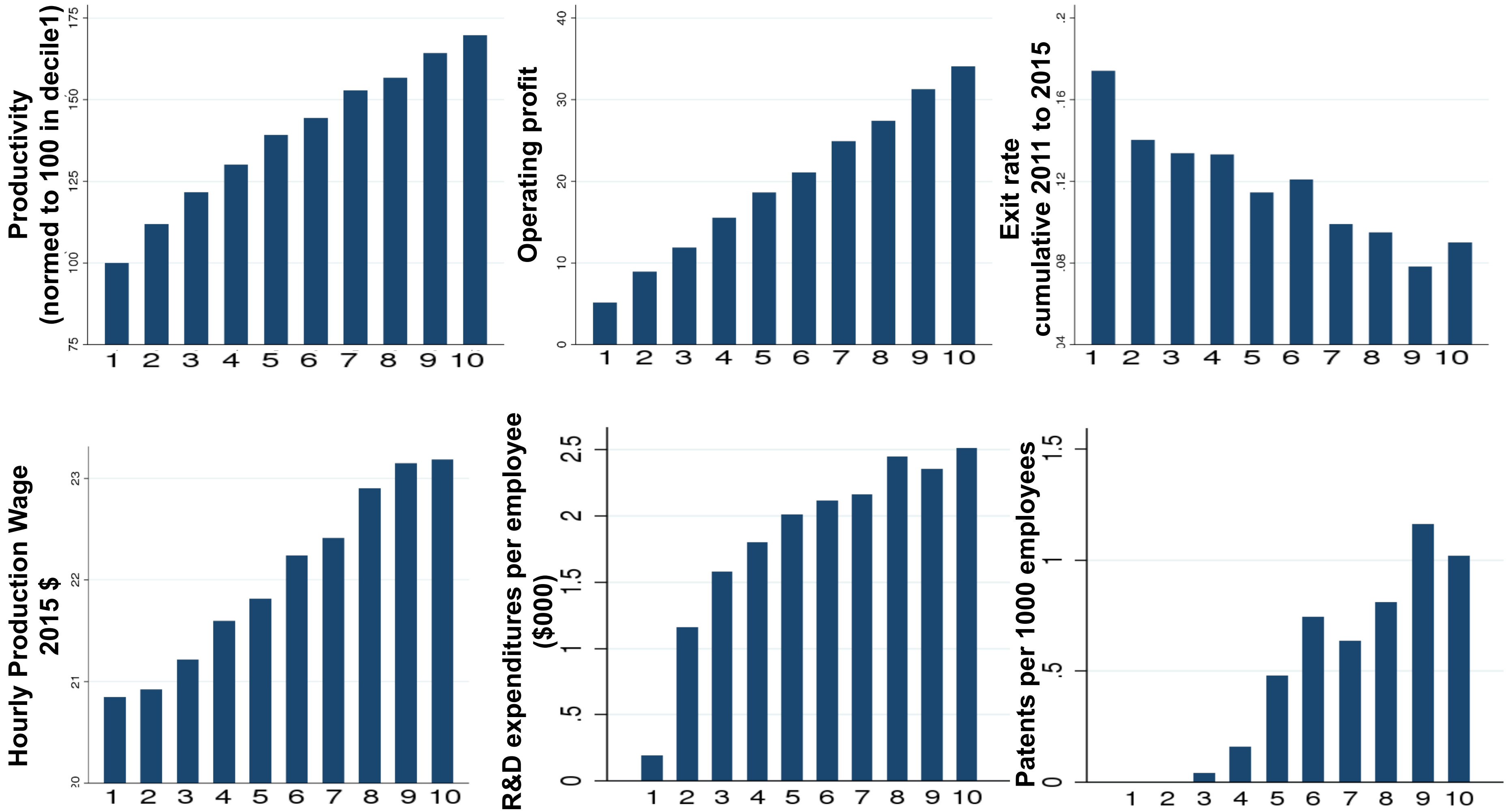
Notes: ***Significant at 1% level, **5% level, *10% level. OLS coefficients with standard errors in parentheses (clustered at the county level). The sample is all MOPS observations with at least 10 non-missing responses to management questions and a successful match to ASM, which were also included in ASM tabulations, have positive value added, positive employment and positive imputed capital in the ASM in counties that were considered by "Million Dollar Plants" (MDPs) as part of the site selection process. The dependent variable is the change from $t-5$ to t. For columns (1)-(2): change in management score winsorized at top and bottom 1%, columns (3) and (4) change in log(TFP) truncated at the top and bottom 1%, calculated using factor share for 3 factors (capital, labor and material), columns (5) and (6) employment growth defined as 0.5*$(emp_t - emp_{t-5})/(emp_t + emp_{t-5})$. The key right-hand side variable is a dummy indicating whether the plant was in the county finally selected for the plant location or not. All regressions have pair, states and recall fixed effects. Panel B interacts the treatment with high and low manager flow between the establishment and the MDP industries, and panel C splits using trade flows. High and low defined using medians, and the regression controls for the non-interacted High dummy. Panel D interacts the treatment with dummy indicating whether the MDP is manufacturing or not. Each panel includes the p-value for equal coefficients over the split. All regressions are weighted by the MDP announcement employment size.

Figure 1: The Wide Spread of Management Scores Across Establishments



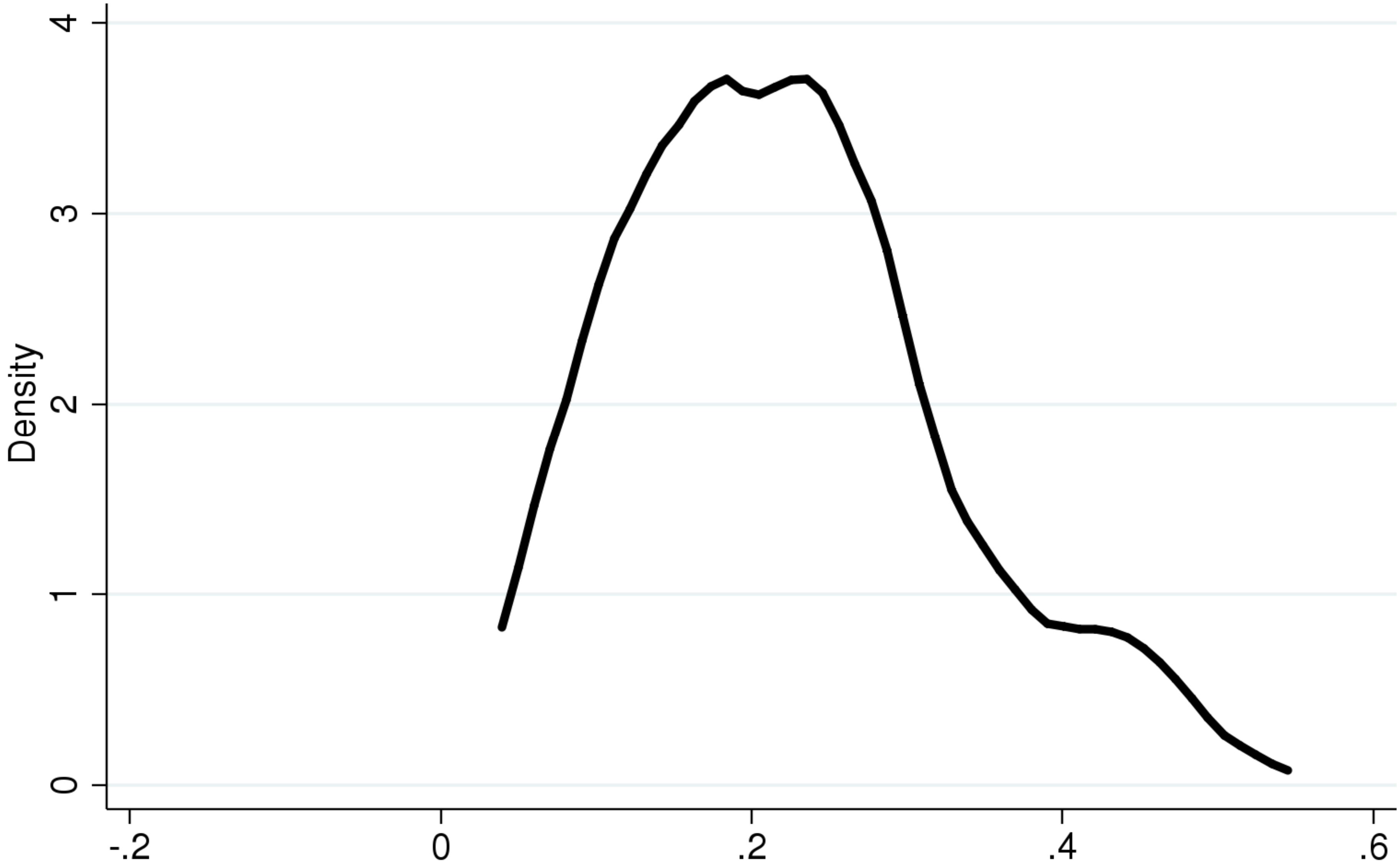
Note: The management score is the unweighted average of the score for each of the 16 questions, where each question is first normalized to be on a 0-1 scale. The sample is all 2010 MOPS observations with at least 10 non-missing responses to management questions and a successful match to ASM, which were also included in ASM tabulations, and have positive value added, positive employment and positive imputed capital in the ASM. Figure is weighted using ASM weights.

