What Drives Differences in Management?

Nicholas Bloom[1], Erik Brynjolfsson[2], Lucia Foster[3], Ron Jarmin[3], Megha Patnaik[4], Itay Saporta-Eksten[5] and John Van Reenen[6]

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Abstract: This paper analyzes a recent Census Bureau survey of "structured" management practices in over 30,000 U.S. plants. Analyzing these data reveals enormous variation in management practices across plants, with 40% of this variation being across plants *within* the same firm. The management index accounts for just under a fifth of the spread of TFP between the 90th and 10th percentiles, a similar fraction to that explained by R&D and over twice as much as explained by IT. We find evidence for four causal "drivers" of management practices: product market competition (e.g. the Lerner index, exchange rate shocks), state business environment (as proxied by "Right to Work" laws), learning spillovers (e.g. proximity to "Million Dollar Plant" openings) and human capital (e.g. proximity to land grant colleges). Collectively these drivers account for about a third of the dispersion of management, suggesting the need to draw upon a wider range of theories to explain the remaining variation.

Keywords: Management and productivity

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[1] Stanford and NBER, [2] MIT and NBER, [3] U.S. Census Bureau, [4] Stanford, [5] Tel-Aviv and UCL, [6] MIT, CEP and NBER

1 Introduction

Economists' interest 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 Census.[1] This interest has persisted until today. For example, Syverson's (2011) survey of productivity devotes a section to management as a potential driver, however noting that "*no driver of productivity has seen a higher ratio of speculation to research.*" Work evaluating differences in management is often limited to small samples of plants (e.g. Ichnioswki, Shaw and Prenushi, 1997; Bresnahan, Brynjolfsson and Hitt, 2002), developing countries (e.g. Bloom, Eifert, Mahajan, McKenzie, and Roberts, 2013, and Bruhn, Karlan and Schoar, 2016) or historical episodes (e.g. Giorcelli, 2016). In addition, while previous work like Bloom, Sadun and Van Reenen (2016) has measured differences in management across firms and countries, there is no large-scale work on the variations in management *within and between* firms. Meanwhile, there is a strong theoretical basis for expecting management to matter. As shown by Gibbons and Henderson (2012), management practices can be a key reason for persistent performance differences across firms in the presence of relational contracts, while Brynjolfsson and Milgrom (2013) emphasize the role of complementarities among practices. Furthermore, Halac and Prat (2014) show that "engagement traps" can lead to heterogeneity in the adoption of practices even when firms are *ex ante* identical. This paper contributes to the empirical literature on the effects of management practices by examining the first large sample of firms in a developed country.

This lack of prior research arises from the absence of large sample data on management practices across plants and firms. This paper exploits a new U.S. Census dataset on management practices – the Management and Organizational Practices Survey (MOPS). This is the first ever mandatory government management survey, covering over 30,000 plants across more than 10,000 firms.[2] The size of the dataset, its coverage of units *within* a firm, its links to other Census data as well as its comprehensive coverage of industries and geographies within the U.S. makes it unique in

[1] Walker was also the second president of MIT and the vice president of the National Academy of Sciences.
[2] See the MOPS description in Bloom, Brynjolfsson, Foster, Jarmin, Saporta-Eksten, and Van Reenen (2013) and Buffington, Foster, Jarmin and Ohlmacher (2016)

addressing some of the major gaps in the recent management literature.

We start by examining the variation in management practices across plants showing three key results. First, there is enormous variation across plants in management practices. While 18% of establishments adopt three quarters or more of a package of basic structured management practices for performance monitoring, targets and incentives, 27% of establishments adopt less than half of such practices. Second, almost half of this 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.[3] The analogy for universities would be that variations in management practices across departments *within* universities are 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, consistent with more local variation in larger firms, which appears to be largely explained by large firms greater industrial and geographic spread.

We then turn to examining whether our management measures are linked to performance. We find that plants using more structured management practices have greater productivity, profitability, innovation (as proxied by R&D and patent intensity) and growth. This relationship is robust to a wide range of controls including industry, education, establishment and firm age, and potential survey noise. The relationship between management and performance also holds over time within establishments (establishments that adopt more of these practices between 2005 and 2010 also saw improvements in their performance in 2010 and after) and across establishments within firms at a point of time (establishments within the same firm with more structured management practices achieve better performance outcomes). These management practices also have a highly significant predictive power for future growth and firm survival up to three years ahead (the current limit of our future data).

The magnitude of this management-productivity relationship is large. Increasing structured

[3] A literature beginning with Schmalensee (1985) has examined how the variance in profitability of business across business units decomposes into effects due to company headquarters, industry and other factors. The plants we examine are more disaggregated than business units and are closer to the US business population than this earlier work.

management from the 10th to 90th percentile can account for about 18% of the comparable 90-10 spread in firm TFP. In the same dataset we also examine the association of productivity with other common drivers, and find that the 90-10 spread in R&D accounts for about 17% of the spread in TFP, employee skills about 11% and IT expenditure per employee about 8%. Of course, all these magnitudes are dependent on a number of other factors, like the degree of measurement error in each variable, but they do highlight that variation in management practices is likely a key factor accounting for variation in TFP. These factors are also interrelated, so when we examine them jointly we find they account for about 33% of the total variation in 90-10 productivity. Given estimates that about 50% of the variation in productivity is measurement error (Collard-Wexler, 2013 and Bloom, Floetotto, Jaimovich, Saporta and Terry, 2016), this suggests that these factors – management, innovation, IT and skills – account for maybe two-thirds of the real spread in firm productivity.

We next examine some "drivers" of management practices. Our analysis is focused on four potential candidates: product market competition, business environment, learning spillovers from large manufacturing plant entry (primarily plants of multinational corporations) and education. The unique features of our data allow us to utilize plausibly exogenous variation which will help identify plausibly causal effects of the different drivers on the adoption of management practices.

To evaluate the causal impact of product market competition, we undertake two strategies. First, we calculate the Lerner index for our plants. Second, we exploit changes in exchange rates that differentially effect industries over time. We find a positive impact on management practices, particularly for those in the lower tail of the structured management distribution.

On business environment, we exploit both the location of plants around the border between "Right to Work" and non-"Right to Work" states, and also the location of firms' oldest surviving plants in multi-plant firms, to identify impacts of business environment on management practices. We find "Right to Work" rules, which proxy for the state business environment, including reduced influence of labor unions as well as "pro-business" policies such as more lax environmental and safety regulations (see Holmes, 1998), seem to increase structured management practices around firing and promotions but seem to have little impact on other practices.

To investigate learning spillovers we build on Greenstone, Hornbeck and Moretti's (2010) identification strategy using "million-dollar-plants" – 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 significant positive impacts on management practices, TFP and employment. Interestingly, these positive effects only occur if the winning plant was also a manufacturing plant, suggesting localized management practice spillovers tend to be mainly within the same sector.

Finally, to obtain causal impacts of education, we follow Moretti (2010) to use the quasi-random location of land-grant colleges as an instrument for local labor supply. We find large significant effects on management practices of being near a land-grant college despite a range of controls for other local variations in population density, income and other county- and firm-level controls.

Back of the envelope estimates suggest that these four drivers account for around a third of the 90-10 between plant spread of structured management practices.

The paper is structured as follows. In Section 2 we describe the management survey, in Section 3 we detail the variation of management practices across and between firms, and in Section 4 we outline the relationship between management and performance, while in Section 5 we examine potential drivers of management practices. Finally, in Section 6 we conclude and highlight areas for future analysis.

2 Management and Organizational Practices Survey

The Management and Organizational Practices Survey (MOPS) was jointly funded by the Census Bureau and the National Science Foundation as a mandatory supplement to the Annual Survey of Manufactures (ASM).[4] The original design was based in part on a survey tool used by

4 For more details see Buffington et al. (2016).

the World Bank and adapted to the U.S. through several months of development and cognitive testing by the Census Bureau. It was sent electronically as well as by mail to the ASM respondent for each establishment,[5] which was typically the accounting, establishment or human-resource manager. Most respondents (58.4%) completed the survey electronically, with the remainder completing the survey by paper. Non-respondents were mailed a follow-up letter after 6 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 merging internet and paper collection data caused some respondents to receive the first follow-up even though they had responded. We exploit this accident to develop a strategy to deal with measurement error in the management scores.

