Management and Pollution

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Abstract

Over the past quarter century there are few economic trends more remarkable than the precipitous drop in emissions that has taken place among United States' manufacturers. While environmental regulations, trade and technology are often cited as key determinants of emissions levels, the impact of "good" management practices has received far less attention. The emerging empirical literature on management practices has shown that well-managed plants are more productive and make more efficient use of labor and energy. This paper explores the role of management practices in explaining manufacturing plant emissions by merging the World Management Survey (WMS), a detailed plant-level survey of manufacturers, together with plant-level emissions data from the National Emissions Inventory (NEI). Findings show that moving from the 25th to the 75th percentile of management quality distribution is associated with a 23% reduction in emissions. Additional analysis suggests that the management - emissions relationship is smaller in plants located in nonattainment counties, providing support to the idea that regulation and management are substitutes in the abatement of pollution.

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1 Introduction

Manufacturers' environmental outcomes have seen dramatic improvements over the past quarter century. During this time period emissions of most pollutants have decreased by around 60 percent, all while real output in manufacturing has increased by over 40 percent (see Figure 1). This steep fall in both emissions rates and emissions levels has contributed to substantial improvements in air quality across the country. For example, ground level ozone, which causes severe health problems and thousands of premature deaths every year, has declined by 34 percent since 1980. Despite these improvements, there remains considerable cross-sectional variation in plants' emissions intensity and air pollution continues to be a major concern both domestically and internationally. Even today, soot and smog are estimated to cause 55,000 premature deaths in the United States and 3.3 million premature deaths worldwide (Lelieveld *et al.* 2015). In light of the large costs associated with emissions, economists have sought to better understand both the determinants of plant emissions and the mechanisms behind the sharp decline that has occurred in the United States. Understanding the determinants is of particular interest for developing countries such as China and India that are attempting to improve their air quality without sacrificing a sector of their economy that has driven their economic growth.

The existing research has explored the roles of regulation, trade policy, industry composition and technology in determining overall levels of emissions. Environmental regulations will either require or incentivize plants to adopt pollution reducing measures (Henderson 1996; Deschenes *et al.* 2012; Shapiro & Walker 2015). Trade may allow a country to offshore the production of pollution intensive industries (Shapiro 2014; Holladay 2010; Antweiler *et al.* 2001). Demand shifts may result in a change in industry composition such that there is growth in clean industries relative to dirty industries (Levinson & O'Brien 2015). Finally, technique changes or technology enhancements that improve productivity or abatement processes will result in fewer emissions per unit of output (Levinson 2009; 2015).

The literature examining the role of technology adoption in reducing emissions has generally defined technology improvements quite broadly. Levinson (2009) performs a statistical decomposition to determine the roles of trade and technology and argues that improvements in technology are by far the primary contributor to the decline in emissions. One specific type of technological improvement a plant may adopt is modern management techniques Bloom *et al.* (2016). For many years economists largely ignored the role management practices played in shaping economic outcomes because data on management practices was not available. However, an emerging economics literature has recently begun to quantify "good" management practices through the use of innovative survey tools (Bloom & Van Reenen 2007).

This research has found that plants using modern management techniques have higher total factor productivity (Bloom & Van Reenen 2007; Bloom *et al.* 2013; 2014) and make more efficient use of their labor and energy inputs (Boyd & Curtis 2014; Bloom *et al.* 2010; Martin *et al.* 2012). The literature on management and energy efficiency has discussed the environmental implications of improving energy efficiency but has not explored whether management impacts the direct environmental outcomes of manufacturing plants.[1]

The improvement in US manufacturing environmental outcomes over the past quarter century has coincided with the adoption of modern management techniques. For example, the just-in-time production techniques first developed by the Japanese were introduced to US plants in the late 1970's and have slowly been disseminating throughout the manufacturing sector. While many US plants were initially hesitant to change their production practices, these modern management techniques are now quite common and are largely accepted as a primary reason for improvements in US manufacturing productivity.[2]

To examine whether these techniques are also responsible for differences in environmental outcomes, this paper combines plant level data from the National Emissions Inventory together with the detailed management data from the World Management Survey. The National Emissions Inventory collects plant level data on the emissions releases of the six criteria pollutants that are regulated by the National Ambient Air Quality Standards (NOx, SO2, PM, VOC's, Lead and CO). The data are collected every three years and cover nearly all point-source emitters in the United States.[3] There are a number of reasons why adoption of these modern management practices may lead to cleaner production and decreased pollution intensity. Just-in-time production techniques, close monitoring of inputs and establishing proper incentives for workers are all likely to result in higher productivity and more efficient use of resources, including pollution emitting capital. Better managed plants may check and replace old and under-performing capital with newer and cleaner technologies. To the extent that management differences drive plant-level variation in capital selection and capital-utilization rates, there is significant scope for management to be a major determinant of observed cross-sectional variation in emissions intensity.

Indeed, performing a straight-forward cross-sectional analysis that controls for a variety

[1] If plants differ in the types of fuel they consume or if their emissions activity is not directly tied to their energy consumption then energy may not be an accurate proxy for emissions. One exception to this is (Bloom *et al.* 2010) which, for a sub-sample of plants in their study, observes fuel types and backs out CO2 emissions based on fuel mixture.

[2] A separate literature has sought to understand the relationship between a plant's productivity outcomes and their environmental outcomes (Shadbegian & Gray 2005; Färe *et al.* 2007; Greenstone *et al.* 2012). These papers ask whether exogenous shocks that force plants to improve environmental outcomes also result in productivity improvements. They find that these shocks have either zero or negative impact on productivity.

[3] See the Data section and the data appendix for specifics on the NEI's coverage.

of plant and firm characteristics, I find a strong relationship between a plant's management quality and it's pollution intensity. Moving from the 25th to the 75th percentile of the management quality distribution reduces emissions intensity, defined as emissions per employee, by 23 percent. This despite the fact that past research has shown well managed firms to be more capital intensive. This result provides evidence that management practices are a major determinant of plant level differences in emissions intensity. While data limitations prevent a deep exploration of the mechanisms, a break down of the management variable suggests that multiple mechanisms are likely to be at play. Lean manufacturing techniques, monitoring and human resource management appear to be especially salient factors.

While the observed management - emissions relationship is strong and quite large, some caution should be taken before treating management as a panacea to environmental concerns. First, because the results are based on a cross-sectional analysis, the findings should be interpreted as the long-term effects of management. The quality of a plant's capital, choice of fuels and energy-specific R&D are all likely to be captured in the management variable. A hypothetical study which randomly assigned management quality and held constant capital quality, choice of fuels, past R&D efforts and quality of the workforce would surely find much smaller effects of management. Nonetheless, in the long-term these variables and others will be largely driven by the firm's management practices. Although the results of the paper do not speak directly to specific emissions reducing activities, it is likely that well-managed firms will be quicker to adopt new technologies, select cleaner fuels and invest more money in R&D efforts that enhance energy efficiency. In this sense, management quality is highly complementary to many other determinants of pollution intensity.

The second part of this paper's analysis explores how regulation interacts with management to reduce emissions. Recent research by Shapiro & Walker (2015) finds that environmental regulation has played a particularly strong role in lowering manufacturing emissions. There are two potential ways that management and environmental regulations may interact. First, it is possible that well-managed plants are better equipped to operate the abatement capital that regulators require be installed. If so, then regulation and management practices may be complements in the production of cleaner air. On the other hand, well-managed plants may already be taking actions to limit emissions before the regulations. If regulation forces all plants, regardless of their prior emissions, to become clean then management will be observed as having a smaller effect in nonattainment counties and regulation would then be a substitute for good management practices. To test for this I exploit geographic variation in nonattainment status across the country. I find the management - pollution relationship is weaker for plants that are located in nonattainment counties and are forced to comply with a variety of regulations. That regulation appears to substitute for management practices has a number of important implications and, as discussed in Section 5, provides further support for the use of market based instruments to regulate pollution.

Before moving forward, a few additional caveats should be made. First, while the analysis focuses on manufacturing emissions, it should be noted that there are many other sources of emissions. The manufacturing sector is responsible for roughly 25% of all emission sources in the US. Furthermore, the results focus on emissions of EPA designated criteria pollutants (NOx, SO2, PM, VOC's, Lead and CO) rather than CO2 emissions for which historical data from manufacturing plants is less readily available. In regards to the empirical results, the nature of the data and cross-sectional analysis does not guarantee the existence of a causal relationship between management and emissions. However, the correlation between the two that persists, despite the inclusion of a large number of controls, is at the very least strongly *suggestive* of a causal relationship that should be the subject of future research.

Despite the caveats mentioned above, the results have important implications. First, they demonstrate that management practices are a crucial determinant of plants' overall emissions and are likely an important pathway through which emissions reductions can be accomplished. Second, given that management practices have seen significant improvements, they provide another explanation for why emissions have declined so significantly over the past quarter century. Finally, though they are not directly analyzed in this paper, the results point to a potential mechanism through which electric utilities and non-US manufacturing plants may reduce their pollution levels. Most electric utilities operate in highly regulated markets with few or no competitors. If lack of competition has led to poor management outcomes (Bloom & Van Reenen 2007) then improvement in management quality may be an important path to improve the environmental performance of the largest source of emissions in the US.[4] There is perhaps even greater scope for environmental improvements in manufacturing plants located in developing countries. These plants tend to lag well behind the United States in their adoption of modern management techniques (Bloom *et al.* 2013) and are far more pollution intensive. Previous literature has emphasized the productivity gains that could come from these management techniques in developing countries but improved management techniques may also help address the significant environmental challenges that countries like China and India currently face.