Figure 2: Performance and Structured Management



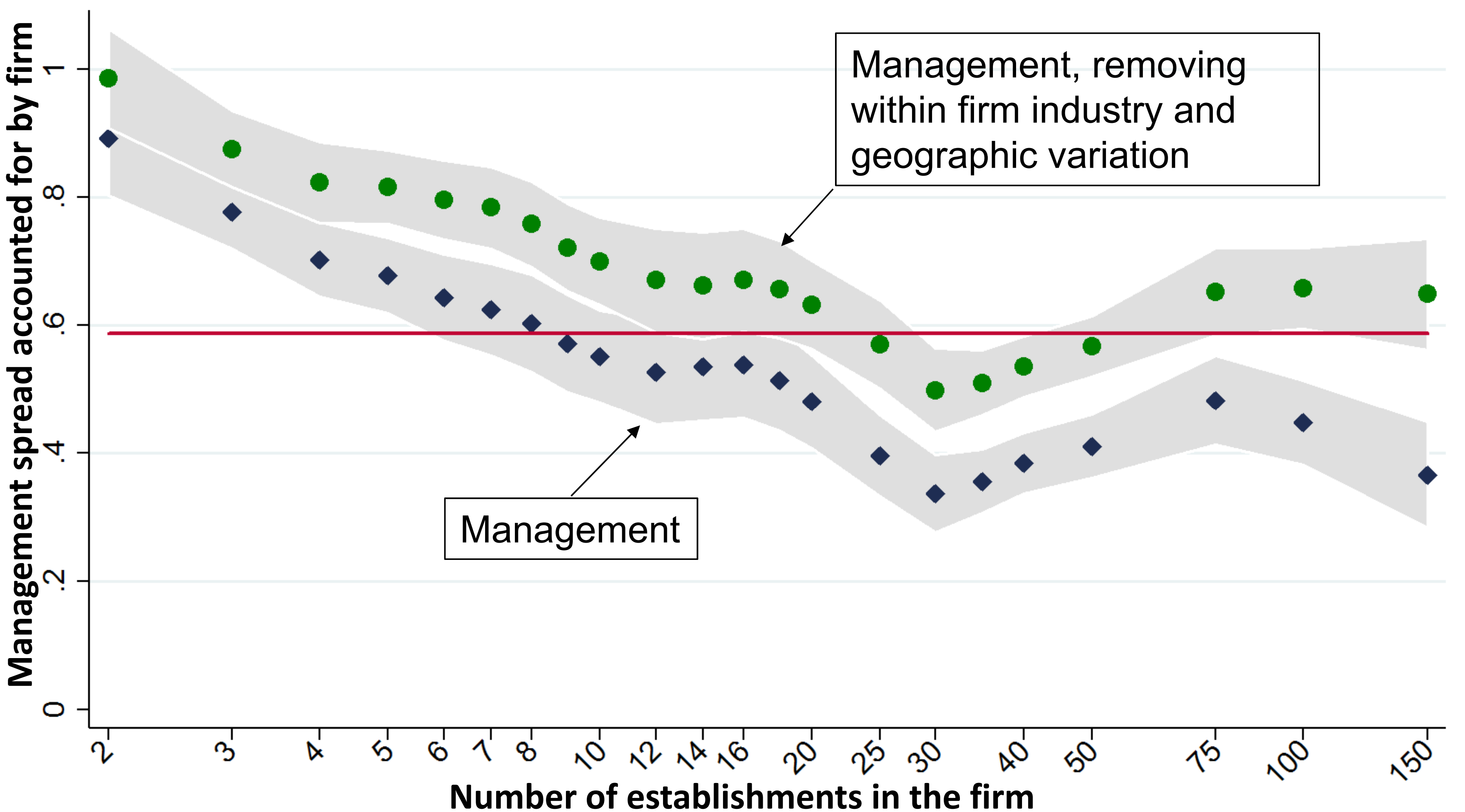
Note: The management score is the unweighted average of the score for each of the 16 questions, where each question is first normalized to be on a 0-1 scale. The sample in columns 1,2, and 6 is all MOPS observations with at least 10 non-missing responses to management questions and a successful match to ASM, which were also included in ASM tabulations, have positive value added, positive employment and positive imputed capital in the ASM. The sample in panels 3, 5 and 6 only uses 2010 observations. In panels 5 and 6 we also condition on non-missing R&D or patents requests count in the BRDIS survey. Management deciles are re-calculated for the different samples. The figures are unweighted.

Figure 3: The distribution of the management regression coefficient over 86 NAICS four-digit industries



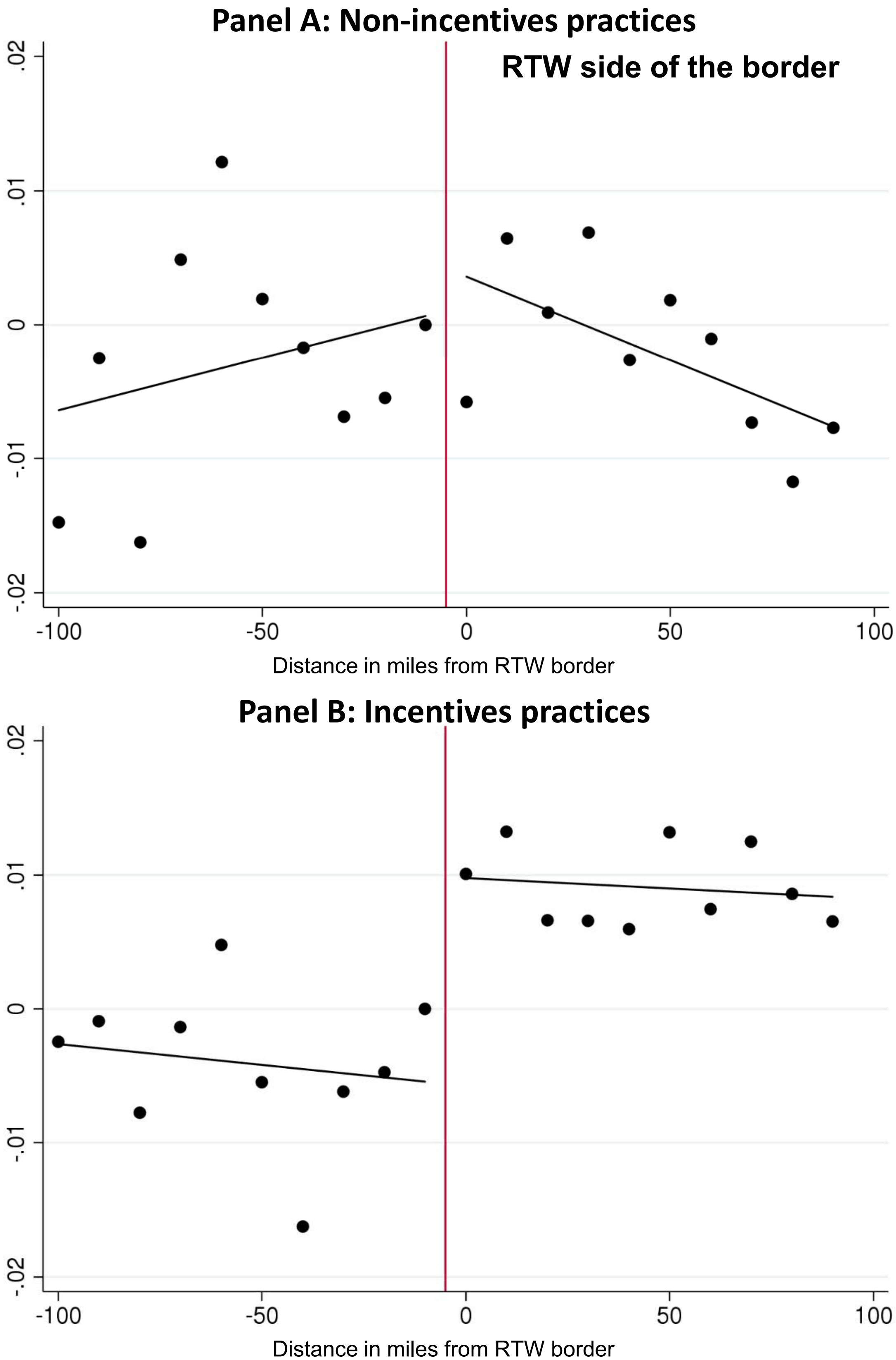
Note: Smoothed density of management coefficients from allowing the regression coefficient in column (2) of Table 1 to vary over the 86 four-digit manufacturing NAICS codes. The raw regression coefficients are then compressed using an Empirical Bayes Shrinkage procedure. The sample of ~82,500 is all MOPS observations with at least 10 non-missing responses to management questions and a successful match to ASM, which were also included in ASM tabulations, have positive value added, positive employment and positive imputed capital in the ASM. Recalls are used for respondents with at least 7 years of tenure at the establishment.

Figure 4: The firm-level share of the variation in management scores (after removing measurement error)



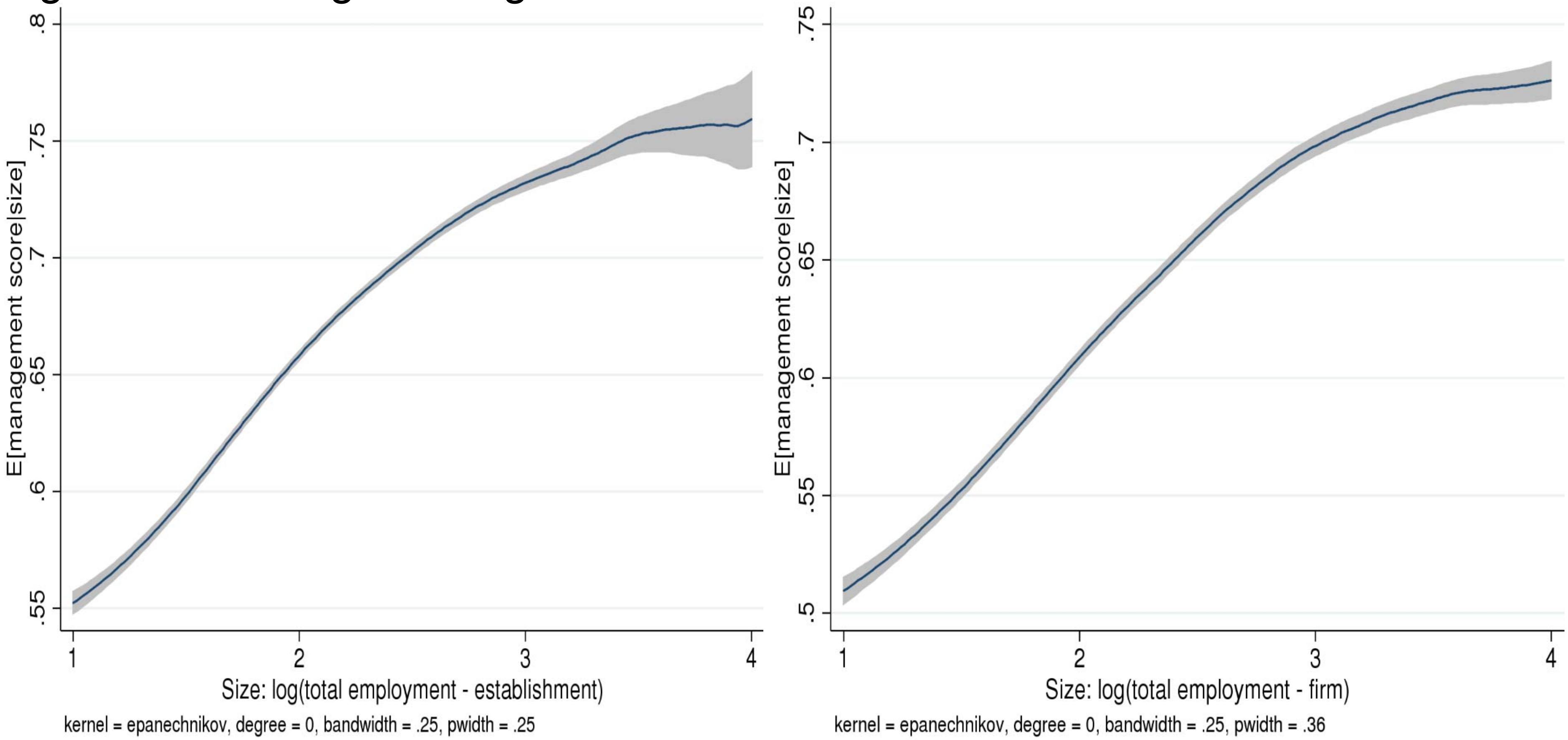
Note: Dots show the share of management score variation accounted for by the firm with different numbers of manufacturing establishments ranging from that number to the next value – so for example, 50 plants refers to 50 to 74 plants. The share of variation is shown after removing the 45.4% accounted for by measurement error. The bootstrap sampled 95% confidence interview shown in grey shading. Sample of 16,500 establishments across the 3,100 firms with 2 or more plants in the 2010 MOPS survey. Industry variation is captured by 6-digit NAICS dummies and geographic variation by MSA dummies (State is the MSA if MSA is missing). The horizontal line is the average share of the variation in score management across plants accounted for by firms, which is 58%.

