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Management Practice in Production

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Abstract

In this paper we account for observed management practice in the estimation of a production function. In our model management practice is observable and we allow it to affect output directly (neutral shift) and indirectly by affecting input productivity. This formulation gives us a semiparametric smooth coefficient model. Empirically, we find that estimates of unobserved (in)efficiency do not correlate highly with observed management. We also find that management affects output both directly and indirectly via all factors of production, i.e., the productivity effect of management is non-neutral. Finally, we find that the indirect effects of conventional inputs vary with management.

JEL Code: D24, C14, M11.

Keywords: Management practice, production functions, semiparametric model.

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1 Introduction

Economists have long recognized that management is an important factor in production (Marshall, 2009; Mundlak, 1961; Leibenstein, 1966). According to Nuthall (2009, p. 413) "... the key factor in the management of land, labour and capital is the management ability applied." The challenge is how to incorporate it in a theoretical model and estimate its impact empirically. Bloom et al. (2009) suggest that predictions of the effect of management on performance measures like productivity and profitability will differ depending on how theoretical models conceptualize management.

Difficulties to measure management led to early attempts to treat it as an unobserved input (Farrell, 1957; Mundlak, 1961). Later studies used input, output or process proxies to measure management. Examples are education, experience (Stefanou and Saxena, 1988; Kirkley et al., 1998), performance (Mefford, 1986; Byma and Tauer, 2007) and practices (Bloom and Van Reenen, 2007). These alternative strategies are also reflected in the famous debate between Leibenstein and Stigler. Leibenstein (1966) treated (unobserved) X-inefficiency (possible resulting from poor management) as a deviation from some best-practice. But Stigler (1976, p. 215) accused Leibenstein of "concealment" and argued that management should be incorporated in production models.

Many empirical models that include management in production (1) treat management as unobserved input possibly confounding it with other unobserved variables like the production environment, (2) include unobserved or observed management variables not flexible enough to capture the 'true' effects of management on productivity and to identify the channels through which management affects productivity.

The effect of management on productivity can be modelled empirically in many ways. First, one can think of management either as an input similar to the conventional inputs such as capital and labour, or a facilitating input (McCloud and Kumbhakar, 2008) which affects productivity of the conventional inputs, i.e., management is an input augmenting factor changing the quality of inputs meaning that good management can get more output using the same input quantities. Second, management is a technology shifter which can be either neutral or non-neutral. Third, management helps in efficient input usage enhancing technical or allocative efficiency. We do not allow for technical inefficiency in our main model and do not model allocative efficiency which would require an explicit behavioural assumption (e.g., profit maximization). Since firms may pursue multiple behaviours, we do not address allocative effects of management in this paper.

In our generalised model management is viewed as technology shifter which means that some (or all) of the production function parameters change with management. The semiparametric smooth coefficient (SPSC) model (Li et al., 2002) fits our conceptual model well. It allows the input (i.e., capital and labour) coefficients to vary with management practice. In doing so, unlike the existing literature, we allow management to affect output directly as well as indirectly through the various conventional inputs. Furthermore, under some (testable) restrictions (discussed later) our generalised model reduces to some of the popular models used in the literature in which management is treated either as a conventional input or as an input augmenting factor. For some parametric specifications these two formulations cannot be separated. However, the SPSC model we use will still be more general. Therefore, our research objective is to improve on the empirical modelling of management in production. This new modelling approach provides new insights on how management effects production, i.e., the channels through which it works.

Using a cross section of the data from Bloom and Van Reenen (2010) who surveyed a large number of firms on their management practices, we find the following results. First, estimates of unobserved efficiency have a statistically significant but low correlation with observed management practices, thereby meaning that efficiency scores are not a good proxy for management. Second, we find that the effect of management is non-neutral, i.e., the effect of management on total factor productivity is not constant but depends on individual factor productivities as well. Third, the effect of management on factor productivity is not constant or linear. The output elasticities of conventional inputs vary with management in systematic ways.

The rest of the paper is organised as follows. Section 2 summarises the relevant literature. Section 3 introduces our analytical approach. Section 4 describes the data. Section 5 gives our results and section 6 concludes.

2 Related Literature

There is a growing literature that studies empirically the impact of management on productivity. The importance of management has long been recognized in the literature on production, productivity and efficiency though its importance is not yet fully recognized in the mainstream economics literature which argues that there is no need to treat management separately because competition would weed out bad management swiftly (Bloom et al., 2011). But, there is no empirical evidence for such a hypothesis. Large numbers of studies have found that differences in firm performance persist over time (Syverson, 2011), and the inability to adopt best management practice is a likely cause.

Management theories broadly distinguish between management as an input, as a technology, and as contingent (Bloom et al., 2009). When management is treated as an input we should expect decreasing marginal productivity at some point just like any conventional input factor (Alvarez and Arias, 2003). If however management is considered free knowledge like the overall production technology there should be no decrease in marginal productivity. Implicitly the distinction between management as input and as technology is one between quantity and quality. Whereas larger quantities lead to decreasing marginal products at some point improvements in quality do not. Also note that textbook production theory suggests that marginal productivity might decrease but never turns negative (i.e. inputs are freely disposable). A third theory treats management as contingent where the impact of management depends on the characteristics of the firm and its environment (Thompson, 2003; Lawrence and Lorsch, 1967). An important implication of this so called contingency theory is that even if better management is costless its marginal impact might be negative because management practices are a bad fit for the firm. In reality firm characteristics including the production environment will always play a role and so the contingency approach is rather complementary to the other two conceptions of management (Bloom and Van Reenen, 2010). Bloom and Van Reenen (2006) categorize these management theories and discuss their relative merits in explaining observed differences in management practices across firms. First, “optimal choice of management practices” type models comprising the input and contingency theories suggest that the benefits and costs of adopting better management practices vary across firms and thus profit maximizing firms adopt different level of management. Second, “managerial inefficiency” type models like management as technology assume that there are exogenous differences in management quality that cannot be arbitraged away and thus persist.