The remainder of the paper is organized as follows. Section 2 discusses the management and emissions data and Section 3 describes the econometric model used to explore the

[4]Past research has explored the role of electricity market deregulation in determining a variety of electric utility outcomes (Cicala 2015; Davis & Wolfram 2012; Fowlie 2010; Fabrizio *et al.* 2007; **?**). Improved management is also likely to be an important mechanism through which deregulation impacted utilities.

management - emissions relationship and presents the baseline results. Section 4 considers extensions of the baseline results and examines whether management and regulation are complements or substitutes. Section 5 discusses the results and their implications. Section 6 concludes.

2 Data

The two primary sources of data used in this paper are the World Management Survey and the National Emissions Inventory. The management data were constructed through the use of a survey tool created by Bloom, Van Reenen and a large global consulting firm. The process of collecting the data relied on a unique survey methodology designed to elicit accurate responses from plant managers regarding their management practices.

Medium to large U.S. manufacturing plants were randomly selected to be surveyed. Once selected, interviewers conducted hour long interviews with plant managers. Plant managers were chosen as the subjects of the interview so as to obtain answers from an individual in the firm who would have intimate knowledge of the plant's floor level operations as well as knowledge of senior management at company headquarters. The interviews were framed to the plant managers as being a "piece of work" which sought to better understand the organization and operations of manufacturing plants. The survey was double-blind so that the plant managers were unaware they were being scored and the interviewers had no prior knowledge of the company's performance. The plant managers were asked open-ended questions on 18 management practices that were designed to elicit information about a specific management topic. Questions asked about the production process, the adoption of lean manufacturing techniques, the types of production and input data that is collected and how capital and workers' performance is measured. Other questions examined how plants managed their workers, how hiring and firing decisions were made and the criteria for bonuses and promotions. Finally, a series of questions were asked about whether the plant had targets, how those targets are implemented, whether or not the targets were stringent and whether there were consequences for failing to meet targets.

The interviewer scored each of the 18 management practices on a scale from 1 to 5 with 5 indicating the best possible management in that category. A number of checks were put in place to ensure consistent scoring by the interviewers. First, a common scoring guide was given to the interviewers to provide examples of typical answers and how these answers should be scored. Second, a number of interviews were conducted with multiple people listening and independently scoring the answers of the plant managers. Bloom & Van Reenen

(2007) show that the scores are robust to these and other consistency checks. Furthermore, because interviewers surveyed on average a total of 50 plant managers, the regressions can use interviewer fixed effects to control for any systemic scoring differences between the interviewers. Additional data was collected on the day of the week the interview took place, the length of the interview, the gender of the plant manager and the plant manager's tenure at the firm. These interview variables are defined as noise controls in the regressions and are included to control for any bias associated with the scoring process itself. After the scoring was completed, an overall management score was created by simply taking the average of the 18 management practice scores.[5] Importantly, the survey also asked the plant manager a variety of other questions that were not directly related to the plant's management practices. Plant managers reported the number of plant employees, the industry of the plant, the percent of workers with a college degree, percent unionized, whether the firm was publicly held and the plant address.

The other primary source of data comes from the National Emissions Inventory. The National Emissions Inventory is a comprehensive list of every pollution point source in the United States. It is collected by the Environmental Protection Agency every three years to provide the government and public with information regarding the location and activities of all stationary pollution sources. Emission levels are reported every three years for each of the six criteria pollutants that are regulated by the Clean Air Act as well as a list of air pollutants defined as hazardous by the EPA.[6] Linking the plant level WMS data into the NEI required matching by company name, county and industry. After the initial match and subsequent cleaning, 672 of the 1,297 observations in the WMS data were successfully merged to the NEI.[7] The 52% percent match rate is comparable to the match rate achieved in previous studies that have matched WMS to US and UK Census data.

WMS surveys were performed between 2002 and 2010 with 93% being undertaken between 2004 and 2009. NEI data is collected every three years and is available in 2002, 2005, 2008 and 2011. Because the WMS and NEI years do not perfectly align, some necessarily ad hoc decisions were made regarding how best to merge WMS observations that were not collected in NEI years. WMS observations from 2002 and 2003 were merged to 2002 NEI data. WMS observations from 2004-2006 were matched to 2005 NEI data, 2007-2009 were merged

[5] The survey itself, along with a more detailed description of the scoring methodology can be found at `http://worldmanagementsurvey.org/wp-content/images/2010/09/Manufacturing-Survey-Instrument.pdf`.

[6] Emissions of Hazardous Air Pollutants (as defined by the Clean Air Act) are also reported. However, CO_2 emissions are not reported in the NEI.

[7] Outliers were removed after the initial match by regressing logged pollution intensity on non-management controls including a set of three-digit NAICS fixed effects. The residuals from this regression were stored and observations whose residuals were in the top and bottom 2% of residuals were dropped.

to 2008 NEI data and 2010 WMS data was matched to 2011 NEI data.

While the match rate is quite high compared to other papers which have attempted similar matches, it is still important to explore potential reasons behind the unmatched plants. Plants in the WMS survey may not match to the NEI for two reasons. First, a plant's name, location and industry code may, for various reasons, be labeled differently in the two datasets. This is a common problem when performing a name match as different interviewees may report different names in different surveys.[8] Unmatched plants are assumed to be missing at random, meaning that there is no statistical difference between the plants that were matched and those that were not. This assumption is tested in Table A1. Matched plants are shown to be slightly smaller, slightly better managed and slightly older than unmatched plants but these differences are not large and the difference in means is not statistically significant.

A second reason that plants may not match is that they are simply not listed in the NEI. Plants surveyed in the WMS that do not emit any criteria or hazardous air pollutants will not be listed in the NEI. The NEI has different reporting thresholds for each criterion pollutant. For three of the pollutants, VOC's, PM 10 and CO, the thresholds vary based on the attainment status of the plant's county. These differing thresholds will result in higher variation of emissions rates in nonattainment counties that in attainment counties for these pollutants. Empirical results on the regulation - management relationship must account for these differing thresholds as it is potentially a threat to the validity of the empirical results.[9] Reporting thresholds must also be considered for the baseline management - pollution results. If best managed plants are not listed in the NEI because they do not emit any pollutants then the sample on which the analysis is run will not be representative of the population of U.S. plants and the results may be biased. Some basic summary statistics on the matched and unmatched plants are provided in Table A1 that suggest this type of matching bias is limited. Matched and unmatched plants have very similar characteristics. Furthermore the match rate is similar to what has been achieved in previous papers that have matched the WMS to the full universe of manufacturing plants. To assuage additional concerns that bias may be entering the results as a result of the matching process, the results section reports regression results both for the matched sample and for the full population of WMS plants where emissions for unmatched WMS plants is imputed to be zero. Imputing the emissions of all unmatched plants to be zero will add significant noise to the dependent variable. Despite this, the main

[8]For example, one may list the name of the parent firm while the other lists the name of the subsidiary. Given the time discrepancy in the match it is also possible that a plant had a different name (or owner) between the time of the WMS survey and the year the NEI data was collected.

[9]In 2005 there were 104,778 manufacturing plants in the United States with more than 20 workers. Because the WMS surveyed "medium-to-large" plants nearly all WMS plants have greater than 20 workers. The 2005 NEI dataset contains 43,966 manufacturing plants. See the Data Appendix for more details.

results of the paper are shown to hold after performing this imputation.

The primary dependent variable used in the analysis is the emissions intensity of the plant defined as the plant's emissions - employment ratio. The NEI reports the tons of each criteria pollutant (NOx, SO2, PM, VOC's, Lead and CO) as well as the tons of hazardous air pollutants emitted by plants. Because hazardous air pollutants are not consistently measured across NEI surveys, this paper focuses on criteria air pollutants which have stayed the same over the time period the WMS was collected. The key emissions variable used in the analysis does not simply sum up the tons of each criteria air pollutant emitted by a plant. Rather it creates a weighted sum where the weights equal the estimated marginal damage of the pollutant. A simple summation of these pollutants would overweight the importance of pollutants like NOx and VOC and underweight the importance of SO2 and PM 2.5 which cause far more damage to society largely due to their effect on human health (Muller & Mendelsohn 2009).[10]

The damage weighted emissions measure is then divided by the number of employees at the plant as reported by the WMS to obtain the plant's emissions intensity measure. A plant's employment level is an imperfect way to measure plant size. Ideally, plant-level output would be observed and used as the baseline, but this is not available in either the WMS or NEI. Other plant-level production inputs, such as capital and intermediate materials are also unobserved. However, robustness tests merge in *firm level* compustat data on the subset of WMS plants that are owned by publicly traded firms to obtain a measure of capital intensity. The primary concern that arises from omitting input ratios is that plants may systematically differ in the extent to which production of the final product occurs within the plant. If plants outsource pollution-intensive processes then they will appear cleaner even though significant pollution is still being emitted to produce the product. Importantly for the validity of this paper's results, previous papers using the same dataset have found that well managed plants tend to be *more* capital intensive and use fewer intermediate materials (Bloom *et al.* 2010). If plants that are well managed are more capital intensive this would suggest prima facie that well managed plants would be more pollution intensive. While input mixture is clearly an important determinant of a plant's emissions level, these previous findings suggest that not controlling for capital in the regressions will result in the management coefficient understating the relationship between management quality and emissions intensity. Robustness checks that use the firm's capital intensity as a proxy for the plant's capital intensity do in fact show that higher capital intensity results in higher emissions intensity, but the management - emissions relationship remains little changed. Other data sources used in the analysis include

[10]The specific marginal damage estimates used come from the final column of Table 1 of Muller & Mendelsohn (2009)

county-level population data and non-attainment status from the EPA and Census.