Figure 5: Right to Work Regression Discontinuity



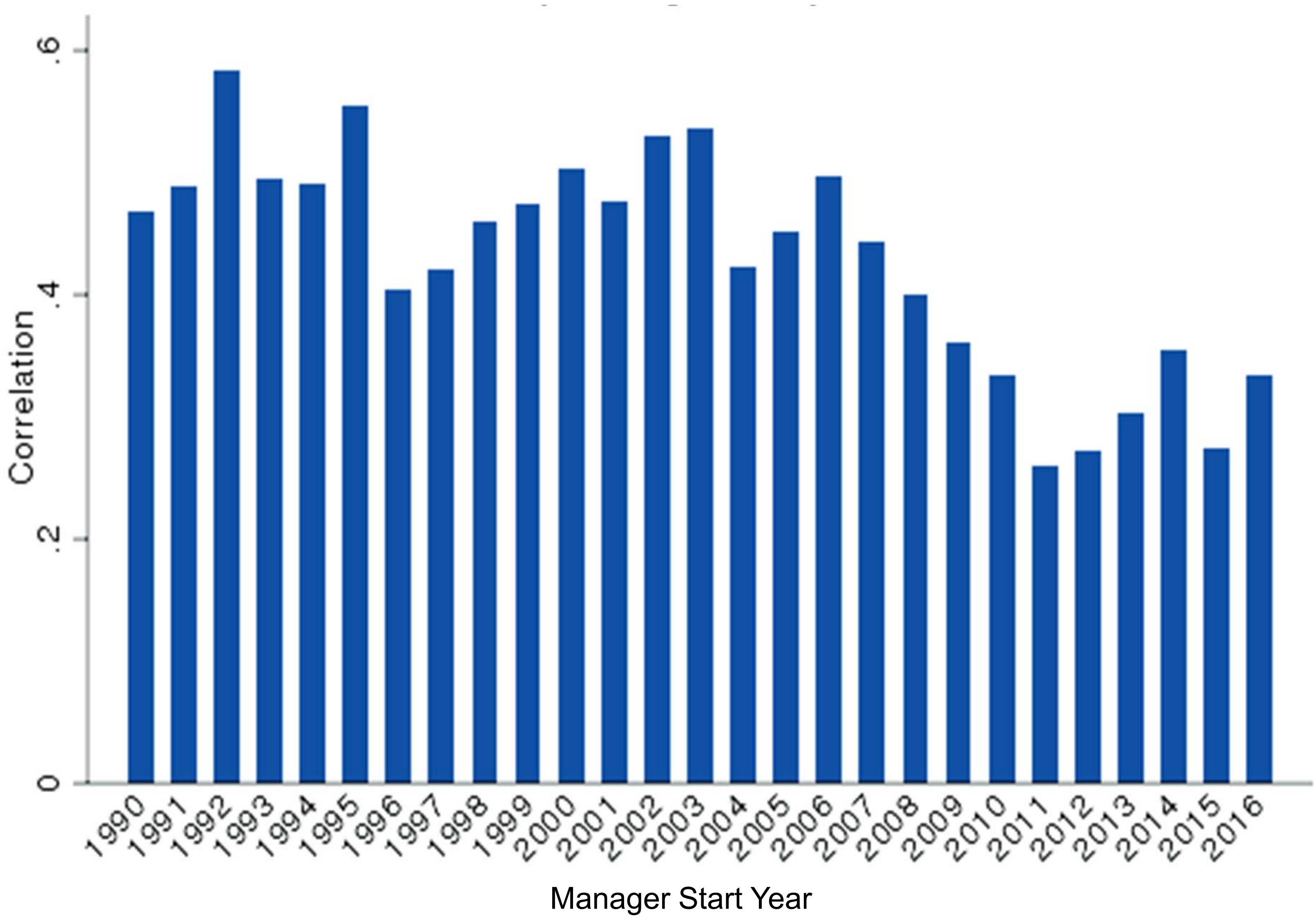
Notes: The management measure in panel A is calculated as the unweighted average of the non-incentives related practices (MOPS questions 1-8), and in panel B as the incentives related practices (MOPS questions 9-16). The sample is all MOPS observations with at least 10 non-missing responses to management questions and a successful match to ASM, which were also included in ASM tabulations, have positive value added, positive employment and positive imputed capital in the ASM from RTW states or states with a RTW border. Recalls are used for respondents with at least 7 years of tenure at the establishment. We figures show 10 mile bin dots.

Figure A1: Average Management Score Rises with Establishment and Firm Size



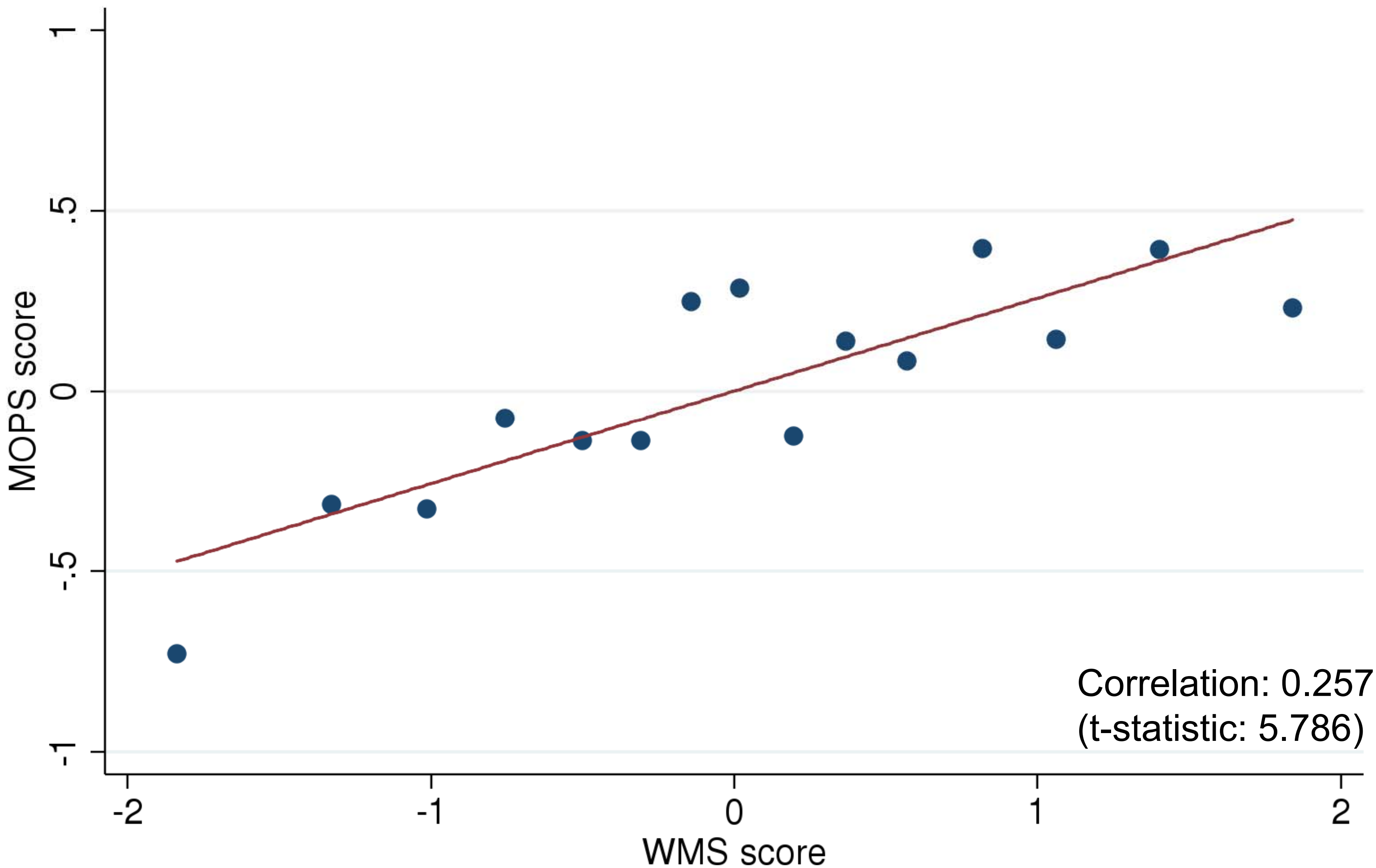
Note: The management score is the unweighted average of the score for each of the 16 questions, where each question is first normalized to be on a 0-1 scale. The sample is all MOPS observations with at least 10 non-missing responses to management questions and a successful match to ASM, which were also included in ASM tabulations, and have positive value added, positive employment and positive imputed capital in the ASM. The figure further restricts to establishments with 10 employees or more, and winsorizes establishment size at 10,000 employees. The figure was generated using a local mean smoother with Epanechnikov kernel and 0.25 bandwidth. The X axis is base 10 logarithm.

Figure A2: The Correlation between 2010 Reported Management Score and 2010 Recall Score (Reported in 2015), by Manager Start Year



Note: On the x-axis the manager start year at the establishment. On the y-axis the correlation between the management score as calculated using the responses to the 2010 MOPS and the score calculated using the recall responses collected in 2015 asking about 2010. The sample includes ~16,500 MOPS establishments which were surveyed in both 2010 and 2015.

Figure A3: Correlation of MOPS and WMS Management Scores



Note: On the x-axis the management score from the World Management Survey (WMS). On the y-axis the management score from MOPS. Sample includes all WMS firms between with observed between 2004 and 2006 which were matched to MOPS establishments (in any wave, see Appendix C for details on the matching). MOPS management scores were calculated as the average over MOPS establishments management scores at the firm level. WMS scores were collected at the firm level. There are 17.65 establishments on average in each MOPS point.

For Online Publication

Appendix A: Data

The Management and Organizational Practice Survey (MOPS)

Sample Selection: The sample for the 2010 MOPS consisted of the approximately 50,000 establishments in the 2010 Annual Survey of Manufacturers (ASM) mailout sample. The mailout sample for the ASM is redesigned at 5-year intervals beginning the second survey year subsequent to the Economic Census. (The Economic Census is conducted every five years in years ending in '2' or '7.') For the 2009 survey year, a new probability sample was selected from a frame of approximately 117,000 manufacturing establishments of multi-location companies and large single-establishment companies in the 2007 Economic Census, which surveys establishments with paid employees located in the United States. Using the Census Bureau's Business Register, the mailout sample was supplemented annually by new establishments, which have paid employees, are located in the United States, and entered business in 2008 - 2010.[1]

Overall, 49,782 MOPS surveys were sent, of which 2,248 were undeliverable as addressed. For the 47,534 surveys which were successfully delivered, 37,177 responses were received, implying a high response rate of 78%. For most of our analysis, we further restrict the sample to establishments with at least 10 non-missing responses to management questions (including those that missed questions by correctly following the skip pattern) and a successful match to ASM, which were also included in ASM tabulations, have a valid identifier in the LBD (LBDNUM), have positive value added, positive employment and positive imputed capital in the ASM (see below for details on capital imputation). For the 2010 sample, Table A3 shows how the numbers of firms and average employment changes as we condition on different sub-samples.

The sample for the 2015 MOPS was constructed following the same methodology, and were matched to the ASM and LBD on the same criteria.

In Table A5, we report the results for linear probability models for the different steps in the sampling process. In column (1) the sample is 2010 ASM observations with positive employment and sales and the dependent variable is an indicator that equals 1 if MOPS was sent to the establishment and zero otherwise. The right hand side of the regression includes the log of employment and a set of region and industry dummies. The establishments that were mailed the MOPS survey are somewhat larger. This difference between the ASM respondents and the MOPS mail sample is in part due to the continued sampling of new births in the ASM throughout the survey year, which focuses particularly on gathering data for large establishments. However, because the MOPS was mailed after the ASM, some ASM cases did not receive the MOPS due to status updates. In column (2), we compare MOPS respondents to the MOPS mail-out sample, finding that MOPS respondents tend to be slightly larger. Finally, in columns (3) to (5), we compare our "clean" sample to the sample of respondents and to the ASM sample, finding again that the "clean" sample has slightly larger establishments, which are also slightly more productive (column (5)).