A theoretical model that applies these ideas of management was introduced by Lucas (1978) who suggested that the size distribution of firms is not driven by the combination of technology and demand but by the distribution of managerial talent. He proposed an equilibrium model where the conventional inputs capital and labour are allocated to managers of varying ability so as to maximize the output of the economy. Lucas suggested that the higher a manager’s ability or effort the more resources he commands. Put differently in a competitive (economy-wide) equilibrium resources are optimally allocated to managers of varying abilities. This model is important for the interpretation of our results because it suggests that the marginal product of improved management should be small in long-run equilibrium (i.e. once the most able managers have been allocated to the most demanding tasks). The building blocks of Lucas’ theory are a *production technology* and a *managerial technology* (p. 511). Whereas the former exhibits constant returns to scale the latter exhibits decreasing returns because of a limited span of managerial control. Thus, Lucas treats management as an input that is qualitatively different from the conventional inputs. As we will discuss below our model allows for such a qualitative difference between the conventional inputs and management.

The empirical productivity literature has long recognized that the omission of management as an input might bias the parameter estimates for production functions (Mundlak, 1961). Early attempts to account for management in empirical production functions were constrained by the difficulty of measuring the management input. Mundlak (1961) worked around the measurement problem by assuming that management is unobserved and can be modelled as a firm-specific (time-invariant) fixed-effects. Although this approach reduces the bias of the parameters of the production function it is unsatisfactory for two reasons. First, it is impossible to separate management from other unobserved variables. Second, this approach contributes little to our understanding of how management influences production. Nevertheless treating management as unobserved has been the preferred approach in the empirical literature.

Another strand of the productivity literature models management as (unobserved) inefficiency assuming that it does not affect the (best available technology) but its efficient use (Meeusen and van den Broeck, 1977; Aigner et al., 1977; Charnes et al., 1978). This literature describes the units of observation as "decision making units" which strongly hints at the implied link between inefficiency and management. These models in a cross-sectional set-up cannot distinguish inefficiency from firm heterogeneity. Such a distinction is only possible in a panel data framework (Kumbhakar, 1990; Alvarez et al., 2004; Greene, 2005; Wang and Ho, 2010). Unlike in our model these models assume that technology and management are independent. For instance, in a recent application Alvarez and Schmidt (2006) use a stochastic frontier random effects model to show that the skills (unobserved efficiency) of fishing captains have less influence on their performance than pure luck (random error).

Parallel to the strands of the literature that treat management as unobserved is a strand that measures management by proxy. This literature distinguishes between input, output, and process proxies. Typical input proxies are experience and education whereas output proxies are financial performance or other criteria of success like the balanced scorecard (Kaplan and Norton, 1992). An example of a process measure is management practices. All these proxies have their shortcomings. In particular, output measures assume that success only depends on management and input measures often relate more to ability than effort. Both input and output measures are often endogenous. Lucas (1978) suggested that better managers might work for bigger firms because that is where they can leverage their superior performance. Process measures might be less prone to endogeneity but assume that the researcher knows what managers should do. As Bloom and Van Reenen (2007, p. 1356) say:

> "Our starting point is that there are likely to be management practices that are on average, 'good' for firm productivity."

Applications are mostly to agriculture, manufacturing and retailing. Mefford (1986) combines three output measures: output goal attainment, cost (factory budget) over- or under-fulfillment, and quality level of the output as a proxy for management. He finds that in a parametric production function using various functional forms the management variable is significant. Griffith et al. (2006) correlate balanced scorecard measures of management with labour productivity and find a positive relationship.

Most recently there have been efforts to measure management more accurately by surveying firms on their management practices. Early work on the link between practices and firm performance concentrated on human resource practices (Huselid, 1995; Black and Lynch, 2001). Black and Lynch (2001) analyse the impact of workplace practices on productivity and find that implementation is important. For instance, they show that simply having Total Quality Management (TQM) is not sufficient to improve productivity. TQM needs to be complemented with other practices like greater employee voice to have an impact. Over time the range of practices has grown. Bloom and Van Reenen (2007) and Siebert and Zubanov (2010) survey firms on a number of practices. Bloom and Van Reenen (2007) and Bloom and Van Reenen (2010) is by far the largest and most elaborate survey of several thousand medium-sized manufacturing firms from several countries and it is their data we use here. They suggest that management is the link or transmission mechanism between firm performance and its ultimate drivers. Bloom and Van Reenen (2007) proceed in two steps. First, because their approach requires assumptions about what "good" management is they "validate" their survey measure with independent measures of firm performance like productivity. They find that across various measure of performance management is positively and significantly correlated. Also they confirm their definition of "good" management practices is the same across the countries in their sample. Second, they investigate possible correlates for management practices. They find that out of a number of candidate variables product market competition and primogeniture (only first born sons are CEOs of family firms) are significant drivers for management practices.