Table 1 presents summary statistics for the primary variables used in the analysis. See the data appendix for more information on the matching and data cleaning process.

3 Management and Emissions

Before discussing the regression analysis it is useful to simply visualize the relationship between management practice and emissions intensity. A plant's emissions intensity can simply be defined as the difference between its logged pollution-employment ratio and the average logged pollution-employment ratio of the three-digit NAICS industry to which the plant belongs. Defining emissions intensity as such controls for naturally occurring differences in the energy required to produce different products, albeit at a somewhat broad level. Using this definition, Figure (2) plots out the pollution intensity distribution of both "well" managed plants and of "poorly" managed plants. "Well" managed plants are defined as plants in the top tercile of the management distribution and "poorly" managed plants are defined as plants in the bottom tercile of the distribution. The figure displays two important characteristics of the data. First, "well" managed plants have a longer left tail and "poorly" managed plants have a (slightly) longer right tail. The tails demonstrate that the cleanest plants in the data are well managed and the dirtiest plants in the data are poorly managed. Second, and perhaps more importantly, nearly the entire distribution of well managed plants is to the left of the distribution of poorly managed plants, suggesting lower *overall* emission rates for well managed plants. This figure presents compelling evidence of a strong relationship between management and emissions intensity but is unable to control for additional factors such as firm age and plant size that may correlate with management that also predict emissions intensity.

3.1 Econometric Model

To more formally explore the relationship between management and emissions, I consider the following regression model.

$$(Poll/Emp)_{it} = \beta_m Manage_{it} + \theta X_{it} + \delta Z_{it} + \alpha_k + \epsilon_{it} \tag{1}$$

where $(Poll/Emp)_{it}$ is the damage weighted pollution intensity of the plant, defined as the ratio of damage weighted tons of criteria pollutants to employment or the natural log of this ratio.[11] X_{it} is a vector of plant characteristics that includes firm age, an indicator variable equal to one if the firm is publicly held, the percent of workers that belong to a union, the percentage of workers with a degree, geographic controls (generally Census Region fixed effects) and the natural log of employment to control for potential economies of scale. Z_{it} is a set of interview controls that includes interviewer fixed effects and seniority of the interviewer and α_k is a full set of three digit NAICS indicator variables. The primary coefficient of interest is β_m which captures the relationship between a plant's management quality and their emissions intensity conditional on these controls. Standard errors are clustered at the plant level as some plants have multiple observations in the data.[12]

The model should be noted both for what it includes and for what it omits. First, industry differences in emissions are directly controlled for in the model through the use of three-digit industry codes. While finer levels of industry categories would have been preferred, there were not enough plants to include these more detailed controls. Next, the nature of the survey necessitated that management scores be based on a somewhat subjective basis. Including interviewer fixed effects reduces the noise that is inherent within the management variable due to any consistent interviewer bias across interviews. Finally, the plant and firm level controls are especially important to the interpretation of the management coefficient. Each of the result tables begins by presenting models with few controls and progressively adds in control variables that may themselves be functions of management quality. For example, better managed plants tend to be larger, have more educated workers and are more likely to be part of a firm that is publicly traded. While adding in these controls is important, it is likely that they will absorb part of the observed effect of management in the models. One important variable that is omitted from the model is a measure of the plant's capital input. Plants will vary in the extent to which the production process occurs inside their plant. Some plants will start with raw materials and are responsible for the entire process, whereas others only put the final cosmetic touches on products that have undergone heavy processing in other plants. Including a measure of capital intensity controls for these differences. While capital data is not available at the plant level, regressions in the appendix merge in firm-level data from Compustat for the publicly traded firms in the sample. Although the sample size drops considerably, the management results are shown to hold when controlling for firm level capital intensity. Past research has found that better managed plants are slightly more capital intensive, suggesting that models that exclude capital intensity may actually understate the

[11] Unless otherwise noted, all pollution intensity measures will be damage weighted.

[12] Clustering at the plant level proved to have the most conservative (largest) standard errors. Other regressions not reported in the paper clustered standard errors at the firm and industry level and generally had smaller standard errors.

size of the management-emissions relationship.

3.2 Results

While a visual examination of the non-parametric distributions of the data are strongly suggestive of a negative relationship between management and pollution intensity, it is necessary to turn to the regression framework to control for the additional potential drivers of pollution intensity. Table 2 presents the baseline regression results examining the management-pollution relationship. Column 1 regresses management on emissions intensity controlling only for NAICS three-digit industry, survey controls and region fixed effects. Ensuing columns control for additional plant or firm characteristics. Column 2 adds in the firm age variable, column 3 includes the logged number of workers at the plant. Column 4 includes an indicator variable for whether the firm is publicly traded and column 5 reports results controlling for the percent of the workforce that is unionized and the percent of workers at the plant with a college degree.

Panel A of Table 2 reports regressions where the dependent variable is defined as total tons of criteria pollutants divided by total employment $(Poll/Emp)$ while Panel B defines the dependent variable as $ln(Poll/Emp)$. Taking the natural log accomplishes two important tasks. First, taking the natural log transforms the distribution of the dependent variable to a shape that approaches a normal distribution. This reduces the influence of outliers in the sample. Second, the log transformation makes the coefficients far easier to interpret.

The results in Panel A and Panel B confirm a negative relationship between plants' management quality and their pollution intensity. In Panel A the coefficients range from -0.594 to -0.497 and in Panel B they range from -0.622 to -0.259. The coefficients from Panel A and Panel B are of similar magnitude, but it must be noted that coefficients in Panel A represent the effect of a one unit change in the management score on *levels* of pollution intensity while coefficients in Panel B can be interpreted as the *percentage* change in pollution that would occur with a one unit change in a plant's management score. Therefore the coefficient in column 5 of Panel A can be interpreted to mean that a one unit increase in management score reduces pollution damage per worker by $690. While the coefficient in column 5 of Panel B implies a one unit increase in management quality reduces a plant's pollution damage by 25.9%.

The coefficient on the management variable becomes progressively smaller in both panels A and B as control variables are added to the regression. This is not surprising as these variables are likely to be determinants of pollution intensity and are also correlated with management quality. Coefficients on the control variables generally point in the expected direction with older and highly unionized firms being more pollution intensive while firms that are larger, publicly traded and employ more college educated workers tend to have lower levels of pollution intensity. As discussed above, many of these controls, particularly the percent of a plant's workers that have a college degree, are correlated with management quality and thus are likely to absorb some of the effect of the management variable. Including the full set of controls in Panel B shrinks the coefficient such that it is no longer statistically significant.

Table 3 addresses the potential concern that some plants in the WMS are not matched to the NEI because they do not emit any emissions. It reports results where pollution levels in all unmatched WMS plants are assigned a zero emissions value. The same regressions are run on this dataset as are run in Panel A of Table 2. There is no Panel B in this Table because the potential values of pollution intensity now include zero. Not surprisingly, the coefficients on the management variable in Table 3 are closer to zero than those in Table 2. However, the coefficients remain negative and statistically significant. Coefficients range from -0.305 to -0.241or about half of what they were in panel A of table 2.

Table 4 reports results where regressions are run separately for each of the eighteen management practice scores. Columns 1 through 5 run the same specifications as columns 1 through 5 in tables 2 and 3. Each result is obtained from a separate regression. The results are best viewed in Figure 3, a bar graph showing the size of the coefficient for each management practice when it is run separately in its own regression. Coefficients are multiplied times negative one for visual purposes, such that positive numbers signify better management practices as associated with fewer emissions. Bars are shaded according to their statistical significance with the darkest shaded bars representing coefficients that are statistically significant at the 5% level or higher. Three management components are significant at this level: Lean 1, which asks about just-in-time and lean management techniques; Performance 10, which asks about clarity of performance goals; and Talent 3, which asks how the plants identify and handle under-performing workers. Five more components are significant at the 10% level and only one component is associated with higher emissions intensity. It can be seen that high scores on almost all of the questions are predictive of lower emissions intensity. Adoption of lean management techniques (questions 1 and 2) and good personnel management are especially strong predictors of lower emissions intensity. These results speak to potential mechanisms behind the management-emissions relationship. Adoption of lean techniques implies that firms are closely monitoring their inputs and that they are able to make quick fixes and install new capital when machinery is performing poorly. Good workers are also more likely to identify and fix issues in the production process. These results are generally consistent with past work (Bloom *et al.* 2010) which has found that adoption of lean techniques is the question most predictive of improved plant outcomes. Boyd & Curtis (2014) finds that questions on targets have little relationship with outcomes that are not directly related to those targets. It may therefore be unsurprising that the relationship with the questions on targets is somewhat weaker than that found with other questions.