2.1 Measuring Management

The survey contained 16 management questions in three main sections: monitoring, targets and incentives, based on Bloom and Van Reenen (2007), which itself was based in part on the principles of continuous monitoring, evaluation and improvement from Lean manufacturing (e.g. Womack, Jones and Roos, 1990). The survey also contains questions on other organizational practices (such as decentralization) as well as some background questions on the establishment and respondent.

The monitoring section asked firms about their collection and use of information to monitor and improve the production process. For example, how frequently were performance indicators tracked at the establishment, with options ranging from "*never*" to "*hourly or more frequently*." The targets section asked about the design, integration and realism of production targets. For example, 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, how were managers promoted at the

[5] The Appendix provides more details on datasets.

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*." The full questionnaire is available on http://www.census.gov/mcd/mops/how_the_data_are_collected/MP-10002_16NOV10.pdf.

In our analysis, we aggregate the results from these 16 check-box questions into a single measure of "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 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.

2.2 Sample and Sample Selection

Overall, 49,782 MOPS surveys were successfully delivered, and 37,177 responses were received, yielding a response rate of 78%, which is similar to the response rate to the main ASM survey. For most of our analysis, we further restrict the sample for establishments with at least 11 non-missing responses to management questions and also have positive value added, positive employment and positive imputed capital in the ASM. Table A3 shows how our various samples are derived from the universe of establishments.[6]

Table A2 provides more descriptive statistics on the samples we use for analysis. The mean establishment size is 167 employees and the median (fuzzed) is 80. The average establishment in

[6] Table A1 reports the results for linear probability models for the different steps in the sampling process. We show that establishments which 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.

our sample has been in operation for 22 years, 44% of managers and 9% of non-managers have college degrees, 13% of their workers are in unions, 42% export and 69% are part of larger multi-plant firms. Finally, Table A3 shows some statistics on the MOPS sample selection, noting that slightly larger plants appeared more willing to respond.

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 the Appendix, we also combine capital stock data from the Census of Manufactures (CM) with investment data from the ASM and apply perpetual inventory method to construct capital stocks at the establishment level which we use to create measures of total factor productivity. For innovation, we use firm-level data from the 2009 Business R&D and Innovation Survey (BRDIS) on R&D expenditure and patent applications by the establishment's parent firm. Finally, we use Compustat to calculate Tobin's q for the parent firm and match these measures to establishments in publicly traded parent firms. Since the Compustat-SSEL bridge is only updated up to 2005, we focus on analysis of the MOPS 2005 recall questions when using Compustat (companies who are publicly listed on the U.S. stock market).

3 Management Practices across Plants and Firms

Figure 1 plots the histogram of the aggregated management score, displaying an enormous dispersion of practices across plants. While 18% of establishments earn 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 (so they adopt less than half the practices).

One important question is to what extent do these variations in management practices across plant occur *within* rather than *between* firms? The voluminous case-study literature on management practices often highlights the importance of variations both within and between organizations, but until now it has been impossible to measure these separately due to the lack of large samples with both firm and plant variation. The benefit of the large MOPS sample is that we have multiple plants per firm, making this the first opportunity to accurately evaluate variations within and between firms.

Before evaluating management spreads within and between firms, we need to address a major challenge, which is the bias induced by measurement error. Measurement error in plant-level management scores will overinflate the plant-level variation and thus bias the role of firm-level variation downwards. Given the estimates in Bloom and Van Reenen (2007) from independent repeat surveys that measurement error accounts for about half of the variation, this is an important issue.

To address this challenge we exploit 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.[7] That is, for this set of plants, two individuals – for example the plant manager and plant comptroller – both independently filled out the MOPS survey. Approximately 1,200 plants from the baseline sample completed the survey more than once, either once on paper and once online or twice on paper, with about 500 of them providing a second response filled out by a different respondent. This is most likely because a follow-up letter mailed in error that included a form and online login information was received by a different individual than the original respondent. These double responses provide very accurate gauges of survey measurement error, since within a narrow three-month window we have two measures of the same plant-level management score provided by two independent respondents. From correlation analysis of the two sets of completed surveys we find that measurement error accounts for 45.4% of the management variation across plants.[8] This measurement also turns out to be independent of any firm- or plant-level observable characteristic such as employment or the number of plants in the

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7 For disclosure avoidance reasons we cannot provide exact sample sizes, but this data is available in the RDC.

8 Assuming the two responses have independent measurement error with standard-deviation σ^M , and defining σ^T as the true management standard-deviation, the correlation between the two surveys will be $\sigma^T/(\sigma^T+\sigma^M)$. Interestingly, this 45.4% share of the variation from measurement error is very similar to the 49% value obtained in the World Management Survey telephone interviews (Bloom and Van Reenen, 2010).

firm (see Appendix Table A4), and thus appears to be effectively white-noise.

Armed with this estimate of 45.4% 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[9] out of 31,793 plants in the sample which are in multi-plant firms with two or more plants in the MOPS survey. While this sample only contains 44% of the overall sample, they are larger plants, and thus account for 74% of total output in the MOPS sample.

Figure 2 plots the share of the plant-level variation in the management score accounted for by the parent firm in firms with 2 or greater plants after scaling by (0.546=1-0.454) to account for the measurement error. To understand this graph, first note that the top left point is for firms with exactly 2 plants. For this sample firm fixed effects account for 90.4% of the adjusted R-squared in management variation across plants[10], with the other 9.6% is 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.

In Figure 2 moving along the x-axis, we see that the share of variation attributable to the parent firm is declining as the firm-size rises – so, for example, in firms with 50-74 plants the parent firm accounts for about 40% of the management variation, and in firms with 150+ plants the parent firms accounts for about 35 % of the variation. Hence, in sample of plants from larger firms there is relatively more within-firm variation and relatively less cross-firm variation in management practices.

From this figure two important results arise. First, both plant- and firm-level factors are important in explaining differences in management practices across plant, with the average share

[9] Note that because of clearance restrictions, many sample sizes have been rounded.

[10] 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 – shown in Appendix Figure A1 - 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.

of management variation accounted for firms being 58% (so 42% is across plants with the same firm). Second, the share of management practice variations accounted for by the parent firm is declining in the overall size of the firm, as measured by the number of establishments. This is because larger firms have less alignment of their management practices across their plants. Interestingly, in the MOPS survey we also asked about the extent of decentralization of plant-level decisions over hiring, investment, new products, pricing and marketing and found this was also significantly higher in larger firms (see Aghion et al., 2015). In the Appendix Table A5 we show that within firm variation of management is correlated with factors in an intuitive way - firms operating across more industries and geographic regions have significantly greater within firm dispersion.

4 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 measures of performance (productivity, growth, survival, profitability, and innovation). We do not attribute a causal interpretation to the results in the section, but rather think about these results as a way to establish whether this management survey is systematically capturing meaningful content rather than just statistical noise.

4.1 Management and Productivity

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

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

where Y_{it} is real value added (output - materials), A_{it} is productivity (excluding management practices), K_{it} denotes the establishment's capital stock at the beginning of the period, L_{it} are labor inputs, X_{it} is a vector of additional factors like industry and education, and M_{it} is our management score.[11] Management is an inherently multi-dimensional concept, so for this study we focus on a single dimension, the extent to which firms adopt more structured practices.[12]

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

$$Log\left(\frac{Y_{it}}{L_{it}}\right) = \alpha \log\left(\frac{K_{it}}{L_{it}}\right) + (\beta + \alpha - 1)\log\left(L_{it}\right) + \gamma X_{it} + \delta M_{it} + f_i + e_{it} \qquad (2)$$

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

In Table 1 column (1) we start by running a basic regression of labor productivity (measured as log(value added/employee)) on our management score without any controls. We find a highly significant coefficient of 1.272, suggesting that every 10% increase in our management score is associated with a 13.6% (13.6% = exp(0.1272)) increase in labor productivity. To get a sense of this magnitude, our management score has a sample mean of 0.64 and a standard deviation of 0.152 (see the sample statistics in Appendix Table A2), so that a one standard-deviation change in management is associated with a 21.3% (21.3% = exp(0.152*1.272)) higher level of labor productivity (see also Table 2). We provide a more detailed analysis of magnitudes in sub-section 2.3.