Management Scores: The management score for each establishment is generated in two steps.[2] First, the responses to each of the 16 management questions are normalized on a 0-1 scale. The response which is associated with the most structured management practice is normalized to 1, and the one associated with the least structured is normalized to zero. Table A2 contains the details on this. We define more structured management practices as those that are more specific, formal, frequent or explicit. For example, when asking "*...when was an under-performing non-manager*

[1] This paragraph is from the official methodological documentation for the 2010 MOPS, which can be found at https://www.census.gov/mcd/mops/how_the_data_are_collected/index.html. The certainty category slightly differs over industries. For more details on the ASM sample design see: http://www.census.gov/programs-surveys/asm/technical-documentation/methodology.html

[2] The full survey instrument is available on https://www.census.gov/programs-surveys/mops/technical-documentation/questionnaires.html

reassigned or dismissed?", the response "*Within 6 months of identifying non-manager under-performance*" is ranked 1 and the response "*Rarely or never*" is ranked 0. If a question has three categories, the "in between" category is assigned the value 0.5. Similarly for four categories the "in between" categories are assigned 1/3 and 2/3 and so on.[3] Second, the management score is calculated as the unweighted average of the normalized responses for the 16 management questions. In robustness tests, we also evaluated another way to average across the 16 individual scores. We used a management z-score, which normalizes each question to have a mean of 0 and a standard deviation of 1 and averaging across these. We found that all our results were extremely similar because the average z-score is extremely correlated with our main management measure.

Recall questions: In each wave, managers were asked to report the answer to each question for both the survey year and for five years earlier (in 2015 we asked about 2010 and in 2010 about 2005). This allows us to construct recall measures for the management score in 2005, and for missing observations in 2010. For all establishments that we observe both in 2010 and in 2015, we have both real and recall data. This provides us with a unique opportunity to benchmark the quality of the recall responses. The key variable that determines the quality of recall management score is the tenure at the establishment of the manager responding to the survey. Appendix Figure A2 shows how the correlation between the 2010 management score and the 2010 recall score (collected in 2015) correlate as a function of the respondent start year at the establishment. As is clear from the figure, for managers who started 2008 or before, the correlation is stable and high (at 0.48). Following this analysis, we only use 2005 and 2010 recall values for the management score when the survey respondent has at least 7 years of tenure at the establishment.

Share of employees with a degree: To generate our firm level measure of employees with a degree we used the mid-point values in the bin responses in questions 34 and 35 (2010 numbering) scaled up by the share of managers and non-managers in the firm calculated from the response to questions 32 and 33.

Decentralization: We calculate decentralization measures in two steps. First, we score MOPS questions 18 through 23 (2010 numbering) on a 0-1 scale, where 0 is least decentralized, and 1 is most decentralized. We then average the scores over those six questions.

Data-driven decision making: We create data driven decision making measures in two steps. First, we score MOPS questions 28 and 28 (2010 numbering) on a 0-1 scale, where 0 is lowest availability/use of data, and 1 for highest. We then average the scores over those two questions.

<u>Additional Databases</u>

<u>Establishment level:</u> Our primary source of establishment-level data in addition to the MOPS is the ASM from 2003 to 2015. We use the Census of Manufactures (CM) from 2002, 2007 and 2012 to obtain data on capital stocks, which is then combined with the ASM data on investment flows to impute capital stock for 2005, 2010 and 2015 (see details below). The CM is conducted every 5 years (for years ending 2 and 7) as part of the Economic Census. It covers all establishments with one or more paid employees in the manufacturing sector (SIC 20-39 or NAICS 31-33) which amounts to 300,000 to 400,000 establishments per survey. Both the CM and the ASM provide detailed data on sales/shipments, value added, labor inputs, labor cost, cost of materials, capital expenditures (including in ICT), inventories and much more. We match the MOPS to the ASM using the SURVU_ID variable, and match the ASM to the CM, as well as ASM and CM over time using the LBDNUM variable. Finally, we use the Longitudinal Business Database (LBD) to describe the universe of establishments in Table A3 as well as for the calculation of firm level characteristics such as age, spread of age and employment, and number of industries and locations the firm operates in.

<u>Firm level</u>: We use the 2009 Business R&D and Innovation Survey (BRDIS) data to obtain information on R&D spending and patent applications by the parent firm associated with each establishment. BRDIS provides a nationally representative sample of all companies with 5 or more employees. It is conducted jointly by the Census Bureau and

[3] For multiple choice questions which allow for the selection of more than one answer per year, we use the average of the normalized answers as the score for the particular question. If the question does not allow for the selection of more than one answer, but more than one box is selected, we treat the observation as missing.

the NSF and collects data on a variety of R&D activities. It replaced the Survey of Industrial Research and Development (SIRD) in 2008. The BRDIS is matched to the ASM (and then to MOPS) using the LBD. We are able to match a total of 13,888 MOPS observations in our "clean" sample to BRDIS observations with non-missing data on R&D spending and patent applications.[4]

Industry level: We use the NBER-CES data for industry-level price indices for total value of shipments (PISHIP), and capital expenditures (PIINV), as well as for total cost of inputs for labor (PAY), used in the construction of cost share. We match the NBER data to the establishment data using 6-digit NAICS codes.[5] We use the BLS multifactor productivity database for constructing industry-level cost of capital and capital depreciation, and the BEA fixed assets tables to transform establishment-level capital book value to market value.[6]

Million-Dollar-Plants (MDPs): We follow the approach in Greenstone, Hornbeck and Moretti (2010) in tracking events where large (mostly multinationals) firms pick a site for a new large establishment. Greenstone, Hornbeck and Moretti (2010) used articles from the feature on "Million Dollar Plants" from Site Selection, a business magazine. Unfortunately this segment has been discontinued, hence to expand our data of MDPs we had to combine data from multiple other sources. First, Site Selection magazine does report 'Top Deals' and 'Honorable Mentions', which we have used. Second, we have used the Southern Business and Development top deals. Third, we use deals from Hyunseob Kim's dataset built for his work titled "How Does Labor Market Size Affect Firm Capital Structure? Evidence from Large Plant Openings".[7] Finally, we included any other site selection deals which we came across while searching for control counties for any of the other deals, as well as web-searching for additional deals using the key terms "blockbuster deal archive," "runner up," "winning bid," "top deals" and "location report."

Once we have the top MDP deals, we have searched for the control locations – counties which were mentioned as runner ups for the chose location. For our final Million Dollar Plants list, we require to have at least one county control.[8]

Industry distance measures: For our analysis of MDPs we construct distance measures between industries. Our main distance measure is based on managers' flow between industries. These flows were constructed using CPS data from the monthly basic files of 2003 to 2015 (downloaded from IPUMS). Using these data, we constructed the CPS panels, and then within each person, we identified job-to-job transitions.[9] For our baseline measure we then only keep transitions of workers in occupations classified as "Executive, Administrative, and Managerial Occupations", corresponding to occupation codes 003 to 037 in the IPUMS harmonized occ1990 variable. We then match the CPS industry codes to NAICS codes (3 digit for manufacturing and mostly 2 digit outside manufacturing – overall 43 categories), and create a transition matrix. When matching the matrix to our sample, we treat the MDP as the source of the flow.
As a robustness test we use a similar measure which is constructed using all workers transition, rather than only workers in managerial occupations.
The other distance measure we use is based on trade flows between industries. To construct this distance measure we simply use the real input-output matrices calculated by the BLS.[10] We take the average of in and out flows as our distance measures between the industries.

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4 For more details see http://www.census.gov/manufacturing/brdis/index.html and http://www.nsf.gov/statistics/srvyindustry/about/brdis/interpret.cfm.

5 See: http://www.nber.org/nberces/ for the public version. We thank CES for providing us with an updated version of the data.

6 For more details about the relevant variables from the BLS and BEA tables, see the appendix to Bloom, Floetotto, Jaimovich, Terry and Saporta (2018).

7 We are grateful to Hyunseob Kim for sharing an updated list of million dollar plants and discussing search strategies from his work Kim (2013)

8 While we do not use them in the analysis, our compiled list of MDPs includes also pairs where the control is at the state level.

9 These can be identified using the CPS interviewer's question whether the person works for the same employer (see for example Fallick and Fleischman, 2004).

10 This can be downloaded from: https://www.bls.gov/emp/ep_data_input_output_matrix.htm

Additional Variable Construction

Capital Imputation: As mentioned above, the capital measures are based on the CM 2002, 2007 and 2012 reported book value of assets. We first transform book values to market using the industry-level BEA fixed assets tables, and then deflate both the initial stock and the investment flows using the NBER deflators. We then apply the perpetual inventory method (PIM) to impute capital stocks for 2005, 2010 and 2015. This procedure only provides us with capital stock values in 2010 for establishments which were in the CM in 2007 and in the ASM in both 2008, 2009 (and analogously 2013, 2014 for 2015 MOPS). To impute capital stock for establishments observed in 2010 or 2015 but do not meet the criteria above, we follow the following procedure:[11]

(a) If investment in 2009 is missing, impute it using the average investment for the plant in 2008 and 2010 (or 2007 and 2010 if 2008 missing).

(b) Similarly, if investment in 2008 is missing, impute it using 2007 and 2009 (or 2007 and 2010 if 2009 is missing).

(c) For 2008 and 2009 births, use the establishment's 2008 or 2009 investment to initialize the capital stock. To do that use the 2007 median ratio of book value to investment for new establishments by 6 digit NAICS (winsorized at the 95%, since some industries have very small number of observations). Run the PIM again using these initial capital stocks, only for observations with missing capital stock in 2010.

(d) For observations that are still missing capital stock, impute it by using the industry median ratio of book value of capital stock to investment (these are establishments which appear in 2008 or 2009 but not in 2007, but are not marked as births). Run the PIM again only on the establishments with missing capital stock in 2010.

(e) Finally, if PIM implied zero capital stock for 2010, but investment in 2010 is positive, impute the 2010 stock using industry median as in (d).

Performance measures: Below is a summary of the measures used in the analysis:

Value added per worker: Calculated as establishment value added over total employment. In Figure 2 raw (nominal) value added is used, while in Table 4 it is deflated using industry level deflators.

Total Factor Productivity (TFP): TFP is calculated using cost shares following for example Foster, Haltiwanger, and Krizan (2001).[12] Our log TFP measure is defined as

$$logTFP_i = logY_i \ - \alpha \log K_i - \beta logL_i \ - \gamma logI_i \ ,$$

where Y_i is real value added, K_i is capital input recovered as described in the capital imputation paragraph above. L_i is labor input calculated as:

$$L_i = \frac{total\ salaries}{production\ worker\ salaries} * production\ hours$$

I_i is intermediate good input, calculated as material and energy cost deflated using NBER-CES industry deflators for those factors. To recover α, β and γ, we use cost shares at the industry 6-digit NAICS industry level. The total cost of labor inputs for industry j (c_j^L) and for materials (c_j^I) are taken from the NBER-CES Manufacturing Industry Database. The cost of capital (c_j^K) is set to be capital income at the industry level. The BLS productivity dataset includes data on capital income at the 3-digit NAICS level. To obtain capital income at 6-digit level we apply the ratio of capital income to capital input calculated using BLS data to the 6-digit NBER-CES real capital stock measure. Once the two input costs are recovered at the industry level, the cost share is simply recovered as

$$s_j^L = \frac{c_j^L}{c_j^L + c_j^K + c_j^I}, s_j^K = \frac{c_j^K}{c_j^L + c_j^K + c_j^I}, s_j^I = \frac{c_j^I}{c_j^L + c_j^K + c_j^I}$$

and measured log(TFP) at the establishment level is measured as:

$$\log(\widehat{TFP_{\iota,J}}) = logY_i \ - s_j^K \log K_i - s_j^L logL_i \ - s_j^I logI_i$$

Note that TFP is always measured within a 6-digit NAICS industry. For further detail about local input prices, see Appendix B.