Finally, irrespective of how management is measured most studies assume that it enters the production function in a neutral way and that its impact is linear or even constant. For instance, Cobb-Douglas, fixed-effects and stochastic frontier models assume that management enters in a neutral fashion, i.e., management affects productivity not through any of the other inputs. And in a popular Cobb-Douglas specification (Black and Lynch, 2001; Bloom and Van Reenen, 2007) management has a constant impact on productivity. But McCloud and Kumbhakar (2008) showed that allowing for indirect effects can lead to different conclusions than allowing for a direct impact only.

3 Analytical Approach

The objective of our approach is to apply a flexible model of production that allows productivity to vary with management. Flexibility means that the effect of management on output is non-neutral, is different for different conventional input factors, and is heterogenous across firms. To start with, it is useful to note that management can affect production in three possible ways. First, it can affect the technology, i.e., the relationship between inputs and outputs. Second, it can affect technical efficiency, i.e., the efficiency with which inputs are converted into outputs for a given technology. Third, it can affect technical change which we will not consider here because our data is cross-sectional. One challenge is to distinguish between these channels empirically. We start with a standard production formulation in which the management variable z is treated like the conventional input x, viz.,

$$y = f\left(x, z\right) \tag{1}$$

where y is output. But the inclusion of z changes the technology. In this model there is no conceptual distinction between x and z. Both inputs affect y directly although for a flexible functional form of $f\left(\cdot\right)$ the effect of management depends on the level of x as well.

Instead of treating x and z in the same fashion we can treat z as a facilitating input that augments the other input factors, x. We can write such a model as,

$$y = f\left(A(z)x\right) \tag{2}$$

where $A(z) > 0$ is an input specific productivity factor. If $A(z) > 1$ for an input, management enhances the productivity of that input by increasing the effective quantity of x (resulting in a move along the production function).[1] This specification allows management to affect different input productivities differently (meaning that $A(z)$ are different for different x) and the overall effect can be positive although some of the individual effects are negative. The more popular specification, which is a special case of (2) above, is

$$y = A\left(z\right) f\left(x\right) \tag{3}$$

[1] Although not necessary, one can constrain $A(z)$ to be greater than unity, so that input productivites are never reduced irrespective of the levels of z.

where management shifts the technology neutrally. That is, management is fully separable from all the conventional inputs. In this framework $A(z)$ is often labeled total factor productivity (TFP) similar to the aggregate growth literature where A is typically a function of time (Solow, 1956). In this formulation z can explain TFP. The fixed-effects model of Mundlak (1961) is a version of this where $A(z)$ is firm specific; other examples are Lau and Yotopoulos (1971) and Griffith et al. (2004).

We can write the production function in a more general form, viz.,

$$y = f^{z}(x) \tag{4}$$

where the superscript z indicates that the production function is different for different values of z. This is our flexible form where z shifts the technology non-neutrally via the parameters. For example, the parameters of the underlying production function can change with different values of z. Our general model uses this specification in which the parameters are functions of z. Note that the neutral shift formulation in (3) is a special case of (4).

There are different ways to empirically estimate these models. For example, if the production function is assumed to be Cobb-Douglas (CD), that is both $f(\cdot)$ and $A(\cdot)$ are log-linear the models specified in (1)-(3) can be expressed as,

$$\ln y_i = \alpha_0 + \ln z'\alpha + \ln x'\beta + u_i \tag{5}$$

where z is a vector of management variables (Mefford, 1986; Black and Lynch, 2001; Bloom and Van Reenen, 2007). Thus, it is not possible to distinguish between the channels through which management could affect productivity in models (1)-(3). For a CD production function they are algebraically equivalent. That is, one can interpret the results differently depending on which theoretical model is assumed although the econometric model is exactly the same (the one in (5)).[2] In the TFP literature the shift parameter A $(= exp(\alpha_0))$ is interpreted as the (Solow) residual between the changes in output and inputs (Caves et al., 1982). If there are unobserved management variables then this residual is likely to be explained by the z variables. Similarly, in the Stochastic Frontier (SF) literature firm specific estimates of inefficiency are defined as the percentage difference between the frontier output (maximum possible output given x) and the actual (observed) output. Again this residual is thought to capture the unobserved z. If

[2] This will not be the case if, however, one uses a more flexible functional form such as the translog. Since the CD specification is widely used in most of the papers published in top journals, we will focus most of our attention to the CD case.

the shift parameter A is firm specific (subscript i is used for firm), we can write it as

$$A_i = A_0 \frac{A_i}{A_0} \equiv A_0 e^{-u_i}, \qquad u_i \geq 0 \tag{6}$$

where

$$A_0 = \max_i \{A_i\}, \qquad \frac{A_i}{A_0} = e^{-u_i} \leq 1 \tag{7}$$

From this we obtain the SF production model, viz.,

$$\ln y_i = \alpha_0 + \ln x_i' \beta + v_i - u_i \tag{8}$$

where

$$\alpha_0 = \ln A_0 \tag{9}$$

and v_i is a random noise component outside firm's control.