In column (2) of Table 1 we estimate the full specification from equation (1) with capital intensity, establishment size and employee education, industry dummies and "noise controls" (for potential survey bias). This reduces the coefficient on management to about 0.5.[13] 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

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11 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.

12 The individual practices are highly correlated which may reflect a common underlying driver or complementarities among the practices (See e.g. Brynjolfsson and Milgrom, 2013). In this exercise we use the mean of the share of practices adopted, but other aggregate measures like the principal factor component or the average z-score yield extremely similar results.

13 Employee education is calculated as a weighted average of managers' and non-managers' education.

measure. Using the 2005 recall questions, matched to the 2005 ASM files, we can construct a two period panel of management, productivity and other controls, to at least partially address this concern over omitted factors. 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 (1)), we can difference them out by running a fixed effect panel regression (the same as a long-difference). Column (3) reports the results for the 2005-2010 pooled panel regression (including a 2010 time dummy).[14] The coefficient on management, 0.298, remains significant at the 1%. Of course this coefficient may still be upwardly biased if management practices are proxies for time-varying unobserved coefficients. 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.[15]

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 we can find a correlation between structured management and labor productivity *within* a firm. When including a firm fixed effect the coefficient on management is identified solely off the variation of management and productivity across plants within each firm in 2010. Column (4) shows our OLS estimates for the sub-sample of multi-establishment firms with firm-effects, so that we are comparing across establishments within the same firm. The within firm management coefficient of 0.233 is highly significant. Hence, even within the very same firm when management practices differ across establishments, we find large differences in productivity associated with these variations in management practices.

4.2 Management and Growth, Profitability and Innovation

In column (5) of Table 1 we examine another performance measure – future employment growth between 2010 and 2013 (currently the most recent year of data) - and show that establishments

[14] Note that for each year the sample is smaller, as we now require non-missing controls also for 2005.

[15] 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.

with more structured management practices grew significantly faster.[16] Column (6) adds total factor productivity as another explanatory variable constructed following the standard approach in Foster, Haltiwanger and Krizan (2000), and not surprisingly finds this also has predictive power for future employment growth. Interestingly, adding TFP does not substantially diminish the coefficient on management, suggesting that both TFP and management provide predictive power for future firm employment growth. Moreover, we also see that the t-statistic on management (~10) is more than double the t-statistic on TFP (~4), which highlights how informative the management score is for plant performance. Columns (7) and (8) perform a similar analysis for a plant's exit probability between 2010 and 2013, and we again find that the management score is highly predictive of future performance. In terms of magnitudes, the unconditional probability of exit between 2010 and 2013 is 7% in our sample, and a one standard deviation increase in management is associated with a 2 percentage point decline in this exit probability. For comparison, a one standard deviation increase in TFP is associated with a 0.8 percentage point decline in exit probability. Column (9) looks at profitability (operating profits divided by sales) and finds establishments with higher management scores are significantly more profitable. Finally, Column (10) looks at a classic measure of innovation – R&D spending per employee – and finds a strongly positive significant correlation with management for a sample of MOPS plants that match the Business Research and Development and Innovation Survey.[17]

We also ran a series of other robustness tests on Table 1, 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.

A non-parametric description of these management and plant performance correlations is shown in Figure 3. This confirms the robust positive and broadly monotonic relationship between structured management and productivity, profitability, growth, exporting, R&D and patenting reported in the regression analysis. Figure 4 cuts the data in another way, plotting the size of establishments and firms against their management scores, showing a continuous positive

[16] To make interpretation and comparison between management score and TFP easier, both management and TFP are normalized by their standard deviation in columns (5)-(8).

[17] Running the same regression on another measure of innovation, log(1+patents), we find a similarly significant coefficient (standard error) of 0.510 (0.101).

relationship from sizes of 10 employees upwards. These figures show that both establishment and firm management scores are rising in size until they reach about 5,000 employees when the relationship levels off. This difference is also quantitatively large. A firm with 10 employees has a management score of 0.5 compared to 0.7 for a firm with 1,000 employees (comparable to moving from approximately the 20^{th} percentile to the 70^{th} percentile of the management score distribution).

4.3 Magnitudes of the Management and Productivity Relationship

To get a better sense of the magnitudes of the management-productivity relation, we compare management to other factors that are considered to be important drivers of productivity: R&D, Information Technology (IT) and human capital. We focus on those three because these are leading factors in driving TFP 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-productivity link. In particular, we ask how much of the 90-10 TFP spread can be accounted for by the 90-10 spread of management, R&D expenditure, IT investment per worker, and human capital (measured as the share of employees with a college degree).

Columns (1)-(4) of Table 2 report the results from firm-level regressions of TFP on those factors. To obtain an aggregate firm-level TFP measure, the dependent variable is calculated as industry-demeaned TFP at the firm level, where the establishments within a firm are weighted by total value of shipments. [18] The bottom row of column (1) shows that the 90-10 spread in management accounts for about 18% of the spread in TFP. In columns (2) to (4) we examine R&D, IT and skills find these measures account for 17%, 8% and 11% of the 90-10 TFP gap. Column (5) shows that the role of management remains large in the presence of the other factors, and that jointly these can account for about a third of the 90-10 spread in TFP. Given estimates that about 50% of firm-level TFP is measurement error (see Collard-Wexler, 2013 and Bloom et al, 2016),

[18] We run the regression at the firm level, because R&D is only measured at the firm level, making it easier to compare between factors. To obtain the firm-level measure, we weight the right hand side variables by their plant's share of total shipments (exactly as we do for the dependent variable).

this indicates these four factors – management, innovation, IT and human capital – can potentially account for about two thirds of the true (non-measurement error) variation in TFP. Moreover, the results in Table 2 also highlight that management practices can account for a relatively large share of this explanatory power for firm-level TFP. [19]

5 Drivers of Management Practices

The previous literature on management has pointed to at a wide variety of potential factors driving management practices. We focus on four factors – competition, business environment, knowledge spillovers and education – which are both regularly discussed in the literature and for which we have good measures with some degree of causal identification.

5.1 Product Market Competition

One of the challenges in evaluating the impact of competition on management is measuring competition. One of the measures of competition most commonly used by economists is the Lerner index,[20] which is defined as (1 – marginal price-cost markup). In practice, the Lerner measure is defined as the average (rather than marginal) markup, measured at the industry level over a recent time period – for example, Aghion et al. (2005) used the average rate of profits/sales over the prior five years. In our evaluation we use the profits (shipments less materials and production wages) to sales ratio in 2007, which was the most recent year of the five-yearly economic census. In Table 3 using this Lerner index at the NAICS six-digit level without any controls (column (1)) and with three-digit industry fixed effects and full controls (column (2)), we find competition is significantly correlated with more structured management practices. In column (3) we also include firm-fixed effects, so we are examining changes in

[19] One obvious concern, however, 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.

[20] The other popular measure is the Herfindahl index, but in manufacturing this is problematic since many competitors are international and our data only covers U.S. firms.

management practices across plants within the same firm against the differences in their Lerner indices (if the plants operate in different industries), and find a positive but not significant relationship.

In columns (4) to (6) of Table 3 we examine *changes* in management practices between 2005 and 2010 against *changes* in the Lerner index between 2007 and 2002 (the most recent Census years preceding the management time dates). Using these difference estimators helps to strip out any time-invariant differences in the measurement of profitability across industries (for example, differences in capital shares given that capital costs are not deducted). In all specifications, we find increases in competition are associated with increases in the management score conditional on surviving. Note that column (6) is a particularly demanding specification as we are allowing for firm specific *trends*, identifying the competition effect solely from differences in the competition shock across plants within the same firm.

Since changes in the Lerner could still be endogenous, we consider a more exogenous shock to competition in columns (7) to (9) which follows Bertrand (2004) in constructing "industry-level exchange rates". Although changes in exchange rates do not vary across industries, the effects of currency changes will be more salient to the sectors who are import more from the country whose value has depreciated against the dollar. Thus, we calculate the industry-specific import shares from each country and multiply this by the change in that country's exchange rate. This creates industry-by-year exchange rates (see Appendix for details). We find that as the U.S. dollar appreciates, increasing domestic competition, the measure of management practices of our U.S. plants significantly increases in all three specifications - without controls, with full firm and industry controls, and with a full set of firm fixed effects. Given that these differences in exchanges rates are driven by factors typically external to the industry – like country-level economic cycles, interest rates and other macro shocks – this provides strong causal evidence for a positive impact of competition on improving management practices.