4 Management and Regulation

Given that recent literature has demonstrated a key role for environmental regulations in reducing emissions, it is interesting to consider whether "good" management practices complement or substitute for environmental regulation. Regulation may substitute for good management practice by requiring poorly managed plants to invest in new capital thereby forcing all plants, regardless of management quality to become clean. This is particularly true for command and control programs such as the nonattainment standards which often require the installation of pollution control technology. On the other hand, management may complement regulation if complying with the regulation requires skill or knowledge on the part of the polluting plant to operate machinery.

4.1 Econometric Model

Table 5 reports results for the following specification which simply interacts a plant's management score with an indicator variable for whether they are in nonattainment for any criteria pollutant:

$$\begin{aligned}(Poll/Emp)_{it} = \beta_{mr}(Manage_{it} \times Reg_i) + \beta_m Manage_{it} + \beta_r Reg_i + \\ + \theta X_{it} + \delta Z_{it} + \alpha_k + \epsilon_{it} \qquad (2)\end{aligned}$$

This model is similar to that in equation (1) but now tests whether environmental regulation is a substitute for management or whether environmental regulation complements management. To examine this, the model includes an indicator variable, Reg_i, which equals one if the plant is located in a county designated as nonattainment for ozone and a separate term that interacts Reg_i with the plant's management score. The coefficient on $Manage_{it} \times Reg_i$ describes whether the management-pollution relationship differs based on the regulatory status of the plant's county. In addition to the control variables included in equation (1), this model also includes the population of the county where the plant is located. Plants in more populated counties are more likely to be in nonattainment and may also be subject to additional pressures to reduce emissions.

Table A2 provides summary statistics for the key variables by attainment status. Plants in nonattainment are similar to those in attainment along most dimensions, but they differ noticeably in their emissions. Despite having a similar industry make-up, plants in nonattainment counties emit roughly half as much as those in attainment. Management scores are similar across both groups with plants in regulated counties being slightly larger and having a slightly more educated workforce. These differences likely reflect the fact that nonattainment counties are more likely to be located in metro areas. Table 5 reports coefficients from the model in equation (2). The management coefficient remains negative and as suspected, the nonattainment indicator variable has a large, though not statistically significant negative coefficient. Coefficients on the $Manage_{it} \times Reg_i$ interaction term are also negative and while not statistically significant, are of a considerable magnitude. We can interpret the $Manage_{it} \times Reg_i$ coefficient in column 5 of Panel B to mean that plants with a one point higher management score reduce emissions by 41% less when they are located in a nonattainment county than when they are located in an attainment county.

5 Discussion

The results suggest that management practices play an important role in determining plants' emissions levels. To more easily understand the results we can consider what would happen to pollution levels of a plant at the 25th percentile of management quality if it were to be moved to the 75th percentile of the management quality distribution. Moving from the 25th to the 75th percentile of the management distribution would increase the management score by 0.889. The coefficient on the Management variable in column 5 in Panel B of Table 2 suggests that increasing a plant's management score by one point results in 25.9% fewer tons of pollutants emitted per worker in a given year, therefore moving a plant from the 25th to the 75th percentile of the management distribution would reduce emissions per worker by 23%. This is a substantial reduction and demonstrates a large potential role for management practices in reducing pollution. These results are consistent across a variety of specifications and robustness checks.

While it is possible that there exists some third factor that is driving both emissions intensity and management, these results are highly suggestive of a causal interpretation. Results in Table 5 imply that there are also complementarities between management and environmental regulation. This may be particularly true for command and control type regulations such as the NAAQS that require the installation of pollution emitting capital without requiring specific pollution reduction goals to be met. Better managed plants may be more effective at monitoring and operating the pollution abating capital. Requiring pollution abating capital to be installed will only reduce emissions if that capital is performing as intended.

As mentioned in the introduction, one reason these results are especially germane is that plants in pollution-intensive industries, by dint of having a production process that requires considerable capital investments and high entry costs, tend to have fewer competitors than plants in less polluting industries. Bloom & Van Reenen (2007) show that plants with fewer competitors also tend to have lower management scores. The implication being that increased competition either pushes poorly managed plants out of the market or forces them to improve their practices. This logic suggests that plants in dirty industries will, on average have lower management scores. Indeed, simply regressing plants' management scores on their industry's emissions intensity shows a strong negative relationship between these two variables. If plants in emissions intensive industries are, on average, further from the management practices frontier, then there may be increased scope for emissions reductions through management practice improvements in the most emissions intensive industries.

Finally, there are a number of important implications to the finding that the management-emissions relationship is smaller in counties designated as nonattainment. First, it suggests that regulation forces poorly managed plants to become cleaner. While this may suggest a positive role for regulation, there are also costs in improving air quality through this type of command and control regulation. By requiring plants to install certain capital, acquire permits and obtain offsets for any expansion, the nonattainment standards increase the entry costs that must be incurred by new entrants. As a result, fewer firms may enter the market and existing firms, even if they are poorly managed, may gain increased market share which will result in decreased product market surplus (Ryan 2012; Fowlie *et al.* 2016).

Market based instruments are likely to interact with management differently than command-and-control regulations. Well-managed plants that are already effective at abating pollution will benefit relative to poorly managed plants that are ineffective at abating pollution. Although they are forcing pollution reductions at poorly managed plants, they are also providing barriers to entry that favor incumbents over potential new entrants. Recent research has suggested that regulation increases firms market power. The cost of this increased market power will be even higher if the firms that gain this power are poorly managed.

6 Conclusion

This paper has taken a first step towards better understanding the role management practices play in determining a plants' pollution intensity. Future work should examine more detailed plant-level data to identify what specific input and production processes lead well managed plants to have better environmental outcomes. The results suggest a promising and overlooked mechanism by which the industrial sector may reduce emissions both within the United States and internationally. Furthermore, given the diffusion of modern management practices that has occurred in the United States over the past half-century, it is likely that management should be considered along with other competing explanations for the recent decline in manufacturing emissions levels.

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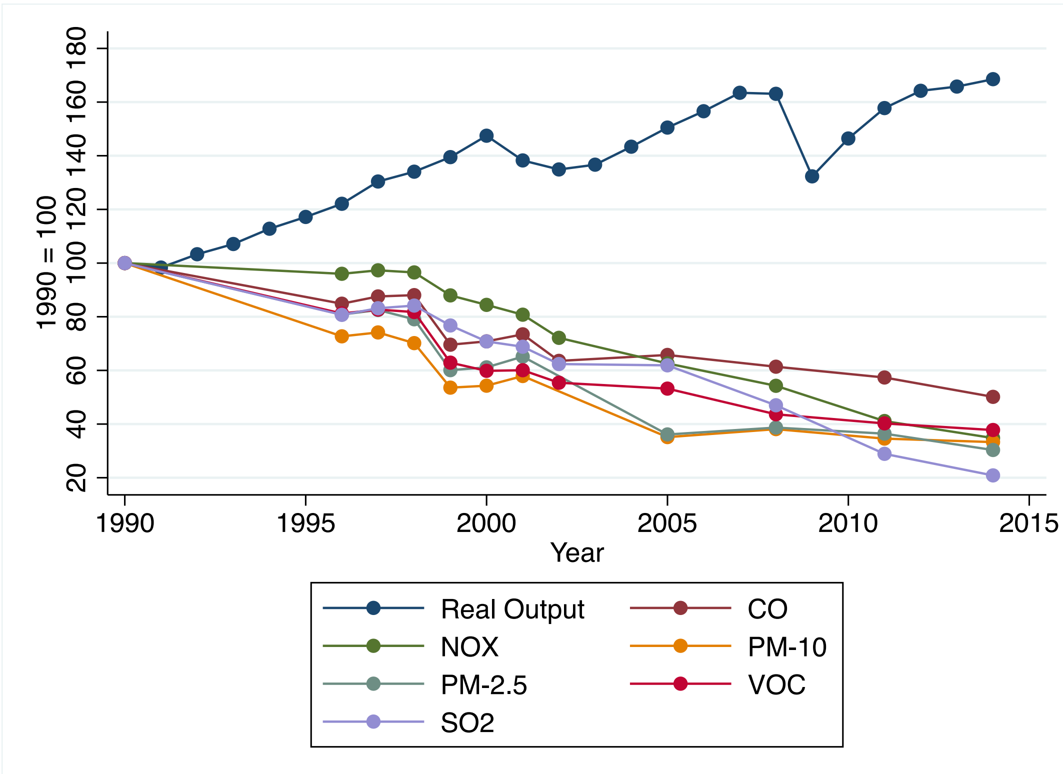
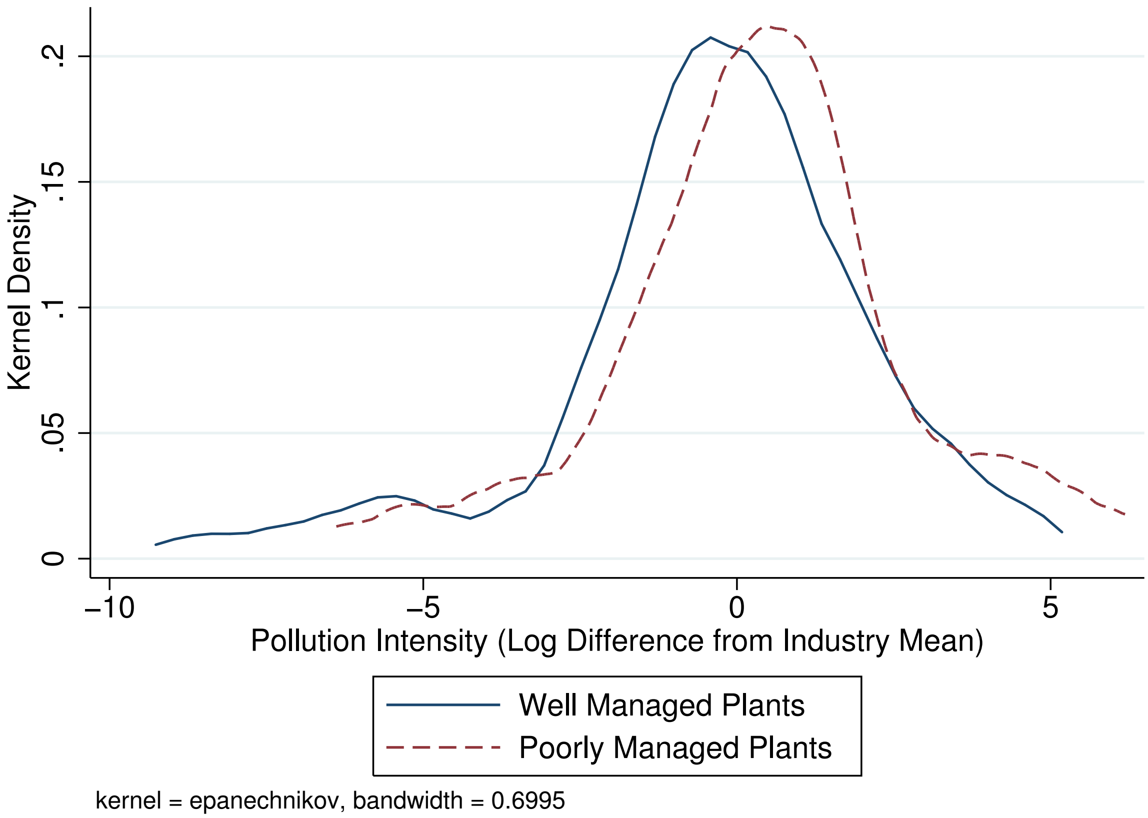
Figures and Tables