This model was first proposed by Aigner et al. (1977) and Meeusen and van den Broeck (1977) but they only identified the combined error term $\epsilon_i = v_i - u_i$. Jondrow et al. (1982) showed how to separate inefficiency from noise and obtain observation specific estimates of inefficiency. The interpretation of this model is that $\alpha_0 + \ln x_i'\beta$ is the best-practice frontier technology. Only efficient firms operate on the frontier. An inefficient firm produces $100u_i$ percent less output compared to an efficient firm using the same amount of inputs. If u is viewed as reflections of management, the output shortfall can be interpreted as managerial inefficiency. But poor management is not the only source of inefficiency. For example, an adverse operating environment might be another reason. As discussed above we require panel data to distinguish between "true" inefficiency and firm heterogeneity. If inefficiency is the same as bad management we can correlate estimated inefficiency and our observed management variable to assess the correlation and therefore the relative importance of management for inefficiency. We correlate inefficiency and management using a two-step and a one-step procedure. In the former we simply run a second-stage OLS regression where the inefficiency estimate from a first-stage is the dependent variable and observed management is the independent variable. The stochastic frontier literature also proposes a number of one one-step procedures. We follow a recent integration of the various approaches by Wang (2002) and make both the inefficiency as well as its variance non-monotonic functions of management. We complete the model in (8) and specify

$$
\begin{aligned}
v_i &\sim N(0, \sigma_{\mathrm{v}}^2) && (10)\\
u_i &\sim N^{+}(\mu_{\mathrm{i}}, \sigma_{\mathrm{i}}^2) && (11)\\
\mu_i &= z_i \delta && (12)\\
\sigma_i^2 &= \exp\left(z_i \gamma\right) && (13)
\end{aligned}
$$

That is, the mean and variance of the inefficiency distribution are functions of z. Wang (2002) refer to the variance as “production uncertainty”.

To motivate our generalized model, we return to (3) where $A(\cdot)$ is a function of z. If we do not specify a linear form for $A(\cdot)$ and write the model in (3) as

$$
Y_i = X_i' \beta + g(Z_i) + u_i, \; i = 1, \ldots, n \qquad (14)
$$

we get the model proposed by Robinson (1988) where $g(Z_i) = A(z_i)$, and Y and X are y and x in logarithms. Note that this model is similar to a TFP model, except that TFP is not a linear function of z. In the above formulation $g(Z)$ is completely unspecified (nonparametric) but the X variables appear in a linear fashion (because the production function is CD). Thus, here x and z are treated differently in the sense that the functional form for x is parametric but it is non-parametric for z. Because of this the model is labeled as partial linear (PL) model. Note that if $g(Z_i)$ is linear in Z_i the above model in (14) reduces to the model in (5).

Li et al. (2002) generalized this model and allowed all parameters to be functions of the z variables, i.e.,

$$
Y_i = \alpha(Z_i) + X^{'} \beta(Z_i) + u_i \qquad (15)
$$

This model is labeled as semiparametric smooth coefficient (SPSC) model.[3] In this model z affects productivity both neutrally and non-neutrally. The neutral effect is captured by $\alpha(Z_i)$ and the non-neutral effects are via the inputs $\beta(Z_i)$. The overall effect of $z_j, j = 1, \ldots, J$ - the

[3]Although (14) is nested in (15) the estimation strategies are very different. For details compare Robinson (1988) and Li et al. (2002).

jth z variable on productivity can be measured from

$$\frac{\partial Y_i}{\partial Z_{ji}} = \frac{\partial \alpha(Z_i)}{\partial Z_{ji}} + \sum_{k=1}^{J} \frac{\partial \beta_k(Z_i)}{\partial Z_{ji}} X_i \tag{16}$$

which is the sum of direct and indirect effects. The indirect effect (via the inputs) are constrained to be zero in the partial linear model in (14).

Equation (15) is a production function which is not linear in parameters since both α and β parameters are functions of z_i which are not necessarily linear. In the SPSC model the β_j functions are completely flexible (non-parametric), i.e., the functional form is not specified. This combination of parametric (in X) and nonparametric (in Z) makes the function semiparametric. Our motivation for using a semiparametric model is twofold. First, it follows the economic intuition that productivity varies with management in a fully flexible manner reflecting a "qualitative unevenness in prior information" (Robinson, 1988, p. 932). Second, at the technical level a semiparametric model strikes a balance between precision and robustness (Robinson, 1988). Although fully parametric models are very precise they suffer from possible functional form mis-specification. Potentially mis-specified fully nonparametric models are robust but are inefficient as they suffer from the curse of dimensionality problem (especially when the number of explanatory variables are large). Thus the mixed approach is a good compromise between flexibility and efficiency. Also, the parametric structure makes the semiparametric model less sensitive to outliers than the fully nonparametric model.[4]

We estimate (15) using a local constant least squares estimator proposed by Li et al. (2002) and Li and Racine (2010). For this we rewrite (15) as

$$Y_i = W_i' \gamma(Z_i) + u_i \tag{17}$$

and then pre-multiply it by W_i and take expectations of it conditional on Z_i, which gives

$$E\left[W_i Y_i \mid Z_i\right] Y_i = E\left[W_i W_i' \mid Z_i\right] \gamma(Z_i) + E\left[W_i u_i \mid Z_i\right] \tag{18}$$

Under the assumption $E\left[W_i u_i \mid Z_i\right] = 0$, we can express $\gamma(\cdot)$ as

[4]Li et al. (2002) suggest that a SPSC model suffers the curse of dimensionality if the dimension of z_i is greater than 1. Our empirical model uses a single z variable.

$$\gamma(Z_i) \quad = \quad \left(E\left[W_i W_i' \mid Z_i\right]\right)^{-1} E\left[W_i Y_i \mid Z_i\right] Y_i \tag{19}$$

This formula can be used to estimate $\gamma(Z_i)$.