In Table 4, we examine the relationship between management and competition for different quantiles of the management score. In column (1), we replicate column (1) of Table 3. Columns (2)-(6) report the results from quantile regressions for different quantiles of the conditional management score (0.1, 0.25, 0.5, 0.75 and 0.9). We find there is a much stronger relationship between competition and management at the lower part of the management distribution. In particular, management is increasing in competition almost 5 times faster at the 10^{th} percentile compared to the 90^{th} percentile of the conditional management distribution. These results are consistent with a combination of selection and improvement of firms through competition, which acts in particular to increase the management practices of low scoring plants or force them to exit.

5.2 Business Environment

In trying to understand the variation in management across plants, the business environment in which plants operate is another often-mentioned driver of management practices. We use "Right To Work" (RTW) regulations, which are state-level laws prohibiting union membership or fees from being a condition of employment at any firm. Holmes (1998) finds that RTW laws likely proxy for other aspects of the state business environment, including "pro-business" policies that benefit manufacturers such as looser environmental or safety regulations, subsidies for manufacturing plant construction, and tax breaks that disproportionately benefit manufacturers. At the time of the MOPS survey, 22 states had RTW laws in place, mostly in the South, West and Midwest, with another four states having introduced them since then.[21]

In Table 5 we estimate the impact of RTW laws on management practices in firms. To try to obtain a causal estimate we follow the approach taken by Holmes (1998) who looked at business regulations and state employment. We compare plants in counties that are within 50km (about 30 miles) of state borders which straddle a RTW regulatory change. In column (1) the regression sample is the 5,143 plant-border pairs within 50km of a state-border between two states with different RTW regulations. We see that after controlling for industry and border fixed effects, the

[21] These are Indiana and Michigan in 2012, Wisconsin in 2015, and West Virginia in 2016, all but the latter of which we will examine in the 2015 MOPS survey wave.

plants on the RTW side of the border have significantly higher management scores.[22] One explanation for this result is that RTW regulations make it easier for firms to link hiring, firing, pay and promotion to employees' ability and performance, thereby increasing their structured management scores.

An alternate explanation is that plants with more structured management practices sort onto the RTW side of the border, possibly because of these RTW regulations or other correlated "pro-business" factors. In column (2) 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 sort on location because of high transport costs.[23] Again, we find RTW states have significantly higher management scores within this sample of relatively non-tradable products for which selecting production location based on "business-friendly" conditions is particularly hard.

As an alternative approach, column (3) takes the sample of all firms with plants in both RTW and non-RTW states, and then divides them by whether the *oldest* surviving plant in the firm is located in a RTW state or not. The idea here is that if the oldest plant in a firm is in a RTW state, the firm management practices are likely to be more tailored to this regulatory environment because of persistence of management practices within firms over time. That is, if the firm was likely founded in a RTW state, and if management practices are somewhat sticky over time within firms, we should see more recently opened plants inheriting some of the practices from the founding plant. Indeed, we see in column (3) that firms with their oldest plants in a RTW state have significantly higher management scores than those with their oldest plants in a non-RTW state, even after including industry and state fixed-effects. This means, for example, that if two plants from different firms were both based in California, but one firm had its oldest plant in Texas (a RTW state) and the other in Massachusetts (a non-RTW state), the plant from the Texan firm would typically have a higher management score. In column (4), rather than using the oldest

[22] These results are also significant when comparing directly between all plants in RTW vs non-RTW states.
[23] Our industry geographic concentration indexes are calculated following Ellison and Glaeser (1997) using the 2007 Census of Manufacturers.

plant, we measure exposure to RTW by the location of the firm's headquarter plant[24] and again find similar results. Columns (5) and (6) push this identification even further by looking only within the set of plants in non-RTW states (column (6)) and RTW states (column (7)), again finding similar results based on the location of the oldest plant in the firm.

In column (7) of Table 5 we use a slightly different cut of the data, focusing on the types of management practices that RTW regulations is likely to support (in part by reducing the influence of unions[25]) – the four questions on the connection between employee ability and performance and promotions and dismissals. We find a large positive significant coefficient. In column (8) we look at the other 12 MOPS questions on monitoring and targets, which are much less directly related to RTW regulations, and find a small but insignificant coefficient.

In summary, we find higher management scores for plants located on the RTW side of a state border compared to those in the non-RTW state on the other side of the border, and this is true even in relatively non-tradable industries where plants typically have limited choice over their location. These differences in management scores appear to be persistent over time so the RTW status of the founding plant in a firm matters, and they arise almost entirely from differences in the promotions and dismissal questions – which are exactly the practices typically influenced by RTW regulations.

5.3 Learning Spillovers

Is it the case that structured management practices "spill over" from one firm to another as would happen if there was learning behavior? With panel data on management, one could ask how management of one establishment is changing with the change in management of a related

[24] The headquarter plant (HQ) is defined as being the establishment in the firm with a NAICS code 551114 (which is "*corporate, subsidiary and regional managing offices*"). If no such establishment exists instead the HQ is defined as the largest plant. Results are robust to only defining the HQ using the largest plant, or only using the sample for which a plant with NAICS code 551114 exists.

[25] Running a regression like column (2), but using a 0/1 dummy for the plant being unionized, generates a highly significant coefficient (standard-error) of -0.056 (0.016).

establishment (through trade, market competition, etc.). It would be impossible, however, to identify a causal effect of management spillovers without exogenous variation in management. To get closer to a causal effect, we study how management in particular counties in the U.S. changes when a new, large and typically multinational establishment, likely to have higher management scores, is opened in the county.[26] 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, which competed for the new establishment (see the Appendix for more details about data construction). 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).

Table 6 contains the results, split into two panels examining all MDPs in Panel A and with manufacturing and non-manufacturing (typically services) split out in Panel B below. Turning first to Panel A in column (1), we see the basic result that in counties where an MDP was opened between 2005 and 2010 we see structured management practice scores significantly increasing compared to the runner-up county. The magnitude of the coefficient is moderately large – winning a large, typically multinational, plant is associated with an improvement of management practices of about 0.017 points which is around 0.1 standard-deviations. Column (2) estimates includes a fuller set of establishment control variables and shows similar results. Columns (3) and (4) look at the change in measured TFP associated with the MDP and find an increase in productivity consistent with the increasing management score, albeit one that is not statically significant. Finally, columns (5) and (6) look at employment and again see a rise (noting this excludes the MDP plant itself by construction, and is instead measuring a rise in employment in pre-existing plants).

In the Panel B of Table 6 we split the MDPs into manufacturing and non-manufacturing and find

[26] Note that we *do not* choose these plant openings using Census data, but using public data only (see more details in the Appendix). 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.

reassuringly that the management, TFP and employment impacts all arise from the manufacturing MDP openings. Given we are examining manufacturing plants in our MOPS data, this is what we would expect – management practices (and hence productivity and wage) improvements will much more rapidly and effectively spillover within industries than across industries. Most manufacturing MDPs are in industries like automotive, aerospace and machinery production in which modern Lean manufacturing practices are highly refined and are applicable across the manufacturing sector. In services the plants span a wide range of sectors – call centers, health-clinics and warehouses – so the management practices spillovers onto domestic manufacturing plants are likely to be far more muted.

One potentially surprising result is the *negative* spillovers of non-manufacturing plants onto the measured TFP of domestic manufacturing plants TFP. The likely reason for this is that the opening of large plants will increase the prices of local inputs (a "congestion effect" as found by Greenstone, Hornbeck and Moretti, 2010). Since our TFP measure uses industry wide factor shares to weight the inputs, these higher inputs prices bias measured TFP downwards. For example, we deflate the plant's material costs by a national index to obtain the quantity of intermediates used. If the MDP increases the local price of materials it will appear as if the plant is using a higher volume of materials than it actually is and so, for a given level of output will have lower measured TFP. This biases downwards the coefficient on both the manufacturing and non-manufacturing MDP so the coefficient in the TFP equation is the net impact of this measurement bias plus any real spillover. Note that this does not affect the management equation as it is independently measured.[27]

Appendix B states these propositions more formally. In particular, if we assume a model where the congestion effects are equal for all MDPs but where only manufacturing plants generate learning spillovers, a manufacturing MDP is associated with about a 22% increase in productivity using column (4) of Table 6.[28]

[27] Another concern is that MDPs may reduce mark-ups through a product market competition effect which will be reflected in lower measured revenue-based TFP ("TFPR" is all we have here). This is unlikely to be the cause of the negative coefficient, however, because our dependent variable is TFPR for manufacturing plants. Non-manufacturing MDPs are not competing in the same output markets as manufacturing plants, so it is hard to see why they should generate a negative effect on mark-ups and TFPR whereas manufacturing MDPs do not.