Figure 1: Manufacturing Emissions and Output 1990-2014



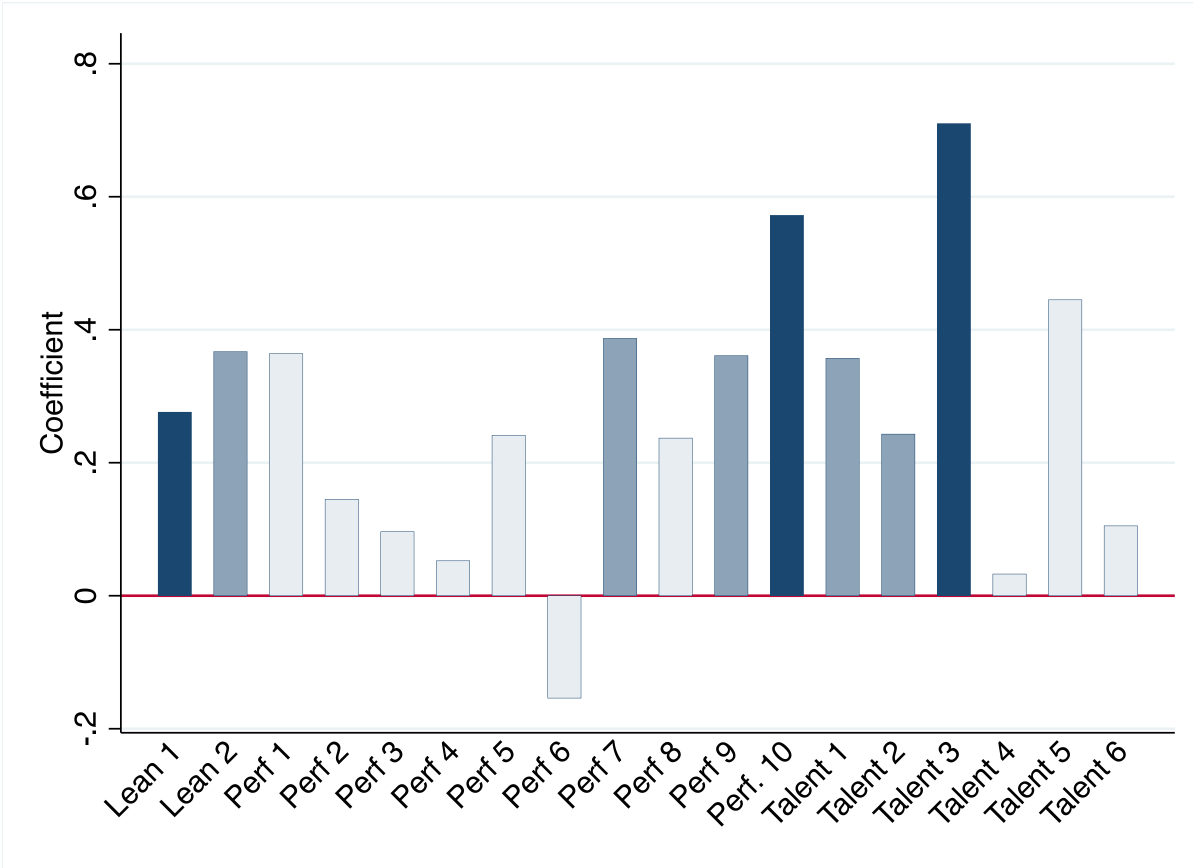
Note: The above figure uses NEI data dating back to 1990, together with real manufacturing output data from the NBER Productivity Database to plot out trends in output and emissions of key pollutants. Real output and emissions levels are normalized to 100 in 1990.

Figure 2: Pollution Intensity Distribution of “Well” Vs. “Poorly” Managed Plants



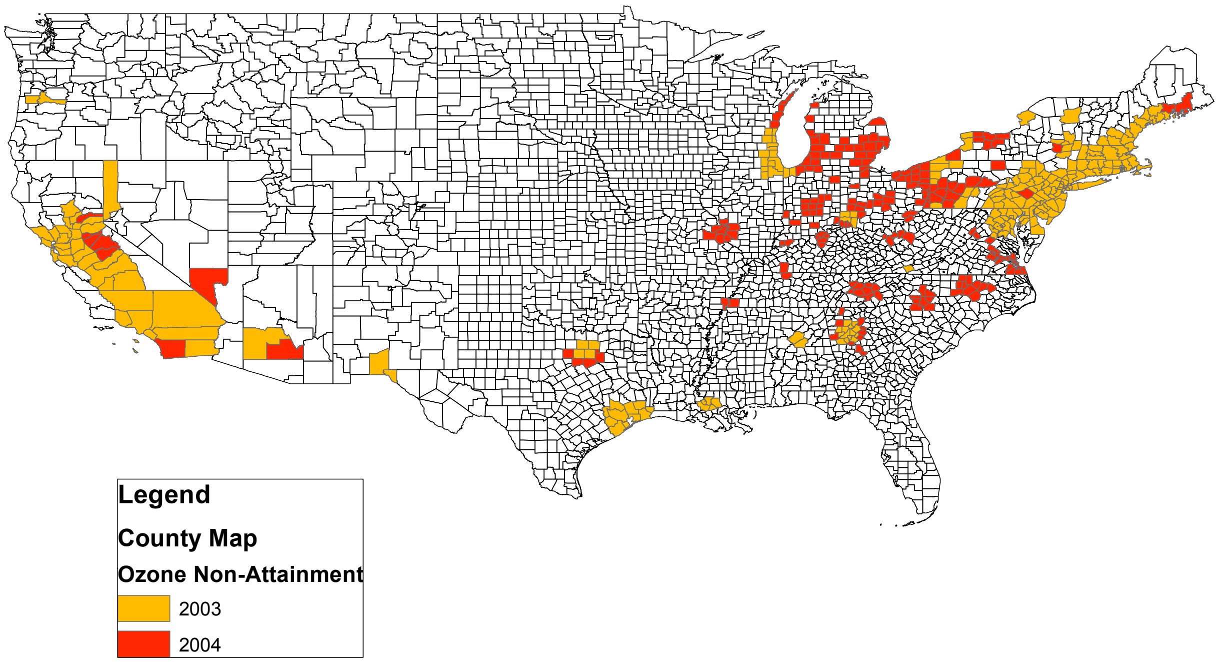
Note: The above figure plots the kernel density for “Well” managed plants (those in the top tercile of the managment distribution) and “Poorly” managed plants (those in the bottom tercile of the management distribution).

Figure 3: Management Component Coefficients



Note: The bar chart plots the coefficients for each of the 18 management components. Shading represents statistical significance with the darkest shaded bars signifying statistical significance at the 5% level, medium shaded bars at the 10% level and the lightest shaded bars as not statistically significant at the even the 10% level). The specific questions used to score each management component can be found in the Data Appendix. The components in the bar graph are listed in the order they were asked such that Lean 1 corresponds to the first question and Talent 6 corresponds to the 18th question in the Data Appendix.

Figure 4: Ozone Nonattainment Counties



Note: The above figure shows the counties in nonattainment for ozone in 2003 and the counties newly designated as nonattainment in 2004.