Employment Growth: We define growth of employment from 2005 to 2010 as (emp_{2010}-emp_{2005})/

[11] To ease notation, the procedure is described for imputing capital in 2010. The same procedure is applied for 2015.

[12] The main difference is that we use a single capital stock, rather than separating equipment and structures, because separate stocks are no longer reported in the CM in recent years.

$(0.5*emp_{2010}+0.5*emp_{2005})$.

Profitability: We measure profitability from ASM data as value added-total salaries. In Figure 2 we use this value for profitability, while in the regressions in Table 1 we use (value added- total salaries)/(total value of shipments).

R&D intensity: R&D intensity is defined as (domestic R&D expenditures)/(domestic employees). In the regressions in Table 4, the dependent variable is log(1+R&D intensity).

Patent intensity: Patent intensity is defined as (patent applications)/(domestic employment). In Figure 2 we report this measure multiplied by a 1,000.

Log wage: Log wage is defined as the log of total salaries for production workers over total hour of production workers at the establishment level.

ICT per worker: the total spending on information and communication technology hardware and software per employee.

Appendix B: A Simple Model of Measured Productivity and the Drivers of Management Practices

Consider a simplified version of the production function in equation (1):

$$Y_i = A_i K_i^{\alpha} L_i^{\beta} I_i^{\gamma} \widetilde{M}_i^{\delta} \tag{B1}$$

Where $\widetilde{M}$ is the unobservable managerial capital stock and M the index we measure in the data, so $log\widetilde{M} = M$. We assume that the factor cost of managerial capital, $\log W_i^M$, has an economy wide component (e.g. management consultancy fees or CEO remuneration), but may be lower due to "drivers" Z (which in our context are Right To Work laws, RTW, and Million Dollar Plants, MDPs). As these drivers are local, we index them at the county level (Z_c). Denote this as:

$$\log W_i^M = -\theta_1 Z_c + v_i \tag{B2}$$

Where v_i are other shocks affecting the factor cost of management capital. For a maximizing profit firm, the first order condition for the firm's level of management capital is (normalizing output price to be 1):

$$log\widetilde{M}_{it} = log\delta - logW_i^M + logY_i$$

Substituting in equation (B2) for the effect of drivers on the management factor cost gives a management equation in observables:

$$M_i = log\delta + \theta_1 Z_c + logY_i - v_i \tag{B3}$$

Congestion effects of Drivers

We illustrate the problem of determining the impact of our drivers in the face of congestion costs which may increase the price of local inputs in limited supply (like commercial rents). We do this in terms of capital, but the argument holds true for any input that has a local component (materials, wages, etc.). Labor, materials and capital are supplied at factor cost W_c, W_c^I and W_c^K respectively in county c. For simplicity assume for the moment that the factor cost of labor and materials are determined in national markets ($W_c = W$; $W_c^I = W^I$), but there is a county-specific aspect of capital (we extend the idea to other factors below). As with management factor costs, one way to think about this is that there is some national cost of capital (e.g. based on national interest rates captured empirically by time dummies) and a local component (e.g. commercial rents which depend on the constrained local supply of land). As is typical, in our data, we do not observe the plant's quantity of capital directly. Imagine that we only have data on the capital costs (e.g. total rental charges), $W_c^K K_i$ and a national (or sometimes industry) price deflator (W^K). We therefore measure capital inputs as $\overline{K_i} = \frac{W_c^K K_i}{W^K}$.[13] The relationship between measured and real capital in logs is:

$$Log\overline{K_i} = logK_i + log\left(\frac{W_c^K}{W^K}\right) \tag{B4}$$

The measurement error will depend on the deviation of factor prices between local and nation-wide costs $\left(\frac{W_c^K}{W^K}\right)$.

[13] As detailed in the Data Appendix A, the construction of the capital stock is more complex than this as it uses past as well as current investment flows. The current price still enters the formula, however, so the biases will still be present. The argument that local factor price inflation induced by MDPs will cause an over-estimate of factor quantities (and therefore an underestimate of measured TFP) is quite general.

We now allow for a congestion effect of our two drivers. MDPs entering the area could drive up land prices through competition for scarce land; RTW encourages entry into the area which also increases demand. We parameterize this "congestion" effect as:

$$log\left(\frac{W_c^K}{W^K}\right) = \varphi Z_c \tag{B5}$$

Where we expect $\varphi \geq 0$. Substituting equation (B4) and (B5) into the production function (B1) gives us an expression for output (using measured capital) as:

$$logY_i \ = -\alpha\varphi Z_c + logA_i \ + \alpha \log \overline{K_i} + \beta \log L_i \ + \gamma \log I_i \ + \delta \, M_i$$

Substituting in the management equation (B3) gives:

$$logY_i \ = \frac{1}{1-\delta}\left(\delta log\delta + (\delta\theta_1 - \alpha\varphi)Z_c + logA_i \ + \alpha \log \overline{K_i} + \beta \log L_i \ + \gamma \log I_i \ - \delta v_i \ \right)$$

As is conventional measured TFP ("MTFP") is calculated as

$$logMTFP_i \ = logY_i \ - s_L logL_i \ - s_K \log \overline{K_i} - s_I logI_i$$

where (s_K, s_L, s_I) are the shares of each factor cost in total costs[14]. This generates the relationship[15]:

$$logMTFP_i \ = \pi_0 + \pi_1 Z_c + e_i \tag{B6}$$

where

$$\pi_1 = \frac{\delta\theta_1 - \alpha\varphi}{1-\delta}$$

and

$$\pi_0 = \frac{1}{1-\delta}\left(\delta log\delta + logA_i \ \right)$$

$$e_i = -\frac{\delta}{1-\delta} v_i$$

It is clear that the sign of the coefficient on our drivers in the measured TFP equation (π_1) will consist of two offsetting effects. MDP and RTW are likely to have positive effects on management as $\theta_1 > 0$ and as consequence also positive effects on measured TFP. But the congestion effect (φ) will have a negative effect. Consequently, although the theoretical impact of our drivers on management is clearly positive from the management equation (B3), the impact on measured TFP in (B6) is ambiguous.

Effect of Drivers on TFPQ?

So far we have considered the effect of the drivers on management and on measured TFP (which does not correct for

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14 As noted by Hall (1988) cost shares will be accurate measures of the technology parameters even if the firm has market power as in the case of monopolistic completion (when factor shares of revenues will be less than the output elasticities due to positive price cost margins).

15 This assumes that the measured factor cost shares are equal to the output elasticities of each factor inflated by (1 - δ), so $\frac{\beta}{1-\delta} = s_L$, etc. The cost share of managerial capital is not directly observed, but will instead be recorded as be a payment to other factors (e.g. senior managerial remuneration will be reflected in the observed labor share). We are assuming that the (unobserved) share of management capital costs in total costs are proportional to the observed shares of the three factors.

management). We could also allow the drivers to have a *direct* effect on TFPQ (A) over and above any effect on management. For example, consider specifying:

$$logA_i = logA_0 + \rho Z_c \tag{B7}$$

In this case the coefficient on the drivers, Z_c, in the measured TFP equation (B6) becomes $\pi'_1 = \frac{\delta\theta_1 + \rho - \alpha\varphi}{1-\delta}$ which is more likely to be positive if $\rho > 0$.

If RTW and MDP also affect TFP through non-managerial channels then we will under-estimate the impact of these drivers on M by conditioning on size in equation (B3).[16] Hence when estimating the management equation our preferred estimates do not condition on output or other measures of size (the unconditional management equation – see below), so that the coefficients on RTW and MDP can contain both direct and indirect effects. But we also examine the estimates of RTW and MDP on size (e.g. as measured by employment) and measured TFP. Additionally, to parse out the direct effects of the drivers on management we also consider regressions controlling for size as in equation (B3), with the caveat that size is potentially endogenous.

Differential MDP Spillover effects

Consider allowing larger spillover effects on management and real productivity (A) for MDPs which have a "managerial connection" as revealed by the managerial labor market vs. others which have smaller effects (using superscript "M" and "NM" to denote managerial vs. non-managerial respectively). Recall we measure this by whether the general flow of managerial labor to the incumbent MDP plant is higher. The generalized model is:

$$\log(W_i^M) = -\theta_1^M Z_c^M - \theta_1^{NM} Z_c^{NM} - v_i$$

with $\theta_1^M > \theta_1^{NM}$. Symmetrically, we could also allow for differential congestion effects and real productivity (A) effects of the drivers:

$$log\left(\frac{W_c^K}{W^K}\right) = logW^K + \varphi^M Z_c^M \quad + \varphi^{NM} Z_c^{NM}$$

$$logA_i = logA_0 + \rho^M Z_c^M \quad + \rho^{NM} Z_c^{NM}$$

Therefore:

$$LogMTFP_i \quad = \pi_0 + \pi^M Z_c^M + \pi^{NM} Z_c^{NM} + e_{it}$$

where

$$\pi^M = \frac{\delta\theta_1^M \quad + \rho^M - \alpha\varphi^M}{1-\delta} \text{ and } \pi^{NM} = \frac{\delta\theta_1^{NM} \quad + \rho^{NM} - \alpha\varphi^{NM}}{1-\delta}.$$

This equation gives us some further insight into the effect of the drivers. Consider a simplified example where all MDPs create equal congestion effects ($\varphi^M = \varphi^{NM} = \varphi$), but only managerial MDPs create positive productivity spillovers ($\theta_1^{NM} = \rho^{NM} = 0$). This gives the measured TFP equation:

$$LogMTFP_i \quad = \pi_0 + \pi^M Z_c^M - \alpha\varphi^{NM} Z_c^{NM} \tag{B8}$$

The pattern of regression coefficients in the TFP equation of Table 8 Panel B columns (3) and (4) is broadly consistent

[16] An increase in TFPQ would increase the marginal product of management, hence the demand for management. Controlling for size helps in shutting down the impact of drivers on management through this channel.

with this simple model with a positive and significant effect of Z_c^M ($\pi^M > 0$), a negative (and insignificant) effect of Z_c^{NM} ($\varphi^{NM} > 0$).

Solving for output as a function of exogenous variables (using the FOC like equation (B3) for all factor inputs) gives:

$$logY_i \ = (1-\varepsilon)^{-1}\begin{pmatrix} logA_i \ -\alpha\log W_c^K - \beta\log W \ \ -\gamma\log W^I - \delta\, logW_c^M \\ +\alpha log\alpha + \beta log\beta + \gamma log\gamma + \delta log\delta \end{pmatrix}.$$

where $\varepsilon = \alpha + \beta + \gamma + \delta$ is a returns to scale parameter. Substituting this into equation (B3) generates the "unconditional management equation":

$$M_i \ = \ \mathrm{c} + \theta^M Z_c^M - \theta^{NM} Z_c^{NM} + \left(\frac{\delta-1+\varepsilon}{1-\varepsilon}\right)\widetilde{v_i} \tag{B9}$$

where $\theta^M = \theta_1^M + (1-\varepsilon)^{-1}(\rho + \theta_1^M\delta - \alpha\varphi)$ and $\theta^{NM} = \alpha\varphi(1-\varepsilon)^{-1}$. Note that $\widetilde{v_i} = \left(\frac{\delta-1+\varepsilon}{1-\varepsilon}\right)v_i$ and $c = (1-\varepsilon)^{-1}\left(logA_0 \ -\alpha\log W^K - \beta\log \mathrm{W} - \gamma\log W^I \quad +\alpha log\alpha + \beta log\beta + \gamma log\gamma + \delta log\delta\right) + log\delta$ is common across firms.