[28] The share of materials is about 50% on average so using the results in Appendix B, the pure learning spillover effect is 0.20 = 0.106 + (0.5*.184) and (exp(0.2) – 1)*100=22%.

Hence, in summary we see strong evidence for the impact of opening of large, typically multinational plants on the management, productivity and employment of pre-existing local manufacturing plants (but not for the opening of non-manufacturing plants). This highlights the importance of localized within-industry learning spillovers.

5.4 Education

The final driver we investigate is the role of education in shaping firm-level management practices. In Bloom and Van Reenen (2007), education was the explanatory variable of variation in management with the largest t-statistic, but because of the lack of any natural variation in firm-level education it was hard to infer any causal interpretation. In this paper, we combine the county-level information on the location of MOPS plants across the U.S. with the quasi-random location of Land Grant Colleges (LGCs) across counties to construct an instrument for the local supply of educated employees. This instrument builds on the work of Moretti (2004) who uses the quasi-random allocation of land-grant colleges, which were created by the Morrill Acts of 1862 and 1890 and typically located in large empty plots of land in the late 1800s, to examine the impact of education on local productivity and wages. [29]

Table 7 column (1) reports an OLS regression of plant-level management practices on a dummy for whether the county contains a LGC, plus controls for population density and local unemployment rate (as controls for regional-level economic development), alongside industry and state fixed-effects and a range of basic plant-level controls (e.g. size, age, etc.). There is a large and significant coefficient on LGCs suggesting that plants within counties that have a LGC have significantly higher management scores. In columns (2) and (3) we split this sample by the industry median skill level,[30] and find the relationship is larger and significant in the high-skill industries (where educational supply is likely to be more important) compared to the lower-skill industries. In column (4) we run a very exacting test by including firm fixed-effects, comparing

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[29] We match the land grant college locations to metropolitan areas in the U.S. For the list of land grant colleges, we rely on the list in Moretti (2004) as well as the lists in the appendix to Nevins (1962).

[30] To define high skill and low skill industries we calculate the average skill by industry using the % with degree variables, which are collected in MOPS in our sample. We define high skill industries as those with above median industry average and low skill industries as below median.

across plants within the same firm, and find those located near LGCs have significantly higher management scores.

In column (5) of Table 7 we look at the relationship between plant-level management practices and a county-level educational measure, which is the share of 25-60 year olds with a BA degree, and find a large significant coefficient. In column (6) we instrument local college graduate share with the existence of a LGC, again finding a significant coefficient. Finally, in columns (7) and (8) we split by above and below industry median skill share, finding this relationship between management and skill supply to be largest and most significant in highly-skilled industries.

Hence, in summary the increased supply of college graduates seems to lead to more structured management practices, even after controlling for local economic development, suggesting a more direct route for higher-educated employees to lead to more structured management practices.

5.5 Quantification

In this section we attempt a rough quantification the impact of the four drivers we examined. To do this we take the coefficients from our preferred baseline specifications for each driver, and scale the coefficient by that drivers 90-10 to get an implied 90-10 variation for management. We do this for each of the four drivers individually and then sum up the total to get an approximate combined magnitude, noting that positive (negative) covariance of these drivers would increase (decrease) the share of total management variation they account for.[31] In terms of the management 90-10 we are trying to explain this is defined as the observed 90-10 in the data – which is 0.385 (see table A2) – scaled by the share of management variation which is estimated to be real (rather than measurement error) which is 54.6% as discussed in section 3.

Our quantification exercise is clearly very approximate, since there are numerous assumptions

[31] Unfortunately, we cannot run a regression with all four drivers in simultaneously because the samples are non-overlapping. For example, the identification strategy underlying knowledge spillovers means we restrict to "winner" and "loser" counties for MDPs whereas the business environment analysis restricts the sample to the borders of RTW and non-RTW states.

built into this,[32] so the values should be taken as a rough indication of the relative importance of these drivers rather than exact values. With this in mind we see in Table 8 that variations in competition, business regulations and spillovers account for something like 5% to 10% of the variations in management practices. Variations in education appear to account for a larger share at around 15%, which interestingly matches the broad results in Bloom and Van Reenen (2007) in their quantification table VI, where they also find education measures have the largest explanatory role for management. Moreover, collectively these drivers account for about over a third of the variations in management practices, suggesting they are collectively important but other drivers of management are likely to play an important role.

6 Conclusions and Future Research

This paper analyzes a recent Census Bureau survey of structured management practices in over 30,000 plants across the U.S. Analyzing these data reveals massive variation in management practices across plants, with strikingly about 50% of this variation being across plants *within* the same firm. These management practices are tightly linked to performance, and 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. Examining the drivers of these management practices, we uncover four factors that are important for increasing the degree of implementation of structured management practices: product market competition, state business environment (as proxied by "Right to Work" laws), learning spillovers from the entry of Million Dollar Plants and education.

Although all of these drivers are qualitatively important, their quantitative size is not enormous, with our estimations suggesting they collectively account for about a third of the variation in management practices. This leaves ample room for new theory, data and designs to help

[32] For example that our results for each driver are causal, that the 90-10 for each driver matches up to the same population for the 90-10 for the management data, that for our total the drivers are orthogonal to each other, and that the measurement error share of the management for the 90-10 is the same as for the whole sample. Despite these are other caveats we think it is useful to get a rough magnitude for the role of these drivers, with our results indicating they appear to play a substantial role (e.g. greater than 10% combined) but do not explain the large majority of management variation (e.g. less than 75% combined).

understand one of the oldest questions in economics and business - why is there such large heterogeneity in management practices?

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Table 1: Establishments Management Scores and Performance

Dependent Variable	Log(VA/Emp)				Emp. Growth 2010-2013		Exit 2010 to 2013		Profit/Sales	R&D/ Emp
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Management	1.272***	0.498***	0.298***	0.233***	0.060***	0.058***	-0.020***	-0.020***	0.058***	0.385***
	(0.05)	(0.037)	(0.065)	(0.082)	0.004	0.005	0.002	0.002	(0.01)	(0.104)
Log(Capital/Emp)		0.179***	0.036*	0.193***					0.01***	0.12***
		(0.007)	(0.02)	(0.016)					(0.002)	(0.016)
Log(Emp)		-0.035***	-0.198***	-0.064***					0.001	0.102***
		(0.006)	(0.029)	(0.012)					(0.002)	(0.014)
Share employees w. a college degree		0.418***	-0.096	0.421***					0.004	1.008***
		(0.041)	(0.138)	(0.076)					(0.011)	(0.09)
Productivity (TFP)						0.032***		-0.008***		
						0.005		0.002		
Observations	31,793	31,793	35,688	17,235	31,793	31,793	31,793	31,793	31,793	13,888
Num. establishments	31,793	31,793	17,844	17,235	31,793	31,793	31,793	31,793	17,843	4,914
Num. firms (clusters)	17,843	17,843	10,557	3,285	17,843	17,843	17,843	17,843	17,843	4,914
Fixed Effects	None	Industry	Establish.	Firm	Industry	Industry	Industry	Industry	Industry	Industry

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 at least 11 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 columns (1) through (4) the dependent variable is log(real value added over total employment). In columns (5) to (6) the dependent variable is employment growth between 2010 and 2013. Growth is calculated as $0.5*(e_{2013}- e_{2010})/ (e_{2013}+e_{2010})$. In columns (7) to (8) the dependent variable is a dummy that takes the value of 1 for exit between 2010 and 2013. In columns (5)-(8), both TFP and management are normalized by their standard deviation for easier comparison of their association with growth and exit. In column (9) profits are measured by value added minus wages and salaries over total value of shipments. Dependent variable in column (10) is log(1+(R&D per 1000 employees)) from BRDIS. When we include establishment fixed effects, we pool the years 2005 and 2010 with a dummy for 2010. Noise controls include: the absolute difference in reported employment in the ASM and MOPS; a dummy for whether filing was online (zero if by mail); filing date; day of week; respondent tenure and seniority.