Table 1: Summary Statistics

	(1) Mean	(2) SD	(3) 10th Ptile	(4) 90th Ptile
Management	3.38	0.66	2.50	4.22
Tons of Emissions of CAP's	524.85	2129.17	0.60	983.92
# Workers	266.72	288.91	60.00	600.00
Poll/Emp	3.06	10.91	0.00	4.92
Poll Damage ($1000's)/Emp	0.88	3.91	0.00	2.43
Public	0.26	0.44	0.00	1.00
% Unionized	0.24	0.37	0.00	0.85
Firm Age	53.22	42.80	7.00	111.00
% Emp with Coll Educ	0.19	0.20	0.01	0.50

Note: The above table provides summary statistics for the matched sample which is used in the baseline analysis. The 10th percentile of Poll/Emp rounds to 0.00 but all observations have strictly positive pollution levels.

Table 2: Baseline Results

	(1)	(2)	(3)	(4)	(5)
Panel A: (Poll / Emp)					
Management	-0.567**	-0.594**	-0.557**	-0.556**	-0.497*
	(0.265)	(0.271)	(0.249)	(0.253)	(0.256)
Firm Age		0.453**	0.472***	0.473***	0.442**
		(0.190)	(0.176)	(0.175)	(0.174)
log (Workers)			-0.100	-0.102	-0.0909
			(0.155)	(0.156)	(0.165)
Public				-0.0910	0.00878
				(0.400)	(0.405)
% Union					0.00866
					(0.00538)
% Emp with Coll Educ					-0.00850
					(0.00597)
Observations	672	672	672	672	672
R^2	0.110	0.128	0.128	0.128	0.133
Panel B: ln(Poll / Emp)	(1)	(2)	(3)	(4)	(5)
Management	-0.596***	-0.622***	-0.421*	-0.408*	-0.259
	(0.230)	(0.232)	(0.243)	(0.241)	(0.232)
Firm Age		-0.0786	0.0250	0.0341	0.00911
		(0.159)	(0.161)	(0.162)	(0.158)
log (Workers)			-0.556***	-0.570***	-0.515***
			(0.138)	(0.138)	(0.143)
Public				-0.642	-0.431
				(0.425)	(0.440)
% Union					0.00480
					(0.00454)
% Emp with Coll Educ					-0.0231***
					(0.00844)
Observations	672	672	672	672	672
R^2	0.125	0.146	0.166	0.168	0.179
Ind FE	Yes	Yes	Yes	Yes	Yes
Interview Controls	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes

Note: ***, ** and * indicate significance at the 1,5 and 10 percent levels respectively. Standard errors are clustered at the plant level.

Table 3: Robustness Check: Imputing Missing Observations

Panel A: (Poll / Emp)					
	(1)	(2)	(3)	(4)	(5)
Management	-0.299**	-0.305**	-0.291**	-0.302**	-0.241*
	(0.135)	(0.135)	(0.122)	(0.128)	(0.128)
Firm Age		0.297***	0.301***	0.297***	0.276***
		(0.111)	(0.106)	(0.105)	(0.104)
log (Workers)			-0.0273	-0.0258	-0.0315
			(0.0999)	(0.0998)	(0.102)
Public				0.408	0.464
				(0.450)	(0.452)
% Union					0.00628
					(0.00394)
% Emp with Coll Educ					-0.00826**
					(0.00383)
Observations	1128	1128	1128	1128	1128
R^2	0.078	0.084	0.084	0.085	0.089
Ind FE	Yes	Yes	Yes	Yes	Yes
Interview Controls	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes

Note: ***, ** and * indicate significance at the 1,5 and 10 percent levels respectively. The above table reports results where equation 1 is run on the full WMS data set, where pollution is set to zero for plants that were not matched to the NEI. Note that Panel B, which takes the natural log of the pollution intensity measure cannot be run because the pollution intensity measure now includes many observations with a value of zero. Standard errors are clustered at the plant level.

Table 4: Question Specific Regression Results

Panel A: (Poll / Emp)					
	(1)	(2)	(3)	(4)	(5)
Lean 1	-0.364**	-0.343**	-0.276**	-0.276**	-0.257*
	(0.143)	(0.143)	(0.139)	(0.140)	(0.141)
Lean 2	-0.406*	-0.436**	-0.367*	-0.367*	-0.350*
	(0.209)	(0.211)	(0.204)	(0.206)	(0.206)
Perf 1	-0.372	-0.428	-0.364	-0.364	-0.347
	(0.317)	(0.314)	(0.302)	(0.303)	(0.303)
Perf 2	-0.183	-0.212	-0.145	-0.145	-0.122
	(0.183)	(0.182)	(0.181)	(0.186)	(0.184)
Perf 3	-0.175	-0.168	-0.0967	-0.0962	-0.0791
	(0.297)	(0.304)	(0.291)	(0.298)	(0.298)
Perf 4	-0.0934	-0.141	-0.0528	-0.0525	-0.0165
	(0.167)	(0.166)	(0.171)	(0.175)	(0.172)
Perf 5	-0.276	-0.321	-0.241	-0.241	-0.198
	(0.202)	(0.199)	(0.190)	(0.188)	(0.185)
Perf 6	0.0400	0.0947	0.154	0.154	0.158
	(0.156)	(0.163)	(0.151)	(0.151)	(0.155)
Perf 7	-0.477**	-0.454*	-0.387*	-0.387*	-0.366
	(0.239)	(0.234)	(0.225)	(0.227)	(0.223)
Perf 8	-0.296	-0.279	-0.235	-0.237	-0.221
	(0.194)	(0.192)	(0.186)	(0.189)	(0.199)
Perf 9	-0.420**	-0.410**	-0.361*	-0.361*	-0.334*
	(0.206)	(0.203)	(0.194)	(0.195)	(0.195)
Perf 10	-0.625***	-0.609***	-0.574***	-0.572***	-0.573***
	(0.208)	(0.207)	(0.205)	(0.204)	(0.197)
Talent 1	-0.462**	-0.421**	-0.357**	-0.357**	-0.313*
	(0.187)	(0.187)	(0.177)	(0.179)	(0.183)
Talent 2	-0.331**	-0.291**	-0.243*	-0.243*	-0.187
	(0.142)	(0.144)	(0.136)	(0.135)	(0.145)
Talent 3	-0.794**	-0.747**	-0.710**	-0.710**	-0.665**
	(0.321)	(0.318)	(0.309)	(0.309)	(0.313)
Talent 4	-0.0892	-0.0863	-0.0334	-0.0326	0.0543
	(0.177)	(0.179)	(0.183)	(0.187)	(0.208)
Talent 5	-0.537*	-0.523*	-0.444	-0.445	-0.392
	(0.300)	(0.301)	(0.285)	(0.289)	(0.295)
Talent 6	-0.215	-0.136	-0.104	-0.105	-0.0671
	(0.217)	(0.226)	(0.218)	(0.217)	(0.222)
Observations	672	672	672	672	672
Ind FE	Yes	Yes	Yes	Yes	Yes
Interview Controls	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes

Note: ***, ** and * indicate significance at the 1,5 and 10 percent levels respectively. The above table reports results where equation 1 is run separately on each of the 18 management questions for each of the five regression specifications in 2 and 3. Column 1 runs the same specification as column 1 in Table 2, column 2 is the same as column 2 and so on. The 18 management questions are found in the data appendix. Standard errors are clustered at the plant level.

Table 5: Non Attainment Results

Panel A: (Poll / Emp)					
	(1)	(2)	(3)	(4)	(5)
ManagexNonatt	0.474	0.478	0.476	0.466	0.471
	(0.392)	(0.391)	(0.390)	(0.381)	(0.384)
Management	-0.652*	-0.655**	-0.631**	-0.636**	-0.585*
	(0.332)	(0.331)	(0.318)	(0.319)	(0.324)
Nonatt	-1.948	-1.960	-1.957	-1.927	-1.929
	(1.440)	(1.437)	(1.436)	(1.406)	(1.415)
Firm Age		0.291***	0.297***	0.293***	0.270**
		(0.112)	(0.107)	(0.106)	(0.106)
log (# Workers)			-0.0474	-0.0456	-0.0506
			(0.0994)	(0.0993)	(0.101)
Public				0.400	0.451
				(0.437)	(0.438)
% Union					0.00666
					(0.00411)
% Emp with Coll Educ					-0.00727*
					(0.00402)
Observations	1,061	1,061	1,061	1,061	1,061
R^2	0.085	0.090	0.090	0.091	0.095
Ind FE	Yes	Yes	Yes	Yes	Yes
Interview Controls	No	Yes	Yes	No	Yes
Region FE	No	No	No	No	Yes
Plant Controls	No	No	Yes	Yes	Yes

Note: ***, ** and * indicate significance at the 1,5 and 10 percent levels respectively. The above regression results use the same model as Table 2 but now include a Management x Ozone interaction term which examines whether management practices have a stronger association with pollution in counties that are more heavily regulated. Standard errors are clustered at the plant level.

A Data Appendix

The National Emissions Inventory and the World Management Survey were merged based on name, county and industry. Near exact matches were required to be made on name and an exact match for county was required for all WMS observations who reported the plant's county. While state was reported for all WMS observations, county was reported for only 68% of observations. Plants in the NEI report emission levels only for the pollutants that they emit. As a result, if the plant is present in the NEI but has missing values for one of the criteria pollutants then that pollutant is assigned a value of zero. Observations whose logged difference from their industry average emissions intensity rates are in the top and bottom 2% of all observations are dropped. This is a way to alleviate concerns that matching errors and outliers are driving the results.