Li and Racine (2010) propose the following local constant estimator

$$\hat{\gamma}(z) \quad = \quad \left[\sum_{j=1}^{n} W_i W_i' K\left(\frac{Z_j - z}{h}\right)\right]^{-1} \sum_{j=1}^{n} W_i Y_i K\left(\frac{Z_j - z}{h}\right) \tag{20}$$

which is a standard least squares estimators but for the inclusion of $K(\cdot)$, a diagonal kernel or weighting matrix where the ith element is $K_i = K_h(z_i, z)$ and h is a vector of bandwidths. The kernel formula weights the nearby observations. We use a Gaussian kernel. The intuition is that if $K(\cdot)$ was a uniform kernel and z was a scalar $\gamma(z)$ would be a least squares estimator for z close to Z. Generally the bandwidth is obtained by minimizing the squared residuals for the regression curve. We obtain bandwidths using the fully automated least-squares cross-validation method where

$$CV(h) \quad = \quad \min_h n^{-1} \sum_{i=1}^{n} \left[Y_i - W_i' \hat{\gamma}_{-i}(Z)\right]^2 M(Z_i) \tag{21}$$

and $\hat{\gamma}_{-i}(z)$ is the leave-one-out estimator and $0 \leq M(\cdot) \leq 1$ a weight function.[5] This procedure validates the regression curve by its ability to predict out of sample. This makes cross-validation sensitive to outliers (Hartarska et al., 2011) and Bloom and Van Reenen (2010, footnote 2) stress that the data we use is noisy. Therefore we employ the outlier detection method proposed by Filzmoser et al. (2008) and remove about 6 percent of the observations. We obtain estimates for $\beta(z_i)$ for each data point as the z variables are observation specific. Confidence intervals for the coefficients are obtained using a wild bootstrap (Hardle and Mammen, 1993). As all the coefficients depend on z taking the derivative of y with respect to z_i is not straightforward. We calculate the derivative using the approach suggested by Kumbhakar and Sun (2011). We conduct our analysis using the np package (Hayfield and Racine, 2008) for R (R Development Core Team, 2008).

In estimating the production functions (5), (8), (14) and (15) we use the following variables. Sales is used to measure output y. The variables in x include the conventional inputs, viz.,

[5] For details see Li and Racine (2010).

capital and labour as well as an indicator for firm ownership. The z variable is an overall index for management practices. The construction of the variables is explained in more detail in the next section. Bloom and Van Reenen (2007) increase the flexibility of their model by interacting the inputs with country dummies. But in a semiparametric model where the coefficients are fully flexible with respect to z it is not necessary to interact them with country dummies.

Given that we are interested in the effect of management on production we will first use a Cobb-Douglas form for the parametric part and leave most of the flexibility to the nonparametric part (SPSC-CD). This will be followed by the Translog function for the parametric part (SPSC-TL). To investigate the neutrality hypothesis of the management effect we use the partial linear model with a parametric Cobb-Douglas form (PL-CD). Finally, we compare and contrast results from these with their fully parametric counterparts (OLS-CD and OLS-TL).

4 Data

All our data is taken from Bloom and Van Reenen (2010). We use a sample of 3140 observations for medium-sized manufacturing firms (after removing outliers) from a number of countries for the year 2006. Medium-sized means that the firms had between 100 and 5000 employees. Accounting data on these firms were gathered from firms' accounts. The firms were surveyed on their management practices using a practice evaluation tool developed by a leading international management consulting firm. The tool defines and scores 18 separate management practices or categories. Each practice was scored using several questions. The responses were given a score from 1 (worst) to 5 (best). The overall management practice score is the unweighted average across all categories. We normalize the score to have zero mean and unit standard deviation (z-score).

The survey targeted middle managers because practices reflect the organization and behaviour of the firm which do not necessarily change with changes in the top management (Bloom and Van Reenen, 2007, p. 1355). Bloom and Van Reenen (2007, p. 1386) state that their measure of management practice captures “organizational capital” rather than employees' raw ability or skills. Therefore the data should capture the quality of management not managers. Bias was minimized by repeating interviews with different managers and different interviewers. Table 1 gives the variable descriptions.

Table 2 replicates Table 1 from Bloom and Van Reenen (2010) and provides detail on the 18 categories of management practices. All individual questions and example responses are listed in Bloom and Van Reenen (2006). It seems that most of the questions relate to the management of labour rather than capital. This potential bias towards labour effectiveness in the overall

Table 1: Variable Description

Name	Description	Measurement
Management	unweighted average across individual questions	z-score
Sales	Sales (US dollars)	log
Capital	Tangible fixed assets (US dollars)	log
Labour	Employee expenses (US dollars)	log
Public ownership	1 if publicly listed, 0 otherwise	indicator

management index is important because we allow management to affect the individual input productivities.

Table 3 provides summary statistics of all the continuous variables we use in our analysis. Note that the mean and standard deviation for the management variable are close to but not equal to zero and one, respectively because we normalize before removing outliers.