Table 2: Drivers of TFP variation

	(1)	(2)	(3)	(4)	(5)
Dependent variable:		**Revenue based Total Factor Productivity**			
Management score	0.684***				0.495***
	(0.040)				(0.041)
R&D		0.098***			0.073***
		(0.009)			(0.009)
IT/worker			0.015***		0.008***
			(0.003)		(0.002)
Skills (% employees				0.527***	0.126**
with college degree)				(0.060)	(0.057)
Observations	17,843	17,843	17,843	17,843	17,843
Share of 90-10 explained	0.181	0.169	0.0752	0.111	0.325

Notes: OLS coefficients with standard errors in parentheses (clustered at the firm level). Dependent variable is firm level TFP built from industry de-meaned plant-level TFP 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, IT investment per worker (1000*investment in computers per employee), skill measured by the share of employees (managers and non-managers) with 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.

Table 3: Management and Competition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable:	**Management**			**Change in Management**					
1-Lerner	0.134***	0.053**	0.014						
	(0.043)	(0.023)	(0.024)						
Change in (1-Lerner)				0.024**	0.030**	0.035**			
				(0.011)	(0.012)	(0.018)			
Change in Industry Exchange Rate							0.102***	0.097***	0.111**
							(0.036)	(0.029)	(0.053)
Full controls		Yes	Yes		Yes	Yes		Yes	Yes
Naics3 FE		Yes	Yes		Yes	Yes		Yes	Yes
Firm FE			Yes			Yes			Yes
Sample	Baseline	Baseline	Baseline	Panel	Panel	Panel	Panel	Panel	Panel
Observations	31,793	31,793	31,793	17,844	17,844	17,844	17,844	17,844	17,844

Notes: The sample in columns (1) to (3) is our baseline sample, and in columns (4) to (9) the panel sample of establishments that have management data for both 2005 and 2010. The right hand side variable is the level of the Lerner index of competition in 2007 columns (1)-(3), and in columns (4) to (6) the change in the Lerner Index from 2002-2007. In columns (7)-(9) the dependent variable is the change in the 4-digit industry measure of exchange rates weighted up using initial period industry trade-shares (noting high values mean a strong dollar, so more competition). Full controls include ASM size (log employment), log capital stock, share of employees with a degree, responder tenure, with values for all controls in 2010 for levels results and in 2005 and 2010 for difference results. Standard errors clustered at the NAICS 6-digit industry level.

Table 4: Competition quantiles

Dep variable: Management Score	(1)	(2)	(3)	(4)	(5)	(6)
Quantile	All	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}
Lerner index	0.134***	0.270**	0.197**	0.143**	0.084*	0.056
	(0.043)	(0.115)	(0.077)	(0.058)	(0.048)	(0.043)
Observations	31,793	31,793	31,793	31,793	31,793	31,793

Notes: Quantile regressions of management score on a competition measure. The sample is our baseline sample. The independent variable is the Lerner measure of competition. Column (1) is replicating column (1) from Table (3) with the addition of the full controls from columns (2)-(3) of Table 3. Columns (2)-(6) correspond to a different quantile regression with the relevant quantile listed at the top of each column. Standard errors are robust to conditional heteroscedasticity (see Koenker, 2005).

Table 5: Management and Business Environment

Dependent variable:	**Management Score**						**Promotion & dismissals**	**All but promotions & dismissals**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RTW state	0.014**	0.022***					0.031***	0.008
	(0.006)	(0.008)					(0.007)	(0.006)
Oldest in RTW state			0.027***		0.030***	0.021***		
			(0.002)		(0.002)	(0.004)		
HQ in RTW state				0.015***				
				(0.003)				
Establishments:	5,143	2,929	16,280	16,280	9,152	7,128	5,143	5,143
Distance from border:	<=50km	<=50km	All	All	All	All	<=50km	<=50km
Sample	All	Non-Tradable	Multi-Unit	Multi-Unit	Multi-Unit, in NRTW	Multi-Unit, in RTW	All	All
Border FE	Yes	Yes	n/a	n/a	n/a	n/a	Yes	Yes
State FE	n/a	n/a	Yes	Yes	Yes	Yes	n/a	n/a

Note: An observation is columns (1)(2), (7) and (8) are establishment-border combinations across a "Right To Work" (RTW) and Non-RTW (NRTW) borders. Non-Tradables are the 118 industry categories (out of 472) with the lowest regional concentration level calculated following Ellison and Glaeser (1997) using data from the 2007 census. Columns (3) to (6) sample includes all establishment in multi-unit firms with at least on establishment in a RTW and one-establishment in a NRTW state. We consider a firm to have a RTW headquarter if it has at least one establishment in the LBD with NAICS code 551114 "*corporate, subsidiary and regional managing offices*" located in a RTW state. If no establishment in the firm has this NAICS code we instead define the HQ as the oldest establishment in the firm. Standard errors using the establishment-border data clustered at the border level, while standard errors in columns (3) to (6) are clustered at the firm level. All specification include industry fixed-effects.

Table 6: Management Knowledge Spillovers

Dependent variable:	**Change in Management**		**Change in TFP**		**Change in Log(employment)**	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All Industries pooled						
Million Dollar Plant Opens	0.017***	0.013**	0.032	0.026	0.124***	0.126***
	(0.006)	(0.005)	(0.050)	(0.050)	(0.020)	(0.018)
Panel B: Manufacturing MDPs Split Out						
Million Dollar Plant Opens×(Manufacturing)	0.021***	0.016***	0.110***	0.106***	0.159***	0.157***
	(0.003)	(0.003)	(0.026)	(0.026)	(0.014)	(0.017)
Million Dollar Plant Opens× (Non-Manufacturing)	0.008	0.003	-0.175***	-0.184***	0.034	0.045
	(0.014)	(0.013)	(0.059)	(0.06)	(0.051)	(0.05)
Full Controls:	No	Yes	No	Yes	No	Yes
Observations	1,152	1,152	1,152	1,152	1,152	1,152

Notes: The sample in all columns is our baseline sample (all MOPS observations with at least 11 non-missing responses to management questions with 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) restricted to plants in counties that were considered by "Million Dollar plants" (MDPs) as part of the site selection process between 2005 and 2010 (inclusive). The dependent variable is the change from 2005 to 2010 in - for columns (1)-(2): change in management score winsorized at top and bottom 1%, columns (3) and (4) log(TFP), columns (5) and (6) change in log(employment). 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 fixed effects and standard errors are at the pair level. Full controls include establishment age, age squared, share of employees with a degree and share of employees in a union. The top panel and bottom panel report results of different regressions.

Table 7: Management and Education

Dependent variable: Management Score								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Specification	OLS	OLS	OLS	OLS	OLS	IV	IV	IV
Sample		Industry skill above median	Industry skill below median				Industry skill above median	Industry skill below median
Land Grant in MSA^	0.528**	0.614**	0.438	0.418*				
	(0.211)	(0.285)	(0.314)	(0.254)				
Share in county with BA+					0.037***	0.133**	0.149**	0.116
					(0.012)	(0.054)	(0.070)	(0.081)
Population density (2000)	-0.309***	-0.318**	-0.304**	-0.120*	-0.433***	-0.778***	-0.840***	-0.711**
	(0.113)	(0.123)	(0.125)	(0.073)	(0.120)	(0.218)	(0.274)	(0.304)
Unemployment rate	-0.025	0.015	-0.067	0.135***	0.021	0.163*	0.244*	0.083
	(0.050)	(0.077)	(0.053)	(0.049)	(0.049)	(0.088)	(0.132)	(0.117)
1^{st} stage F-stat						31.42	35.82	24.89
Firm FE	No	No	No	Yes	No	No	No	No
Observations	31,793	16,414	15,379	17,235	31,793	31,793	16,414	15,379

Notes: All columns have industry and state fixed effects. All columns have establishment controls are log(employment), log(age), multi-unit dummy, exporter dummy and union share. High skill and low skill industries are above and below median industries using the degree variable in our sample. Coefficient and standard error on Land Grand Colleges multiplied by 100. Standard errors clustered at the MSA level.