The NEI reporting thresholds vary for each pollutant and are based off of the maximum possible amount of pollution the plant could emit rather than the actual amount that they emit. For NOx, PM2.5 and SOx, the reporting threshold is 100 tons per year. For lead, the threshold is 5 tons per year. For VOC's the threshold varies by Ozone attainment status. The threshold is 100 tons for plants in attainment and plants in counties that are in Moderate nonattainment. Plants in counties designated as "Serious" nonattainment for Ozone have a reporting threshold of 50 tons. Plants in counties designated as "Severe" nonattainment for Ozone have a reporting threshold of 25 tons. Plants in counties designated as "Extreme" nonattainment for Ozone have a reporting threshold of 10 tons. For CO, plants in attainment had a 1000 ton reporting requirement and plants in nonattainment (all designations) for ozone and CO had a 100 ton reporting requirement. For PM10, plants designates as "Serious" nonattainment had a 70 ton reporting requirement while all other plants had a 100 ton reporting requirement.

Differences in reporting requirements may increase the number of observations in the lower tail of the pollution intensity distribution. As a result, the management - regulation regressions should ensure that the lower tail is not driving the results.

In practice, states will often report emissions from facilities that are far below the levels stated above. States also vary in how they collect the data itself. Emissions data from the largest industrial facilities is obtained using continuous emissions monitoring systems. However, emissions from the majority of facilities is calculated using an emissions factor whereby plants report the specific types of capital they use in production and their specific pollution abating capital. They report the amount of fuel they use and this data is then used to calculate total emissions. The specific formulas used to estimate emissions are based off of a large number of tests performed by the EPA on a wide range production and pollution abatement capital used in the manufacturing sector. The NEI does not provide information on whether a facility's emissions were observed directly or imputed using the emissions factor formula.

See `http://www3.epa.gov/ttnchie1/eidocs/eiguid/eiguidfinal_nov2005.pdf` for these and more details about the reporting requirements. I thank Ron Ryan from the EPA for help in understanding the sources of the NEI data.

The survey used to collect the WMS management data is found at the end of this paper. Each of the eighteen questions are included as well as potential answers and how they would be scored. The survey numbers the questions 1 through 18, but the WMS data defines the first two questions to be Lean 1 and Lean 2, the next ten questions (3-12 on the survey) are Perf 1 - Perf 10 respectively. Questions 13-18 on the survey are Talent 1 through Talent 6 respectively.

Table A1: Summary Statistics: Matched vs. Unmatched Observations

	(1)	(2)
	Unmatched	Matched
Management	3.175	3.375
	(0.670)	(0.655)
# Workers	231.744	275.903
	(588.501)	(338.821)
Public	0.322	0.263
	(0.468)	(0.441)
% Unionized	12.509	24.150
	(27.928)	(36.538)
Firm Age	44.473	52.762
	(43.851)	(42.731)
% Emp with Coll Educ	22.763	19.360
	(23.282)	(19.705)
Observations	635	589

Note: The above table provides summary statistics for both the set of matched and unmatched observations in the management data. Note that some matched observations are excluded from the baseline analysis either because they are outliers (defined as observations whose logged difference from their industry average fall in the top and bottom 2% of all observations) or because one or more of the control variables is missing.

Table A2: Summary Statistics: Attainment vs. Nonattainment Observations

	(1) Attainment	(2) Nonattainment
Management	3.339	3.301
	(0.627)	(0.672)
Poll/Emp	0.673	0.371
	(4.117)	(2.928)
# Workers	537.650	672.553
	(1202.425)	(2777.848)
Firm Age	52.907	54.058
	(41.143)	(47.234)
Public	0.089	0.115
	(0.285)	(0.320)
% Unionized	16.837	18.265
	(32.226)	(32.911)
% Emp with Coll Educ	18.167	21.948
	(17.563)	(20.865)
% in "Dirty" Ind.	0.353	0.356
	(0.479)	(0.479)
Observations	529	599

Note: The above table provides summary statistics for plants in attainment and in nonattainment counties.

Table A3: Robustness Check: Controlling for Firm Capital Intensity

	(Poll / Emp)				
	(1)	(2)	(3)	(4)	(5)
Management	-0.719*	-0.713*	-0.672	-0.676	-0.688
	(0.433)	(0.428)	(0.413)	(0.429)	(0.456)
Capital Intensity	0.351	0.349	0.350	0.352	0.328
	(0.239)	(0.229)	(0.230)	(0.226)	(0.211)
Firm Age		0.444*	0.478**	0.471**	0.495**
		(0.226)	(0.218)	(0.215)	(0.241)
log (# Workers)			-0.0968	-0.0913	-0.0708
			(0.118)	(0.119)	(0.136)
Public				0.104	0.0800
				(0.728)	(0.725)
% Union					-0.0114
					(0.0135)
% Emp with Coll Educ					-0.00871
					(0.0118)
Observations	329	329	329	329	329
R^2	0.172	0.178	0.179	0.179	0.184
Ind FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Interview Controls	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports regression results that control for the capital intensity of the firm to which the plant belongs. Capital intensity data is defined as the value of the firm's capital stock divided by the value of the firm's revenue. The data come from Compustat and are only available for publicly traded firms, hence the large drop in the number of observations.

Interview Details	Company and Manager's Information
Company ID: ______________________ Company Name: ______________________ Interviewer Name: ______________ Date (DD/MM/YY): ______________ Time (24 hour clock): ______________ Running interview ☐ Listening to interview ☐	a) Position: ______________________ b) Tenure in post (*number of years*): ______________ c) Tenure in company (*number of years*): ______________ d) When was your factory built (*number of years*)? ________ e) Country: ______________ f) Region: ______________ g) Number of competitors: ________ (*i.e. major domestic and international competitors*)

Management Questions

1) Introducing Lean (Modern) Techniques *Tests how well lean (modern)manufacturing management techniques have been introduced* Score: 1☐ 2☐ 3☐ 4☐ 5☐ -99☐	a) Can you describe the production process for me? b) What kinds of lean (modern) manufacturing processes have you introduced? How long has this practice been in place? Can you give me specific examples? c) How do you manage inventory levels? What is done to balance the line? What is the takt time of your manufacturing processes?		
	Score 1: Other than JIT delivery from suppliers few modern manufacturing techniques have been introduced (or have been introduced in an ad-hoc manner)	Score 3: Some aspects of modern (lean) manufacturing techniques have been introduced, through informal/isolated change programmes	Score 5: All major aspects of modern/lean manufacturing have been introduced (Just-in-time, autonomation, flexible manpower, support systems, attitudes and behaviour) in a formal way
2) Rationale for Introducing Lean (Modern)Techniques *Tests the motivation and impetus behind changes to operations and what change story was communicated* Score: 1☐ 2☐ 3☐ 4☐ 5☐ -99☐	a) Can you take me through the rationale to introduce these processes? b) What factors led to the adoption of these lean (modern) management practices?		
	Score 1: Modern (lean) manufacturing techniques were introduced because others were using them	Score 3: Modern (lean) manufacturing techniques were introduced to reduce costs	Score 5: Modern (lean) manufacturing techniques were introduced to enable us to meet our business objectives (including costs)

3) Process Documentation and Continuous Improvement

Tests processes for and attitudes to continuous improvement and whether learnings are captured/ documented

a) How do problems typically get exposed and fixed?
b) Talk me through the process for a recent problem.
c) How can the staff suggest process improvements?

Score:

1☐ 2☐ 3☐ 4☐ 5☐ -99☐

Score 1	Score 3	Score 5
Score 1: No process improvements are made when problems occur	Score 3: Improvements are made in 1 week workshops involving all staff (to improve performance in their area of the plant)	Score 5: Exposing problems in a structured way is integral to individuals' responsibilities and resolution occurs as a part of normal business processes rather than by extraordinary effort/teams

4) Performance Tracking

Tests whether performance is tracked using meaningful metrics and with appropriate regularity

a) What kind of KPIs would you use for performance tracking?
b) How frequently are these measured? Who gets to see this KPI data?
c) If I were to walk through your factory could I tell how you were doing against your KPIs?

Score:

1☐ 2☐ 3☐ 4☐ 5☐ -99☐

Score 1	Score 3	Score 5
Score 1: Measures tracked do not indicate directly if overall business objectives are being met. Tracking is an ad-hoc process (certain processes aren't tracked at all)	Score 3: Most key performance indicators are tracked formally; tracking is overseen by senior management	Score 5: Performance is continuously tracked and communicated, both formally and informally, to all staff using a range of visual management tools

5) Performance Review

Tests whether performance is reviewed with appropriate frequency and communicated to staff

a) How do you review your KPIs?
b) Tell me about a recent meeting.
c) Who is involved in these meetings? Who gets to see the results of this review?
d) What is the follow up plan?

Score:

1☐ 2☐ 3☐ 4☐ 5☐ -99☐

Score 1	Score 3	Score 5
Score 1: Performance is reviewed infrequently or in an un-meaningful way (e.g. only success or failure is noted)	Score 3: Performance is reviewed periodically with both successes and failures identified; Results are communicated to senior management; No clear follow-up plan is adopted	Score 5: Performance is continually reviewed, based on indicators tracked; All aspects are followed up to ensure continuous improvement; Results are communicated to all staff

6) Performance Dialogue

Tests the quality of review conversations

a) How are these meetings structured? Tell me about your most recent meeting.
b) How would the agenda for the meeting be determined?
c) What type of feedback occurs in these meetings?
d) For a given problem, how would you identify the root cause?