We expect the coefficient on Z_c^M in the unconditional management equation (B9) to be positive ($i.e.\, \theta^M > 0$) because the driver causes (i) a direct substitution effect towards management away from other factors (θ_1^M); (ii) raises TFPQ ($\rho > 0$) generating an *indirect* output scale effect raising management; (iii) raises management which will also generate an *indirect* output scale effect. However, to the extent that the driver increases congestion ($-\alpha\varphi$) this will tend to decrease output and therefore offset the positive effects on management.

In summary, the discussion implies a positive effect of drivers on management and an ambiguous coefficient in the measured TFP equation. When diving the MDP driver into Z_c^M and Z_c^{NM} we expect (a) a positive effect of Z_c^M in the management and measured TFP equations; (b) a negative effect of Z_c^{NM} in the management and measured TFP equation.

Mismeasurement of output prices and Product Market Competition

In the production function literature, there has been a greater focus on mismeasurement of *output* prices (e.g. de Loecker, 2011) than the input price effect we discuss here. As is well known, in the absence of plant-specific output prices, MTFP will not be a quantity-based measure but rather a revenue-based measure (TFPR).[17] It will contain a price-cost margin. For example, if the entrance of an MDP creates more local output market competition this will tend to reduce price-cost margins. This will be a further effect that pushes down MTFP (Aitken and Harrison, 1999). In this case, the coefficient on MDP will then be a function of three unobserved structural parameters, causing us to underestimate the positive effects of productivity spillovers.

We can assess the importance of this competition mechanism by again disaggregating MDPs into manufacturing and non-manufacturing entrants. Since we are only looking at the impact of MDPs on manufacturing plants, we would only expect to see these negative effects at play for manufacturing MDPs as they are in similar product markets and not expect to see any negative effects from non-manufacturing MDPs competing in different markets to our plants.

In fact, we see very similar associations between the productivity of our ASM plants to manufacturing and non-manufacturing MDPs. As discussed above this is consistent with input congestion effects, but not product market competition.

[17] Exceptionally, Foster, Haltiwanger, and Syverson (2008) derive plant-specific output prices for a selection of homogenous goods for which value and physical quantity measures of output are available from the CM.

Congestion effects in other factor inputs

The congestion effects argument we make here could also be true for other inputs such as labor and materials. For intermediate inputs, local supply costs will likely rise with exactly the same mechanisms we have described. For labor, we observe employment and hours separately from the wage bill, so it is less of an issue. However, since our labor service measure for TFP uses some information on plant wages to compute the contribution non-production workers, it is also potentially suffers from this bias.

Appendix C: Comparison of Management and Organizational Practices and the World Management Surveys

The two methods for gathering management data are: (i) Open Ended questions (those with a wide variety of possible answers) used by the World Management Survey (WMS); and (ii) Closed Ended questions (those with a list of potential answers like "Yes or No") used in the Management and Organizational Practices Surveys (MOPS). We compare the instruments in this Appendix (more details are in Bloom, Sadun and Van Reenen, 2010 and Bloom, Lemos, Sadun, Scur and Van Reenen, 2014).

Open Ended Questions: World Management Survey (WMS): The WMS approach is modelled on what leading management consulting firms do when interviewing client firms in consulting engagements. Bloom and Van Reenen first implemented this in 2004 in a survey developed jointly with the consulting firm McKinsey & Co. (Bloom and Van Reenen, 2007). They used open questions to collect information. For example, on monitoring, they begin with asking the open question "*can you tell me how you monitor your production process?*". They continued 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 monitoring dimension is "*what kinds of measures would you use to track performance?*" and the third is "*if I walked round your factory could I tell how each person was performing?*". These open questions are designed to mimize the chance we steer respondents to a particular answer

They target production plant managers using a 'double-blind' technique. One part of this technique is that managers were not told in advance they were being scored or shown the scoring grid. They were only told they were being "*interviewed about management practices for a piece of work.*" (we avoid the words "survey" or "research" because of connotations with market research). The other side of the technique is that interviewers were not told in advance about the firm's performance. They were only provided with the company name, telephone number and industry. Since the survey requires some degree of business acumen and knowledge, they hired skilled interviewers – usually graduate students with business qualifications to run interviews. This double-blind approach tries to prevent firms from biasing their responses towards higher-scores, and interviewers from biasing their scores based on knowledge of the firm's performance.

To score these interview responses they had a grid for each question running on a scale from 1 to 5, where for example on the monitoring question discussed above a score of 1 was defined as "*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)*" while a score of 5 was defined as "*Performance is continuously tracked and communicated, both formally and informally, to all staff using a range of visual management tools*". From this example it is clear that designing these surveys take some expertise in terms of selecting questions and response grids, and our experience was that this is an iterative process involving repeated rounds of testing and refinement. The full questionnaire is available on www.worldmanagementsurvey.com.

Finally, these surveys have to be run as an interactive conversation, which they did over the telephone to reduce travel time and ensure consistency. They obtained response rates of about 40%, interviewing managers for around 45 minutes. They provided one week of intense training combined with daily coaching and monitoring for their interview team.

Response rates to surveys in general have been falling in the US and other countries over time. For these type of surveys, private sector companies often only have response rates of 5-10% and although attempts are made to balance these on observables such as size, industry and geography there is an obvious concern over selection on unobservables. The much higher response rates achieved by the WMS are partly due to interviewer persistence, as senior managers are hard to reach and convince to take part on our interviews, but also because the survey itself is very interactive and thus more enjoyable for managers than simply being "pumped for information."

They also use endorsement letters from senior officials from respected institutions such as the Central Bank, Finance Ministry and Employers Federation. Given the high overhead costs to administer these surveys, each interview is budgeted at between US$400 and US$500.

Close Ended Questions: Management and Organizational Practices Survey (MOPS): Closed ended surveys allow respondents to choose from a menu of answers, so the survey does not need an interviewer to run it over the telephone or face-to-face. As outlined above, the MOPS, which was designed in collaboration with the US Census Bureau to be comparable to the WMS questions, is a closed ended survey. For example, in the monitoring section we asked how frequently were performance indicators tracked at the establishment, with options ranging from "*hourly", "daily", "weekly", "monthly, "quarterly", "yearly"* to *"never"*. The targets section asked about the design, integration and realism of production targets and the incentives section asked about non-managerial and managerial bonus, promotion and reassignment/dismissal practices. The full questionnaire is available on http://bhs.econ.census.gov/bhs/mops/form.html.

Comparison of Open vs Closed Ended Surveys: No one method clearly dominates the other, with the WMS vs MOPS a quality-cost and flexibility-scale tradeoff. In summary, the WMS approach likely elicits more accurate responses as respondents can be probed more deeply and asked for examples. It also can be run without any government support and still achieve reasonable response rates. However, the WMS has the disadvantage that it requires trained highly quality interviewers, which is expensive and harder to organize.

For the closed approach, collaborating with national statistical agencies like the US Census Bureau is a major advantage. First, it is possible to leverage off the sampling frames of existing surveys like the ASM. Second, it makes it easier to link to data on productivity from these surveys. Third and most importantly, if it goes out as a mandatory survey alongside the standard official surveys, response rates can be much higher (around 75% in the case of MOPS) and the survey can be administered at a larger scale. Overall, the WMS method has the advantage of accuracy, but the MOPS has the advantage of lower per-survey cost.

The WMS randomly samples medium-sized manufacturing firms (employing between 50 and 5,000 workers). Bloom and Van Reenen's initial view was that in smaller firms formal management practices may be less valuable. In very large firms they worried that one plant-interview would be too limited to evaluate the whole firm. By contrast, in MOPS, we covered the entire firm size distribution using plant-level interviews. Although it was true that large firms were more likely to have higher management scores, we found that the link with performance extended throughout the size distribution, similar to McKenzie and Woodruff (2015) who find an important role for management in micro-firms in developing countries.

Comparison of WMS and MOPS Management Scores for Matched Sample

We conducted a quantitative comparison of WMS and MOPS management scores by matching observations from the two surveys. To do that, we first constructed a name-address based bridge between census firm identifiers and Compustat CUSIP identifiers.[18] WMS data already include CUSIP identifiers, hence we were able to use these to match MOPS with the CUSIPs to WMS. To maximize the matched sample we used two WMS waves with US manufacturing data (2004 and 2006), and matched to any MOPS observation in our sample (2005 to 2015). We were able to match a few hundred WMS firms to a few thousands of MOPS surveys. Each CUSIP maps to multiple census firm identifiers, and each census firm identifier maps to multiple MOPS establishments, hence we ended up with an average of 17.65 MOPS management scores per WMS score. We take the average management score over all MOPS observations that match to a WMS identifier, and compare those averages to the WMS management score.

Appendix Figure A3 shows a bin-scatter of MOPS scores (y-axis) over WMS scores (x-axis). The two scores are highly correlated, with a correlation coefficient of 0.26 (t-stat of 5.79), and the shape of the relation is close to linear. To benchmark this correlation, recall that the upper bound that can be expected for such correlation is 0.55 – the correlation between two duplicate MOPS observations calculated using the same survey instrument in about the same time for the same establishment (see section 3.3 in the paper). There are at least three reasons why we would expect a

[18] We thank Veronika Penciakova from the Center for Economic Studies in Census for providing the code used for the matching.

lower correlation between MOPS and WMS. First, the two instruments use different scoring tools. Second, it is likely that the matching is not perfect, in which case wrong matches would drive down the correlation. Finally, The MOPS data are reported for 2005, 2010 and 2015 (mostly 2010 and 2015), while the WMS data refers to 2004 and 2006. Given that the management score is not fixed over time, but include some stochatic component, we would expect further reduction in the correlation.

Appendix Bibliography

Aitken, Brian J., and Ann E. Harrison (1999) "Do Domestic Firms Benefit from Direct Foreign Investment? Evidence from Venezuela," *American Economic Review*, 89(3), 605-618.

Bloom, Nicholas, Max Floetotto, Nir Jaimovich, Itay Saporta-Eksten and Stephen Terry, (2018), "Really Uncertain Business Cycles," forthcoming, *Econometrica*

Bloom, Nicholas, Renata Lemos, Raffaella Sadun, Daniela Scur and John Van Reenen (2016) "International data on measuring management practices" *American Economic Review Papers and Proceedings* 106(5), 152-156

Bloom, Nicholas and John Van Reenen. (2010) "New approaches to surveying organizations" *American Economic Review Papers and Proceedings* 100(5), 105-109.

De Loecker, Jan (2011) "Product Differentiation, Multi-product Firms and Estimating the Impact of Trade Liberalization on Productivity", *Econometrica* 79(5) 1407–1451

Fallick, Bruce C., Charles A. Fleischman (2004). "Employer-to-employer flows in the U.S. labor market: the complete picture of gross worker flows," Finance and Economics Discussion Series 2004-34, Board of Governors of the Federal Reserve System (U.S.).

Flood, Sarah, Miriam King, Steven Ruggles, and J. Robert Warren. Integrated Public Use Microdata Series, Current Population Survey: Version 5.0. [dataset]. Minneapolis: University of Minnesota, 2017. https://doi.org/10.18128/D030.V5.0.