Table 8: Quantification of Management Drivers

	Driver 90-10	Coefficient	Implied 90-10	Implied share of true management 90-10
	(1)	(2)	(3)	(4)
Competition	0.25	0.053	0.013	6.3%
Business Regulation	1	0.022	0.022	10.5%
Spillovers (Million Dollar Plants)	1	0.013	0.013	6.2%
Education	0.25	0.133	0.033	15.7%
Total				**38.7%**

Notes: *"Driver 90-10"* is the 90-10 spread of the variable in the data (for competition and education this comes from estimates from Compustat and the ACS since we have not yet cleared out sample values). "*Coefficient*'" is our regression coefficient from our preferred regression result for that driver – which for competition, business regulation, spillovers and education is col (2) Table 3, col (3) Table 5, col (2) Table 6, and col (6) Table 7 respectively. The "*Implied 90-10*" is column (1) multiplied by column (2). Finally, "*Implied share of true management 90-10*" is the implied 90-10 from column (3) as a percentage of 0.210, which is our calculated true management 90-10. This value of 0.210 comes from the measured management 90-10 (which is 0.385, as shown in Table A2) multiplied by the 0.546 (the share of this variation that is real rather than measurement error as discussed in Section 3).

Online Appendices – Not Intended for Publication
Appendix A: Data

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.[33]

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 11 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). Table A3 shows how the numbers of firms and average employment changes as we condition on different sub-samples.

In Table A1 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 which 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, there also seems to be an unexplained sample or mail error that contributes to the fact that some ASM respondents did not receive the MOPS. 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.[34] First, the responses to of the 16 management each 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. 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 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.[35] Second, the

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[33] This paragraph is 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

[34] The full survey instrument is available on http://www.census.gov/mcd/mops/how_the_data_are_collected/MP-10002_16NOV10.pdf

[35] 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.

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.

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 scaled up by the share of managers and non-managers in the firm calculated from the response to questions 32 and 33.

Additional Databases:
Establishment level: Our primary source of establishment-level external data is the ASM from 2003 to 2010. We use the CM from 2002 and 2007 to obtain data on capital stocks, which is then combined with the ASM data on investment flows to impute capital stock for 2005 and 2010 (see details below). The CM has been conducted every 5 years (for years ending 2 and 7) since 1967. 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, 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 1 of the main paper.

Firm level: 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 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.[36] We use Compustat to calculate Tobin's q for firms. We then use the FIRMID variable to match establishments to the Compustat-SSEL bridge which allows us to match establishments with publicly traded parent firms to the parent firm record in Compustat. Since the Compustat-SSEL bridge is only updated up to 2005, we focus on analysis of the MOPS 2005 recall questions when using Compustat.

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.[37] 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.[38]

Competition: We use cross-sectional as well as changes in the industry competition measures to study the effect of competition on management. For import penetration, we use publically available trade data by detailed NAICS

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

[37] See: http://www.nber.org/data/nbprod2005.html for the public version. We thank Wayne Gray for sharing his version of the dataset that is updated to 2009. Since The NBER-CES data are available only up to 2009, we use the 2009 values for 2010 for all external data. There are 2 industries (327111, 327112) that are missing MATCOST for 2008, and two (331411, 331419) that are missing it starting 2006. These observations are therefore missing cost shares for (which are used to calculate TFP). For these 4 industries we roll forward the last value for which we have cost shares.

[38] For more details about the relevant variables from the BLS and BEA tables, see the appendix to Bloom, Floetotto, Jaimovich, Terry and Saporta (2012).

codes complied by the U.S. Census.[39] Lerner indexes are calculated by us using the CM. Finally, for exchange rate shocks, we follow Bertrand (2004) and Bloom et al. (2016) in using changes in exchange rates to generate exogenous variation in trade competition. We use three additional data sets in the construction of these exchange rate shocks. The IMF IFS website is used for downloading exchange rates between local currencies of 15 countries and the U.S. dollar. We then obtain price deflators for the 15 countries from the OECD website. We use data from Peter K. Schott's website for exports and imports share by country to generate industry-weighted exchange rates.

Multinationals: We use Site Selection to find "Million Dollar Plants" as described by Greenstone, Hornbeck and Moretti (2008). However, the original feature in Site Selection that lists impactful plant openings stopped in 1997, so we recreate the list based on articles about plant openings and key terms for which to search.[40] The key terms used include "blockbuster deal archive," "runner up," "winning bid," "top deals" and "location report." To include an establishment in the Million Dollar Plants list, we require the following criteria – the winner and runner-up locations announced, at least one runner-up location to be in the U.S., and plant should be started between 2005 and 2010.

Capital Imputation: As mentioned above, the capital measures are based on the CM 2002 and 2007 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 and 2010. 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 in the ASM 2010 but do not follow this criteria:

(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 which 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 2 it is deflated using industry level deflators.
Value added TFP: Value-added TFP is calculated using cost shares following for example Foster, Haltiwanger, and Krizan (2001).[41] Our log TFP measure is defined as

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

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

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

Finally, to recover α and β we use cost share at the industry 6-digit NAICS industry level. The total cost of labor inputs for industry j (c_j^L) is taken from the NBER-CES Manufacturing Industry Database (PAY). The cost of capital

39 http://sasweb.ssd.census.gov/relatedparty/

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

41 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.

(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

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

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

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

(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})/ (0.5*emp_{201}+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 2 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 2, the dependent variable is log(1+R&D intensity).

Patent intensity: R&D intensity is defined as (patent applications)/(domestic employment). In Figure 2 we report this measure multiplied by a 1,000. In the footnote to the text discussing Table 2, the dependent variable is log(1+patent intensity).

Interview and Interviewee Characteristics: For many of the regressions we run, we check that the results are robust to including interview and interviewee Characteristics, referred to as "noise" controls or variables. These include:

- Measures for the distance between ASM and MOPS reported employment for 2005 and 2010. These are calculated as the absolute values of the difference between the MOPS and ASM reported March employment for 2010 and 2005 respectively.
- Online filing indicator.
- Date of filing in calendar weeks and the date squared. This variable would capture differences in filing patterns between early and late respondents.
- Day of week.
- Tenure of the respondent, calculated as number of years since the respondent started working at the establishment (see MOPS question 31).
- Seniority of the respondent, introduced as a set of dummy variables to capture the categories in MOPS question 30 (CEO or Executive Officer, Manager of multiple establishments, Manager of one establishment, Non-manager, Other).

Appendix B: Productivity and Million Dollar Plants – congestion, spillovers and market power

We illustrate the problem of determining the impact of MDPs on knowledge spillovers in the face of congestion costs driving up local input prices (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.)

Baseline Model with congestion

Consider our standard Cobb-Douglas production function:

$$logY_i \quad = logA_i \; + \alpha logK_i \; + \beta \log L_i \tag{B1}$$

Where Y_i is output of plant *i*, L is labor and K is capital that are supplied at a user cost w_c^K in county *c*. A natural way of thinking about this is that there is some national cost of capital (e.g. based on national interest rates) and a local component (e.g. commercial rents which depend on the constrained local supply of land). For now, assume other factor inputs are supplied solely in national markets, so there is no local component. 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 sometime industry) price deflator (w^K). We therefore measure capital inputs as $\overline{K_\iota} = \frac{w_c^K K_i}{w^K}$.[42] The relationship between measured and real capital in logs is:

$$Log\overline{K_\iota} = logK_i \ + log\left(\frac{w_c^K}{w^K}\right) \tag{B2}$$

The measurement error will depend on the deviation of factor prices between local and national costs $\left(\frac{w_c^K}{w^N}\right)$.