Bloom and Van Reenen collected two waves of data. We faced a trade-off because for the publicly available data the first wave (Bloom and Van Reenen, 2007) has fewer observations but more detail than the second wave (Bloom and Van Reenen, 2010). In particular, for the first wave the separate practice types are available but not for the second wave. We ran various models on both data sets and eventually decided to use the second wave only because our estimation technique is very data intense and the results are stronger. Although the results are qualitatively similar for both waves.

Table 2: The Management Practice Dimensions

Categories	Score from 1-5 based on:
1) Introduction of modern manufacturing techniques	What aspects of manufacturing have been formally introduced, including just-in-time delivery from suppliers, autonomation, flexible manpower, support systems, attitudes, and behavior?
2) Rationale for introduction of modern manufacturing techniques	Were modern manufacturing techniques adopted just because others were using them, or are they linked to meeting business objectives like reducing costs and improving quality?
3) Process problem documentation	Are process improvements made only when problems arise, or are they actively sought out for continuous improvement as part of a normal business process?
4) Performance tracking	Is tracking ad hoc and incomplete, or is performance continually tracked and communicated to all staff?
5) Performance review	Is performance reviewed infrequently and only on a success/failure scale, or is performance reviewed continually with an expectation of continuous improvement?
6) Performance dialogue	In review/performance conversations, to what extent is the purpose, data, agenda, and follow-up steps (like coaching) clear to all parties?
7) Consequence management	To what extent does failure to achieve agreed objectives carry consequences, which can include retraining or reassignment to other jobs?
8) Target balance	Are the goals exclusively financial, or is there a balance of financial and nonfinancial targets?
9) Target interconnection	Are goals based on accounting value, or are they based on shareholder value in a way that works through business units and ultimately is connected to individual performance expectations?
10) Target time horizon	Does top management focus mainly on the short term, or does it visualize short-term targets as a "staircase" toward the main focus on long-term goals?
11) Targets are stretching	Are goals too easy to achieve, especially for some "sacred cows" areas of the firm, or are goals demanding but attainable for all parts of the firm?
12) Performance clarity	Are performance measures ill-defined, poorly understood, and private, or are they well-defined, clearly communicated, and made public?
13) Managing human capital	To what extent are senior managers evaluated and held accountable for attracting, retaining, and developing talent throughout the organization?
14) Rewarding high performance	To what extent are people in the firm rewarded equally irrespective of performance level, or are rewards related to performance and effort?
15) Removing poor performers	Are poor performers rarely removed, or are they retrained and/or moved into different roles or out of the company as soon as the weakness is identified?
16) Promoting high performers	Are people promoted mainly on the basis of tenure, or does the firm actively identify, develop, and promote its top performers?
17) Attracting human capital	Do competitors offer stronger reasons for talented people to join their companies, or does a firm provide a wide range of reasons to encourage talented people to join?
18) Retaining human capital	Does the firm do relatively little to retain top talent or do whatever it takes to retain top talent when they look likely to leave?

Note: This table is reproduced from Bloom and Van Reenen (2010).

Table 3: Summary Statistics

Variable	Min	q_1	$\tilde{x}$	$\bar{x}$	q_3	Max
ln(Sales)	2.721	9.971	10.734	10.798	11.610	16.252
ln(Capital)	3.367	6.951	8.674	8.416	9.880	14.252
ln(Labour)	2.708	5.024	5.572	5.736	6.277	9.119
Management (z-score)	-2.847	-0.618	0.042	0.017	0.685	2.849

5 Results

Before we report our main results from the semiparametric models we explore the effect of management on productivity and inefficiency using parametric models. First, we estimate (5) using both a Cobb-Douglas[6] and a Translog functional form (which is more flexible than the Cobb-Douglas). Table 4 reports the results for these two parametric models in columns 3 and 4. The first two columns report the results without the management variable for comparison. A standard test rejects the null hypothesis that the Cobb-Douglas form is nested in the Translog model at the 1 percent level. The results for the Cobb-Douglas model differ from Bloom and Van Reenen (2010) because we use a different model specification, drop some of the original control variables (in particular the industry and country fixed effects), remove outliers (to be consistent with the semiparametric models), and do not use the entire panel but a single cross-section. Since the management variable has a z-score scaling, increasing management practice from the lower to the upper quartile (i.e., by 1 standard deviation) increases output (on average) by 27 per cent for the Cobb-Douglas model in column 3. The estimates of the interaction terms with management in column 4 provide evidence that management and labour are complements but management and capital are substitutes. Last, we note that omitting management hardly alters the coefficient estimates for capital and labour.

Next we estimate the SF model in (8) to obtain estimates of firm level efficiency. Since we are interested in checking whether estimated efficiency can be treated as a proxy for management, it is natural to examine the correlation between estimated efficiency and management.[7] For this we regress estimated efficiency using a Cobb-Douglas specification on management and its squared term. The purpose of this regression is not to check whether management determines efficiency but to see how closely (estimated) efficiency is related to observed management practices in terms of the R^2 value.

[6]When testing the Cobb-Douglas model against a fully nonparametric alternative using the test proposed by Hsiao et al. (2007) we reject the parametric specification at the 1 per cent level. The Null hypothesis of their test is $E\left(u_i|X_i = x\right) = 0$ for almost all x, where the null model is the parametric model and the alternative is a fully nonparametric model.

[7]Note that u in (8) is inefficiency, and $exp(-u)$ is efficiency.