Hall, Robert (1988) "The Relation between Price and Marginal cost in US Industry" *Journal of Political Economy*, 96(5), 921-47

Kim, Hyunseob, (2013), "Labor Market Size and Firm Capital Structure: Evidence from Large Plant Openings," Working paper.

Table A1: The Most Common Titles and Categories of MOPS Contacts

Panel A: Categories	**Share**
Manager (except CEO)	53%
Finance (except CFO)	23%
CEO	8%
CFO	5%
HR/admin (non-manager)	4%
Missing	6%

Panel B: Titles	**Share**
Plant manager	13%
Financial controller	10%
CEO	8%
CFO	4%
General manager	3%
Other (e.g. vice-president of engineering, COO or production manager)	64%

Note: Data from the MOPS 2015 survey meta data on the titles of MOPS contact in the certification section (question 47). This requests a range of details on the survey response, including "*Name of person to contact regarding this report*" and "*Title*".

Table A2: Scoring MOPS Survey Questions

Question	Question Text	Response	Score
1	What best describes what happens at your firm when a problem in the production process arises? Examples: Finding a quality defect in a service, product, or a piece of equipment breaks down.	We fixed it but did not take further action	1/3
		We fixed it and took action to make sure that it did not happen again	2/3
		We fixed it and took action to make sure that it did not happen again, and had a continuous improvement process to anticipate problems like these in advance	1
		No action was taken	0
2	How many key performance indicators are monitored in your firm? Examples: Metrics on service quality, customer satisfaction, production, cost, waste, quality, inventory, and absenteeism.	1-2 key performance indicators	1/3
		3-9 key performance indicators	2/3
		10 or more key performance indicators	1
		No key performance indicators (If no key performance indicators in both years, SKIP to (6))	0
3	How frequently are key performance indicators typically **reviewed** by **managers** at your firm?	Yearly	1/6
		Quarterly	1/3
		Monthly	1/2
		Weekly	2/3
		Daily	5/6
		Hourly or more frequently	1
		Never	0
4	How frequently are key performance indicators typically **reviewed** by **non-managers** at your firm?	See question 3	See question 3
5	Where are display boards showing service quality, output and other key performance indicators located in your firm?	All display boards were located in one place (e.g. in the store back office or at the end of the production line)	1/2
		Display boards were located in multiple places (e.g. at multiple places in the store or establishment)	1

Question	Question Text	Response	Score
		We did not have any display boards	0
6	What best describes the time frame of operational targets at your firm? Examples of operational targets are: customer satisfaction, wait-times, production, quality, efficiency, on-time delivery.	Main focus was on short-term (less than one year) targets	1/3
		Main focus was on long-term (more than one year) targets	2/3
		Combination of short-term and long-term targets	1
		No targets (If no targets in both years, SKIP to (13))	0
7	How easy or difficult is it in your firm for people to typically achieve their operational targets?	Possible to achieve without much effort	0
		Possible to achieve with some effort	½
		Possible to achieve with normal amount of effort	¾
		Possible to achieve with more than normal effort	1
		Only possible to achieve with extraordinary effort	¼
8	Who was aware of the operational targets at your firm?	Only senior managers	0
		Most managers and some workers	1/3
		Most managers and most workers	2/3
		All managers and most workers	1
9	What are **non-managers'** performance bonuses usually based on in your firm?	Their own performance	1
		Their team or shift performance	3/4
		Their local establishment or branch's performance	1/2
		Their entire company's performance	1/4
		No performance bonuses (If no performance bonuses in both years, SKIP to (11))	0
10	When targets are met, what percent of **non-managers** received performance bonuses?	0%	1/5
		1-33%	2/5
		34-66%	3/5
		67-99%	4/5
		100%	1
		Targets not met	0

Question	Question Text	Response	Score
11	What were **managers'** performance bonuses usually based on in your firm?	See question 9 (If no performance bonuses in both years, SKIP pattern directs respondent to SKIP to (13))	See question 9
12	When production targets are met, what percent of **managers** at your firm received performance bonuses?	See question 10	See question 10
13	What is the primary way **non-managers** are promoted in your firm?	Promotions are based solely on performance and ability	1
		Promotions are based partly on performance and ability, and partly on other factors (for example, tenure or family connections)	2/3
		Promotions are based mainly on factors other than performance and ability (for example, tenure or family connections)	1/3
		Non-managers are normally not promoted	0
14	What is the primary way **managers** are promoted in your firm?	See question 13 (Replace "non-managers" with "managers")	See question 13
15	When is an under-performing **non-manager** usually reassigned or dismissed?	Within 6 months of identifying non-manager under-performance	1
		After 6 months of identifying non-manager under-performance	1/2
		Rarely or never	0
16	When an under-performing manager is usually reassigned or dismissed?	See question 15 (Replace "non-manager" with "manager")	See question 15

Note: Questions 3, 4 and 5 are scored at 0 if missing, which typically arises from firms reporting "no performance indicators" to question 2 and skipping to question 6. The rationale for this is that firms with no performance indicators have no managerial or non-managerial review of performance indicators, and have no performance display boards.

A3: MOPS Sample of Approximately 32,000 Manufacturing Establishments

Sample	Source	Sample Criteria	Number of establishments (in thousands)	Total employment (in thousands)	Average employment
(1) Universe of establishments	LBD	None	7,041	134 ,637	19.1
(2) Manufacturing	LBD	NAICS 31-33	298	12,027	40.4
(3) Annual Survey of Manufactures	ASM	NAICS 31-33, and either over 500 employees, or in ASM stratified random sample. Positive employment and sales, and tabbed	51	7,387	143.5
(4) MOPS respondents	MOPS	As in (3), also responded to MOPS	36	5,629	155.8
(5) MOPS clean (baseline sample)	MOPS	As in (4) with 11+ non-missing responses, match to ASM, tabbed in ASM and have positive value added, employment and imputed capital in ASM 2010	32	5,308	167

Note: The LBD numbers are from 2009. ASM and MOPS numbers are for 2010.

Table A4: Descriptive Statistics

A. Management Descriptives	Mean	S.D.	p(10)	p(25)	p(50)	p(75)	p(90)
Management score	0.615	0.172	0.379	0.521	0.648	0.742	0.806
Non-incentive management	0.643	0.199	0.365	0.521	0.677	0.792	0.865
Incentives	0.583	0.215	0.3	0.474	0.623	0.739	0.819
B. Establishment Characteristics							
Size (Establishment employment)	177.2	398.5	16.8	36.0	86.0	186.0	382.0
Parent firm size	3359.0	9034.0	25.0	63.4	255.5	1862.0	8424.0
Establishment Age	21.0	10.1	4.0	12.0	25.0	30.0	30.0
Parent firm age	25.4	8.3	10.0	24.0	30.0	30.0	30.0
% of managers with degree	44.0%	30.9%	10.0%	10.0%	44.0%	70.0%	90.0%
% of non-managers with degree	9.8%	12.2%	0%	5.0%	5.0%	15.0%	40.0%
% of union members	12.2%	27.0%	0%	0%	0%	0%	70.0%
Multi-unit Parent	67.9%	46.7%	0	0	1	1	1

Note: The management score is the unweighted average of the score for each of the 16 questions, where each question is first normalized to be on a 0-1 scale. The sample in all columns is all MOPS observations with at least 10 non-missing responses to management questions and a successful match to ASM, which were also included in ASM tabulations, have positive value added, positive employment and positive imputed capital in the ASM. Recalls are used for respondents with at least 7 years of tenure at the establishment. For the few cases where establishment characteristics had missing values (for the degree and union questions), we replaced these with the means in the sample, so to keep a constant sample size. P(n) is the value at the n-th percentile, e.g. p(50) is the median value (fuzzed). Data from MOPS 2010.

Table A5: Linear regressions for sample selection

	Mailed MOPS vs ASM	MOPS Respondents vs. Mailed MOPS	Clean sample vs. MOPS respondents	Clean sample vs. ASM	Clean sample vs. ASM
Log(employment)	0.059***	0.031***	0.057***	0.096***	0.094***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Log(Output/employment)					0.038***
					(0.004)
F-stat (region)	5.591	45.381	1.1	34.665	33.443
(p-value)	(0.001)	(0)	(0.348)	(0)	(0)
F-stat (industry)	10.213	7.871	8.399	15.267	11.948
(p-value)	(0)	(0)	(0)	(0)	(0)
Observations	51,461	47,503	36,140	51,461	51,461
Number of firms	28,905	26,345	20,694	28,905	28,905

Note: The table reports the results from linear probability regressions. In column 1 the sample is 2010 ASM observations with positive employment and sales, which were tabbed, and the dependent variable is an indicator that equals 1 if MOPS was sent to the establishment. In column 2 the sample is the subsample of the one in column 1, also conditioning on MOPS mailed, and the dependent variable is an indicator that equals 1 if MOPS survey was filled. In column 3 the sample is the subsample of the one in column 2, also conditioning on MOPS respondent, and the dependent variable is an indicator that equals 1 if the observation is in our baseline "clean" sample. In columns 4 and 5 the sample is as in column 1, and the dependent variable is an indicator that equals 1 if the observation is in our baseline "clean" sample. Standard errors are clustered at the firm level.

Table A6: Question by Question Management-Performance Relation

#	Question (short version)	Mean	log(output)	log(output/emp.)	Exit 10-15	Emp growth 10-15
		(1)	(2)	(3)	(4)	(5)
1	What happens when a problem arise?	0.846	1.753***	0.569***	-0.092***	0.2***
		(0.213)	(0.041)	(0.024)	(0.011)	(0.027)
2	# of key performance indicators (KPI)	0.753	2.318***	0.762***	-0.099***	0.199***
		(0.267)	(0.039)	(0.025)	(0.009)	(0.021)
3	Frequently KPI reviewed by managers	0.524	1.798***	0.528***	-0.051***	0.104***
		(0.222)	(0.041)	(0.022)	(0.01)	(0.023)
4	Frequently KPI reviewed by non-managers	0.426	1.596***	0.547***	-0.046***	0.086***
		(0.281)	(0.035)	(0.02)	(0.007)	(0.017)
5	Display boards location	0.513	1.482***	0.368***	-0.036***	0.066***
		(0.442)	(0.022)	(0.014)	(0.005)	(0.011)
6	Time frame of operational targets	0.684	1.116***	0.381***	-0.05***	0.114***
		(0.363)	(0.024)	(0.016)	(0.006)	(0.015)
7	Difficulty to achieve operational targets	0.746	0.816***	0.233***	-0.035***	0.074***
		(0.252)	(0.027)	(0.016)	(0.007)	(0.017)
8	Awareness of operational targets	0.713	0.969***	0.41***	-0.027***	0.052***
		(0.329)	(0.027)	(0.018)	(0.006)	(0.015)
9	What are non-managers' bonuses based on?	0.266	0.5***	0.26***	-0.042***	0.107***
		(0.299)	(0.036)	(0.024)	(0.006)	(0.016)
10	Percent of non-managers receiving bonuses	0.69	0.688***	0.427***	-0.066***	0.162***
		(0.265)	(0.034)	(0.022)	(0.007)	(0.016)
11	What are managers' bonuses based on?	0.332	0.968***	0.46***	-0.069***	0.147***
		(0.278)	(0.038)	(0.023)	(0.007)	(0.017)
12	Percent of managers receiving bonuses	0.73	0.675***	0.426***	-0.073***	0.182***
		(0.282)	(0.034)	(0.022)	(0.006)	(0.016)
13	Criteria for non-managers' promotion	0.834	1.16***	0.315***	-0.048***	0.124***
		(0.32)	(0.025)	(0.014)	(0.007)	(0.016)
14	Criteria for non-managers' promotion	0.81	1.4***	0.44***	-0.034***	0.068***
		(0.356)	(0.025)	(0.015)	(0.006)	(0.014)
15	When is an under-performing non-manager reassigned or dismissed?	0.619	0.449***	0.013	-0.005	0.044***
		(0.412)	(0.019)	(0.011)	(0.005)	(0.012)
16	When is an under-performing manager reassigned or dismissed?	0.521	0.657***	0.087***	0.002	0.004
		(0.415)	(0.02)	(0.012)	(0.005)	(0.011)
	Management Score	0.615	4.264***	1.351***	-0.18***	0.412***
		(0.172)	(0.057)	(0.039)	(0.014)	(0.033)
	Observations	~82,500	~82,500	~82,500	~32,000	~32,000