Define the presence of a Million Dollar Plant (*MDP*) in the county where the plant is located as MDP_c = 1 and zero otherwise. We assume that there are two potential effects of an *MDP*. First, as discussed in the text and argued in Greenstone et al (2010) there may be an effect of MDPs on the productivity of other plants in the area (e.g. via learning better management practices). We parameterize this effect as:

$$logA_i = logA_0 + \pi MDP_c \tag{B3}$$

Where we expect $\pi \geq 0$. Second, the presence of an *MDP* could increase local factor prices by driving up the costs of commercial rents through higher demand (since the plants are very large). We parameterize this "congestion" effect as:

$$log\left(\frac{w_c^K}{w^K}\right) = \varphi MDP_c \tag{B4}$$

Where we expect $\varphi \geq 0$. Substituting equation (B3) and (B4) into the production function (B1) gives us an expression for the output relationship (using measured capital) as:

$$logY_i \ = (\pi - \alpha\varphi)MDP_c + logA_0 \ + \beta \log L_i \ + \alpha \log \overline{K_\iota}$$

In terms of conventionally measured TFP ("MTFP") we use industry level averages of the factor shares of total costs (s_K, s_L) to measure the output elasticities of the factors (α, β).[43] Under the assumptions of the model this will generate the relationship

$$logMTFP_i \ = (\pi - s_N\varphi)MDP_c + logA_0$$

where[44]

$$logMTFP_i \ = logY_i \ - s_L logL_i \ - s_K \log \overline{K_\iota}$$

It is clear that the coefficient on MDP consists of two offsetting effects $(\pi - s_K\varphi)$. The spillover effect (π) will tend to create a positive coefficient, but the congestion effect (φ) will create a negative coefficient, so the sign on MDP is ambiguous and reflects the net outcome of these two forces.

Manufacturing vs. non-manufacturing MDPs

Can we separately identify the productivity spillover vs. the congestion effect? Consider allowing differential effects for manufacturing vs. non-manufacturing MDPs (using superscript "M" and "NM" to denote manufacturing and

[42] As detailed in the Data Appendix, 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.

[43] 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).

[44] Note that although the quantity of capital is mis-measured at the plant level, the share s_K remains correctly measured.

non-manufacturing respectively). This is plausible if we believe that some of the learning is industry-specific and/or large international manufacturing firms are more likely to bring better technology than non-manufacturing firms. The generalized model is:

$$log\left(\frac{w_c^K}{w^K}\right) = logw^K + \varphi^M MDP_c^M \quad + \varphi^{NM} MDP_c^{NM}$$

$$logA_i = logA_0 + \pi^M MDP_c^M \quad + \pi^{NM} MDP_c^{NM}$$

Therefore:

$$LogMTFP_i \quad = +logA_0 \ + (\pi^M - s_K\varphi^M)MDP_c^M + (\pi^{NM} - s_K\varphi^{NM})MDP_c^{NM}$$

This equation gives some insight into the net effect of the different type of MDPs. Consider a simple example where all MDPs create equal congestion effects ($\varphi^M = \varphi^{NM} = \varphi$) but only manufacturing plants (MDP_c^M) create positive productivity spillovers ($\pi^{NM} = 0$). This gives the equation:

$$LogMTFP_i \quad = (\pi^M - s_K\varphi^M)MDP_c^M + s_K\varphi^{NM} MDP_c^{NM} + logA_0$$

Notice that we can now recover the spillover parameter π^M from the regression coefficient on manufacturing MDPs to take account of congestion effects identified from the coefficient on non-manufacturing MDPs ($s_K\varphi^{NM}$).

The pattern of regression coefficients in the TFP equation is broadly similar to this simple model.

Management

The production function in equation (2) assumes that management (*M*) is an important factor for TFP. The set-up above can be easily adapted to management by changing equation (B3) to

$$logA_i = logA_0 + \mu logM_i$$

and

$$logM_i = logM_{0i} + \pi^M MDP_c^M \quad + \pi^{NM} MDP_c^{NM}$$

This will generate regressions very similar to the "reduced form" TFP model above. However, it illustrates an additional test of the model. Management regressions offer us a direct way to examine whether there is a spillover from MDPs to management (and whether it differs between manufacturing and non-manufacturing MDPs). The restricted model were there are only positive productivity spillovers from manufacturing MDPs implies that we should observe $\pi^M > 0$ and $\pi^{NM} = 0$ in the regressions were management is the dependent variable. We do not have to worry about the confounding influence of congestion effects on materials input prices as we do in the TFP equation (under the plausible assumption MDPs do not drive up the factor cost of management).

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). [45] It will contain a price-cost margin. 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

[45] Exceptionally, Foster, Haltiwanger, and Syverson (2008) have plant-specific output prices for a selection of homogenous good industries.

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 almost the exact opposite in the empirical results. There is a significant negative association between the productivity of our ASM plants and non-manufacturing MDPs. As discussed above this is consistent with input congestion effects, but not product market competition. By contrast, the coefficient on manufacturing MDPs in the TFP equation is positive. To the extent that there are competition effects solely from manufacturing MDPs, this would again cause us to *underestimate* the importance of the positive effects of MDPs on productivity.

Congestions 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. In our application we use a value added production function, but deducting off material costs will still mean that we are creating a downward bias on TFP.

For labor we observe employment separately from the wage bill, so it is less of an issue. In specifications where we use the wage bill to proxy for labor services and deflate by industry or national deflators, however exactly the same issues are at play. Since we observe plant-specific wages in principle we can test directly whether MDPs drive up the factor price for labor. The problem is that there could be other reasons for this positive correlation such as an effect on increasing unobserved skills or rent-sharing in productivity gains.

Appendix Bibliography

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Table A1: 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(sales/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 A2: Descriptive Statistics

A. Management Descriptives	**Mean**	**S.D.**	**p(10)**	**p(25)**	**p(50)**	**p(75)**	**p(90)**
Management score	0.640	0.152	0.427	0.553	0.667	0.753	0.812
Data driven performance monitoring	0.665	0.180	0.417	0.556	0.694	0.806	0.868
Incentives and targets	0.623	0.176	0.381	0.526	0.650	0.750	0.825
B. Establishment Characteristics							
Size	167.0	385.1	15.0	33.6	80.0	174.9	359.0
Parent firm size	3332.6	8739.8	24.0	60.0	258.3	1938.7	8327.6
Establishment Age	22.0	12.1	4.0	11.0	24.0	35.0	35.0
Parent firm age	28.4	10.4	9.0	24.0	35.0	35.0	35.0
% of managers with degree	43.6%	31.1%	10.0%	10.0%	43.6%	70.0%	90.0%
% of non-managers with degree	9.4%	12.0%	0.0%	5.0%	5.0%	15.0%	40.0%
% of union members	12.6%	27.6%	0.0%	0.0%	0.0%	0.0%	70.0%
Exporter	42.2%	49.4%	0	0	0	1	1
Multi-unit Parent	69%	46.2%	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 11 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. 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).

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 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: Measurement Error is Independent of Observables

Dependent Variable	**Absolute Value of Diff in Management Score Between Double Surveyed Establishments**					
	(1)	(2)	(3)	(4)	(5)	(6)
Log(number plants in the firm - CM)	-0.0002					
	(0.0070)					
Log(number plants in the firm - LBD)		0.0018				
		(0.0048)				
Log(employees in the plant)			-0.0087			
			(0.0143)			
Log(employees in the firm - CM)				-0.0007		
				(0.0057)		
Log(employees in the firm - LBD)					-0.0007	
					(0.0047)	
Log(firm age)						-0.0192
						(0.0189)
Observations	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.

Table A5: Within Firm (and across plant) Variation in Management

Dep Var: SD of Management spread within Firm	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of Establishments (in logs)	0.418***	0.0698					
	(0.0671)	(0.112)					
Number of Manufacturing Establishments (in logs)		0.662***	0.991***		0.208	0.206	0.186
		(0.162)	(0.089)		(0.179)	(0.180)	(0.180)
Mean Management score (in logs)			-0.170***	-0.178***	-0.178***	-0.178***	-0.179***
			(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Number of Manufacturing Industries (in logs)				0.384***	0.288*	0.288*	0.245
				(0.147)	(0.171)	(0.171)	(0.171)
Number of Manufacturing States (in logs)				1.070***	0.933***	0.934***	0.893***
				(0.140)	(0.184)	(0.184)	(0.184)
Std Dev of Age of Manufacturing Establishments						0.0395	
						(0.294)	
Oldest Manufacturing Establishment							0.492*
							(0.267)
Number of Firms	3,100	3,100	3,100	3,100	3,100	3,100	3,100
R-squared	0.01	0.014	0.098	0.105	0.106	0.106	0.107

Notes: 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 and the different number of states these establishments span are all calculated from the Longitudinal Business Database (LBD). Robust standard errors are reported in parenthesis. Establishment ages are in logs. For scaling purposes all coefficients and standard errors have been multiplied by 100 except for the mean management score.