Table 4: Parametric regression results

	(1)	(2)	(3)	(4)
(Intercept)	5.070*	5.579*	5.381*	5.347*
	(0.120)	(0.601)	(0.118)	(0.590)
ln(K)	0.284*	0.063	0.282*	0.024
	(0.010)	(0.071)	(0.010)	(0.069)
ln(L)	0.579*	0.702*	0.526*	0.912*
	(0.023)	(0.206)	(0.023)	(0.204)
Management			0.270*	−0.285*
			(0.018)	(0.125)
Management^2				−0.029*
				(0.014)
ln(K)^2		0.018*		0.007
		(0.006)		(0.006)
ln(L)^2		−0.003		−0.054*
		(0.022)		(0.022)
ln(K)*ln(L)		−0.012		0.027
		(0.017)		(0.017)
ln(K)*Management				−0.068*
				(0.010)
ln(L)*Management				0.196*
				(0.024)
Public	0.253*	0.224*	0.221*	0.134
	(0.070)	(0.073)	(0.068)	(0.070)
N	3140	3140	3140	3140
adj. R^2	0.500	0.502	0.533	0.545
Resid. sd	0.981	0.979	0.947	0.936

Standard errors in parentheses

* indicates significance at $p < 0.05$

Table 5: Observed vs. Unobserved

	(1)	(2)
	2 Stage	1 Stage
main		
Management	0.058***	
	[0.00]	
Management^2	−0.003	
	[0.00]	
ln(K)		0.251***
		[0.01]
ln(L)		0.594***
		[0.03]
Publicy traded		0.118*
		[0.05]
Constant	0.491***	5.920***
	[0.00]	[0.12]
mu		
Management		−0.828***
		[0.12]
Constant		−6.106
		[4.26]
usigmas		
Management		−0.431***
		[0.04]
Constant		1.489***
		[0.57]
vsigmas		
Constant		−0.868***
		[0.07]
Observations	3226	3226
Ll	1265.040	−4126.938
R-squared	0.104	

Standard errors in brackets

Dependent variable is estimated efficiency.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

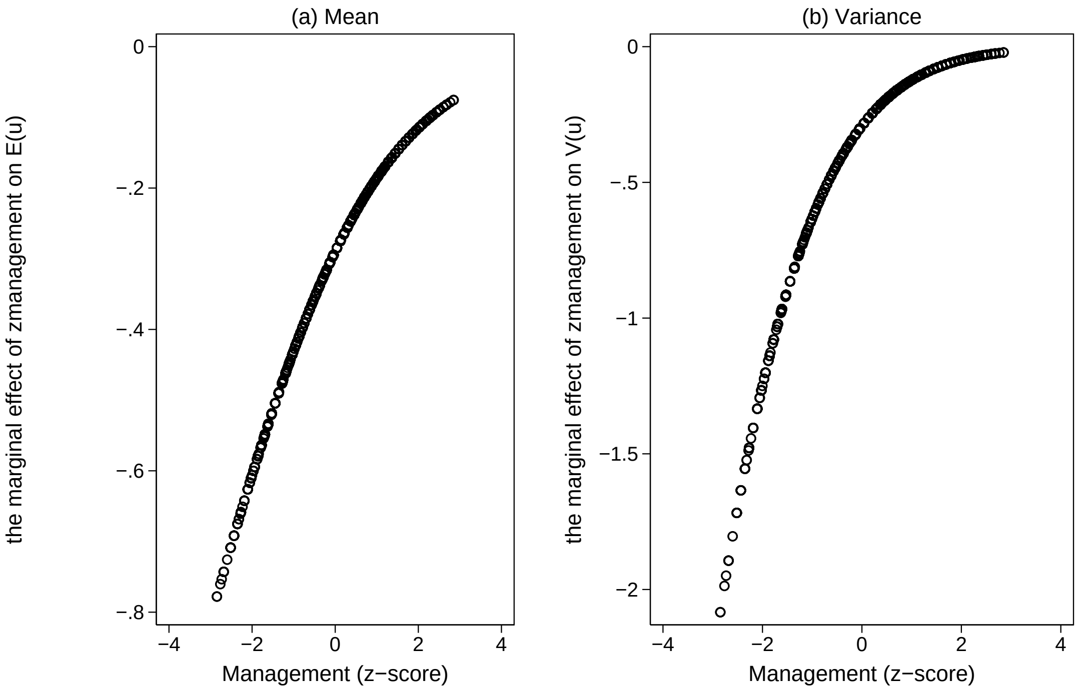

Figure 1: This graph plots the mean of the distribution of inefficiency (a) and the variance of the inefficiency distribution (b) against the level of management.

The relationship between efficiency and management is positive and significant as shown in the first column of Table 5. As we would expect the squared term is insignificant. However, the adjusted R^2 is only 0.10. This suggests that efficiency estimates are not a good proxy/measure for management since observed management practices explain only a fraction of variance of estimated efficiency. For comparison we also estimate a model where management correlates with the mean of the inefficiency distribution and its variance in column 2. Management is significant and the negative signs imply that better management practices correlate with lower inefficiency and with a lower variance for inefficiency. The marginal effects on the mean and variance are observation specific and we plot them against the level of management in Figure 1. Panel (a) shows that for higher levels of management the marginal impact of management on the mean of the distribution of inefficiency is lower in absolute terms. That is better management decreases inefficiency but at a decreasing rate. Panel (b) shows that the same is true for the variance of the inefficiency distribution. It seems that efficiency estimates mostly capture firm heterogeneity and that the relative importance of heterogeneity increases as management practices improve.