Score:

1☐ 2☐ 3☐ 4☐ 5☐ -99☐

Score 1	Score 3	Score 5
Score 1: The right data or information for a constructive discussion is often not present or conversations overly focus on data that is not meaningful; Clear agenda is not known and purpose is not stated explicitly	Score 3: Review conversations are held with the appropriate data and information present; Objectives of meetings are clear to all participating and a clear agenda is present. Conversations do not, as a matter of course, drive to the root causes of the problems	Score 5: Regular review/performance conversations focus on problem solving and addressing root causes; Purpose, agenda and follow-up steps are clear to all. Meetings are an opportunity for constructive feedback and coaching

7) Consequence Management *Tests whether differing levels of performance (not personal but plan/ process based) lead to different consequences* Score: 1☐ 2☐ 3☐ 4☐ 5☐ -99☐	a) Let's say you've agreed to a follow up plan at one of your meetings, what would happen if the plan weren't enacted? b) How long is it between when a problem is identified to when it is solved? Can you give me a recent example? c) How do you deal with repeated failures in a specific business segment?		
	Score 1: Failure to achieve agreed objectives does not carry any consequences	Score 3: Failure to achieve agreed results is tolerated for a period before action is taken	Score 5: A failure to achieve agreed targets drives retraining in identified areas of weakness or moving individuals to where their skills are appropriate
8) Types and Balance of Targets *Tests whether targets cover a sufficiently broad set of metrics and whether financial and non-financial targets are balanced* Score: 1☐ 2☐ 3☐ 4☐ 5☐ -99☐	a) What types of targets are set for the company? What are the goals for your plant? b) Tell me about the non-financial goals?		
	Score 1: Goals are exclusively financial or operational	Score 3: Goals include non-financial targets, which form part of the performance appraisal of top management only (they are not reinforced throughout the rest of organisation)	Score 5: Goals are a balance of financial and non-financial targets; Senior managers believe the non-financial targets are often more inspiring and challenging than financials alone (e.g. 60% market share by 2003)
9) Interconnection of Targets *Tests whether targets are tied the organization's objectives and how well they cascade down the organisation* Score: 1☐ 2☐ 3☐ 4☐ 5☐ -99☐	a) What is the motivation behind your goals? b) How are these goals cascaded down to the individual workers? c) How are your targets linked to company performance and their goals?		
	Score 1: Goals are based purely on accounting figures (with no clear connection to shareholder value)	Score 3: Corporate goals are based on shareholder value but are not clearly cascaded down to individuals	Score 5: Corporate goals focus on shareholder value. They increase in specificity as they cascade through business units ultimately defining individual performance expectations
10) Time Horizon of Targets *Tests whether firm has a '3 horizons' approach to planning and targets* Score: 1☐ 2☐ 3☐ 4☐ 5☐ -99☐	a) What kind of time scale are you looking at with your targets? b) Which goals receive the most emphasis? c) Are long term and short term goals set independently? d) Could you meet all your short-run goals but miss your long-run goals?		
	Score 1: Top management's main focus is on short term targets	Score 3: There are short and long term goals for all levels of the organisation. As they are set independently, they are not necessarily linked to each other	Score 5: Long term goals are translated into specific short term targets so that short term targets become a "staircase" to reach long term goals

<table>
<tr><td rowspan="2"><u>11) Target Stretch</u>

Tests whether targets are based on a solid rationale and are appropriately difficult to achieve

Score:

1☐ 2☐ 3☐ 4☐ 5☐ -99☐</td><td colspan="3">a) How tough are your targets? Do you feel pushed by them?
b) On average, how often would you say that you meet your targets?
c) Do you feel that all groups receive the same degree of difficulty, in terms of targets? Do some groups get easy targets?
d) What is the rationale behind the targets?</td></tr>
<tr><td>Score 1: Goals are either too easy or impossible to achieve; managers low-ball estimates to ensure easy goals</td><td>Score 3: In most areas, top management pushes for aggressive goals based on solid economic rationale. There are a few "sacred cows" that are not held to the same rigorous standard</td><td>Score 5: Goals are genuinely demanding for all divisions. They are grounded in solid, solid economic rationale</td></tr>
<tr><td rowspan="2"><u>12) Clarity and Comparability of Goals</u>

Tests how easily understandable performance measures are and whether performance is openly communicated to staff

Score:

1☐ 2☐ 3☐ 4☐ 5☐ -99☐</td><td colspan="3">a) If I asked your staff directly about individual targets what would they tell me?
b) Does anyone complain that the targets are too complex?
c) How do people know about their own performance compared to other people’s performance?</td></tr>
<tr><td>Score 1: Performance measures are complex and not clearly understood. Individual performance is not made public</td><td>Score 3: Performance measures are well defined and communicated; performance is public in all levels but comparisons are discouraged</td><td>Score 5: Performance measures are well defined, strongly communicated and reinforced at all reviews; performance and rankings are made public to induce competition</td></tr>
<tr><td rowspan="2"><u>13) Instilling a talent mindset/ Managing Talent</u>

Tests what emphasis is out on overall talent management within the organization

Score:

1☐ 2☐ 3☐ 4☐ 5☐ -99☐</td><td colspan="3">a) How do senior managers show that attracting and developing talent is a top priority?
b) Do senior managers get any rewards for bringing in and keeping talented people in the company?</td></tr>
<tr><td>Score 1: Senior management do not communicate that attracting, retaining and developing talent throughout the organisation is a top priority</td><td>Score 3: Senior management believe and communicate that having top talent throughout the organisation is a key way to win</td><td>Score 5: Senior managers are evaluated and held accountable on the strength of the talent pool they actively build</td></tr>
<tr><td rowspan="2"><u>14) Building a High-Performance Culture through Incentives and Appraisals</u>

Tests whether there is a systematic approach to identifying good and bad performers and rewarding them proportionately

Score:

1☐ 2☐ 3☐ 4☐ 5☐ -99☐</td><td colspan="3">a) How does your appraisal system work? Tell me about the most recent round?
b) How does the bonus system work?
c) Are there any non-financial rewards for top performers?
d) How does your reward system compare to your competitors?</td></tr>
<tr><td>Score 1: People within our firm are rewarded equally irrespective of performance level</td><td>Score 3: Our company has an evaluation system for the awarding of performance related rewards</td><td>Score 5: We strive to outperform the competitors by providing ambitious stretch targets with clear performance related accountability and rewards</td></tr>
</table>

Manager's Bonus: What is your bonus as a percentage of salary? ______ What is your percentage increase of salary, when you receive a promotion?_______	% of the bonus based on individual performance __________ % of the bonus based on team/plant performance __________ % of the bonus based on company performance __________	*Refused to answer* Yes ☐ No ☐ *Bonus on individual, team, and company performance MUST add up to 100*

<u>15) Removing Poor Performers/ Making Room for Talent</u> *Tests how well the organization is able to deal with underperformers* Score: 1☐ 2☐ 3☐ 4☐ 5☐ -99☐	a) If you had a worker who could not do his job what would you do? Could you give me a recent example? b) How long would underperformance be tolerated? c) Do you find any workers who lead a sort of charmed life? Do some individuals always just manage to avoid being fixed/fired?		
	Score 1: Poor performers are rarely removed from their positions	Score 3: Suspected poor performers stay in a position for a few years before action is taken	Score 5: We move poor performers out of the company or to less critical roles as soon as a weakness is identified
<u>16) Developing Talent and Promoting High-Performers</u> *Tests whether promotion is performance based and whether talent is developed within the organization* Score: 1☐ 2☐ 3☐ 4☐ 5☐ -99☐	a) Tell me about your promotion system. b) What about poor performers? What happens with them? Are there any examples you can think of? c) How would you identify and develop your star performers? d) If two people both joined the company 5 years ago and one was much better than the other what job opportunities would he/she have in the company?		
	Score 1: People are promoted primarily upon the basis of tenure	Score 3: People are promoted upon the basis of performance	Score 5: We actively identify, develop and promote our top performers
<u>17) Distinctive Employee Value Proposition</u> *Tests the strength of the employee value proposition* Score: 1☐ 2☐ 3☐ 4☐ 5☐ -99☐	a) What makes it distinctive to work at your company as opposed to your competitors? b) If you were trying to sell your firm to me how would you do this (get them to try to do this)? c) What don't people like about working in your firm?		
	Score 1: Our competitors offer stronger reasons for talented people to join their companies	Score 3: Our value proposition to those joining our company is comparable to those offered by others in the sector	Score 5: We provide a unique value proposition above our competitors to encourage talented people to join our company
<u>18) Retaining Talent</u> *Tests whether the organization will go out of its way to keep its top talent* Score: 1☐ 2☐ 3☐ 4☐ 5☐ -99☐	a) If you had a star performer who wanted to leave what would the company do? b) Could you give me an example of a star performers being persuaded to stay after wanting to leave? c) Could you give me an example of a star performer who left the company without anyone trying to keep them?		
	Score 1: We do little to try and keep our top talent	Score 3: We usually work hard to keep our top talent	Score 5: We do whatever it takes to retain our talent