Notes: ***Significant at 1% level, **5% level, *10% level. Each row (1-16) corresponds to one MOPS question, where each question is first normalized to be on a 0-1 scale. The "Management Score" row reports results for the total management score as used in the rest of the paper (the unweighted average of the score for each of the 16 questions). Questions with missing values were replaced with the mean in the sample. Column (1) shows the mean and standard deviation of each question. Columns 2 to 5 show OLS coefficients with standard errors in parentheses (clustered at the firm level). The sample in columns (1) to (3), is all MOPS observations with at least 10 non-missing responses to management questions and a successful match to ASM, which were also included in ASM tabulations, have positive value added, positive employment and positive imputed capital in the ASM. Recalls are used for respondents with at least 7 years of tenure at the establishment. Sample in columns (4) and (5) is restricted to 2010 MOPS observations. The dependent variable is log(real output) in columns (2), log(real output over total employment) in column (2), exit dummy between 2010 and 2015, and employment growth between 2010 and 2015. All regressions include year fixed effect and recall dummy.

Table A7: Measurement Error is Uncorrelated with Observables

Dependent Variable	**Absolute Value of Diff in Management Score Between Double Surveyed Establishments**							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(number plants in the firm - CM)	0.0003							
	(0.0029)							
Log(number plants in the firm - LBD)		0.0006						
		(0.0023)						
Log(employees in the plant)			-0.0059					
			(0.0045)					
Log(employees in the firm - CM)				-0.0004				
				(0.0024)				
Log(employees in the firm - LBD)					-0.00004			
					(0.0022)			
Log(firm age)						-0.0044		
						(0.0055)		
Log(Value added/Emp)							0.00073	
							(0.0053)	
Log(Total Factor Productivity)								-0.00366
								(0.0084)
Observations	~500	~500	~500	~500	~500	~500	~500	~500

Note: The management score is the unweighted average of the score for each of the 16 questions, where each question is first normalized to be on a 0-1 scale. The sample is approximate 500 plants from the baseline sample that filled-out two surveys by different responders for MOPS 2010. The exact number of plants is suppressed to prevent disclosure of confidential information. The regression controls for the total management score.

Table A8: Management and Performance by Establishment Age

Dependent Variable	Employment growth 2010-2015			Exit 2010-2015			Log(Output/Emp)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Management	0.343***	0.302***	0.612***	-0.144***	-0.124***	-0.248***	0.283***	0.280***	0.311***
	(0.033)	(0.039)	(0.080)	(0.014)	(0.016)	(0.034)	(0.021)	(0.024)	(0.039)
Management X (age≤5 years)	0.285***	0.326***		-0.114**	-0.134***		0.047	0.048	
	(0.108)	(0.110)		(0.046)	(0.047)		(0.049)	(0.051)	
Management X (5<age≤20 years)		0.114*			-0.046			0.003	
		(0.069)			(0.028)			(0.035)	
Management X age			-0.011***			0.004***			-0.001
			(0.003)			(0.001)			(0.002)
Observations	~32,000	~32,000	~32,000	~32,000	~32,000	~32,000	~32,000	~32,000	~32,000

Notes: ***Significant at 1% level, **5% level, *10% level. OLS coefficients with standard errors in parentheses (clustered at the firm level). The management score is the unweighted average of the score for each of the 16 questions, where each question is first normalized to be on a 0-1 scale. The sample in all columns is all MOPS observations with valid management score in 2010 and a successful match to ASM, which were also included in ASM tabulations, have positive value added, positive employment and positive imputed capital in the ASM. In columns (1) to (3), the dependent variable is employment growth between 2010 and 2015. Growth between years s and t is calculated as $0.5*(e_t - e_s)/(e_t + e_s)$. In columns (4) to (6), the dependent variable is a dummy that takes the value of 1 for exit between 2010 and 2015. In columns (7) to (9) the dependent variable is log(output over total employees). In those 3 columns we control for log(Capital/Employment), log(Materials/Employment), log(Employment), and share of employee with college degree. Establishment age is from the Longitudinal Business Database (LBD), and truncated at age 30. In columns (1), (2), (4), (5), (7), and (8) we also control for the two age categories, and in columns (3), (6) and (9) we control for age.

Table A9: Management and Performance Controlling for other Organizational Variables

Dependent variable:	**Log(Output/Employment)**											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Management	0.200***	0.193***	0.180***	0.173***	0.075*	0.075*	0.079*	0.078*	0.074***	0.080***	0.061**	0.067***
	(0.022)	(0.021)	(0.023)	(0.022)	(0.045)	(0.045)	(0.046)	(0.046)	(0.025)	(0.025)	(0.026)	(0.025)
Decentralization		-0.106***		-0.106***		0.003		0.003		-0.091***		-0.092***
		(0.017)		(0.017)		(0.035)		(0.035)		(0.021)		(0.021)
Data driven decision making			0.050***	0.049***			-0.009	-0.009			0.035**	0.036**
			(0.017)	(0.016)			(0.031)	(0.031)			(0.017)	(0.017)
Observations	43,000	43,000	43,000	43,000	19,500	19,500	19,500	19,500	43,000	43,000	43,000	43,000
Fixed effects	Industry	Industry	Industry	Industry	Establish.	Establish.	Establish.	Establish.	FirmXYear	FirmXYear	FirmXYear	FirmXYear

Notes: ***Significant at 1% level, **5% level, *10% level. OLS coefficients with standard errors in parentheses (clustered at the firm level). The management score is the unweighted average of the score for each of the 16 questions, where each question is first normalized to be on a 0-1 scale. The sample in columns (1)-(4), (9)-(12) is all MOPS observations with at least 10 non-missing responses to management questions and a successful match to ASM, which were also included in ASM tabulations, have positive value added, positive employment and positive imputed capital in the ASM. Recalls are used for respondents with at least 7 years of tenure at the establishment. It further conditions on the establishment having at least one sibling (i.e. from the same parent firm) in MOPS within the year. The sample in columns (5)-(8) uses the same sample with the extra restriction that the establishment has 2 non-recall observations (in 2010 and 2015), and excludes 2005. In all columns the dependent variable is log(real output over total employment). Decentralization measure is defined as the unweighted response to questions 18 to 24 in MOPS. Data Driven Decision Making score is calculated as the average of questions 27 and 28 in MOPS (2010 numbering). All columns include controls for log(capital/Employment), log(material/ Employment), log(Employment), share of employee with college degree, year fixed effect and a recall dummy.

Table A10: Drivers of Productivity Variation using Production Function Approach at *firm* level

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	**Firm Level Log(Labor Productivity)**				
Management score	0.307***				0.242***
	(0.022)				(0.023)
R&D		0.048***			0.037***
		(0.005)			(0.005)
ICT/worker			0.018***		0.013***
			(0.003)		(0.003)
Skills (% employees with college degree)				0.295***	0.117***
				(0.03)	(0.031)
Log(Capital/Emp)	0.131***	0.127***	0.132***	0.131***	0.124***
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)
Log(Material/Emp)	0.493***	0.496***	0.496***	0.497***	0.488***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Log(Emp)	0.017***	0.02***	0.035***	0.03***	0.007*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	~18,000	~18,000	~18,000	~18,000	~18,000
Share of 90-10 explained	0.082	0.083	0.037	0.062	0.181
Share of S.D explained	0.069	0.082	0.043	0.057	0.108

Notes: OLS coefficients with standard errors in parentheses (clustered at the firm level). Dependent variable is firm level Log(Output over Employment) built from industry de-meaned plant-level Log(Output over Employment) weighted up by plant's shipments. Right-hand side variables are management score, R&D from BRDIS measured as log(1+R&D intensity) where R&D intensity is the total domestic R&D expenditure divided by total domestic employment, ICT investment per worker (1000* spending on information and communication technology hardware and software per employee), skill measured by the share of employees (managers and non-managers) with a college degree. All these variables are also weighted up to the firm level using plant's total value of shipments. Missing values have been replaced by zero for R&D and by means for the other variables. Industry demeaning is at NAICS 6 level. All regressions are weighted by the number of establishments in the firm. "Share of 90-10 explained" is calculated by multiplying the coefficient on the key driver variable (e.g., management in column 1) by its 90-10 spread and dividing this by the 90-10 spread of TFP. Share of S.D. explained corresponds to the marginal square root of the R^2 of the relevant factors in the regression.

Table A11: MDP Balancing Tests

	All	Million Dollar Plant Opens ×(High worker flow)	Million Dollar Plant Opens ×(Low worker flow)	Observations
	(1)	(2)	(3)	
Panel A: $t-5$ Levels of:				
Management score	-0.011	-0.024**	0.011	~2,500
	(0.007)	(0.010)	(0.015)	
log(TFP)	-0.005	-0.016	0.012	~2,500
	(0.064)	(0.074)	(0.080)	
Log(employment)	-0.143***	-0.216***	-0.030	~2,500
	(0.029)	(0.050)	(0.074)	
Establishment age	0.853	0.503	1.399	~2,500
	(0.578)	(0.837)	(0.949)	
Share of employees with a degree	0.002	0.005	-0.002	~2,500
	(0.018)	(0.020)	(0.016)	
High Unionization (>80%)	0.013*	0.016*	0.008	~2,500
	(0.008)	(0.009)	(0.021)	
Panel B: $t-10$ to $t-5$ Change in (establishment level):				
log(TFP)	-0.023			~4,100
	(0.018)			
Employment^	0.001			~4,100
	(0.008)			
Log(value added)	0.0003			~4,100
	(0.055)			
Panel C: $t-10$ to $t-5$ Change in (county level):				
Change in Log(#establishments)	-0.001			~100
	(0.013)			
Change in Log(#manufacturing plants)	-0.053			~100
	(0.074)			
Exit rate	-0.0001			~100
	(0.004)			
Exit rate in manufacturing	-0.007			~100
	(0.007)			
Birth rate	0.005			~100
	(0.004)			
Birth rate in manufacturing	~0			~100
	(0.008)			

Notes: The sample in panel A is identical to the MDP sample in Table 8, and the variables are the same ones used in the regressions in Table 8. In panel B the sample includes all ASM establishments with valid TFP for $t-10$ and $t-5$ in counties which were included in the MDP analysis in Table 8. In panel C we report aggregate statistics from the Longitudinal Business Database (LBD) for the sample of counties which were part of the MDP analysis. Column 1 reports results from a regression of each variable on the MDP dummy, while columns (2) and (3) report the results from a regression where MDP dummies are interacted dummies for high and low worker flow between the establishment and the MDP industry codes.

^ For consistency with Table 8, for employment change we report here the employment growth defined as $0.5*(emp_t - emp_{t-5})/(emp_t + emp_{t-5})$