Now we turn to the results for the two semiparametric models (14) and (15) in which the intercept is a nonparametric function of management. We therefore report the intercepts for

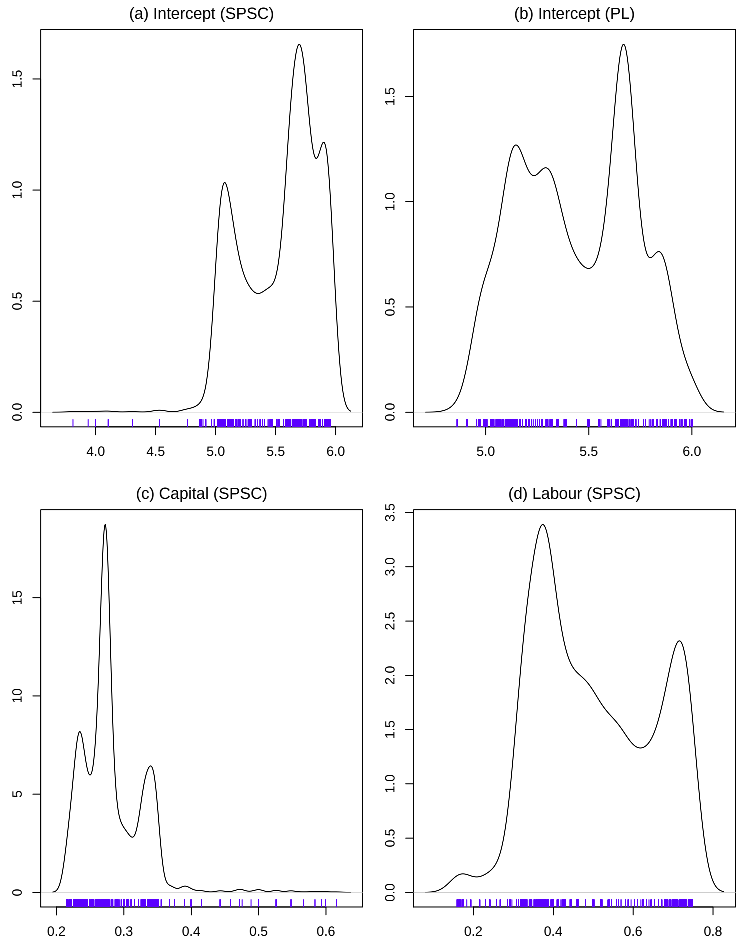

Figure 2: This graphs plots kernel densities for the coefficient estimates for the intercepts for the SPSC-CD and PL-CD model in the upper two panels and for capital and labour for the SPSC-CD model in the lower panels.

both models and the input coefficients for the SPSC model only. Otherwise (if not mentioned) we always refer to the Cobb-Douglas specification of the SPSC model. Figure 2 plots histograms of the distributions of the estimated coefficients which give a first indication of how management affects productivity. Panel (a) is for the intercept of the SPSC model and panel (b) is for the intercept for the PL model. We notice that for both intercepts the distributions are quite similar. Both distributions seem bi-modal. The lower panels are for the capital and labour coefficients of the SPSC model. Again both distributions seem bi-modal. We do not show this here but some of the bi-modality seems to be due to the distinction between private and public firms. Most importantly, for labour productivity the lower mode represents private firms though a minority of private firms share the higher mode with the majority of publicly traded firms.

To explore further the relationship between input productivities (coefficients) and management we plot the coefficient values against the management variable in Figure 3. The upper and lower solid lines mark the bootstrapped 95 percent confidence intervals (for the SPSC model only). For the SPSC model the dashed lines mark the OLS coefficients for the models *including* management and the dotted lines mark the OLS coefficients for the models *excluding* management as shown in Table 4. These two lines are very close or overlap as the input coefficients hardly change with the inclusion of management in the parametric model. The OLS coefficients fall within the confidence intervals for the SPSC coefficients only around the mean of management for the capital and labour coefficients. For the intercept this is true for the extremes of management. Our results stress that the economic relation between factor productivity and management is unlikely to be constant or even linear (except for the PL model). The bandwidth for management is 0.29 indicating that the impact of management is indeed not constant as the value is far less than two times the standard deviation of the management variable (Kumbhakar and Sun, 2011). To compare the fit between the parametric and semiparametric models we shuffle the data and split it into two subsets with $n_1 = 2000$ observations for the training data and $n_2 = 1140$ observations for the evaluation data. We then fit the model to the training data and evaluate the model on the hold-out observations using the predicted square error criterion $n_2^{-1} \sum_{i=1}^{n_2} (y_i - \hat{y_i})^2$. The predicted square error for the parametric model is 0.726 but only 0.704 for the semiparametric model. That is the latter predicts more accurately out of sample.

Whereas the intercept for the SPSC model (a) first increases and then declines the intercept of the PL model (b) shows an almost linear upward trend. The intercept of the PL model is almost indistinguishable from the OLS line which represents the model in (5) where TFP, to make the models comparable, is a linear function of z that is $\alpha_0 + \alpha z$. However it is not appropriate to compare the intercepts of the SPSC (a) and PL (b) models since the overall productivity in the PL model includes both the neutral and non-neutral effects whereas in the SPSC model it captures the neutral effect only. The difference between the two intercepts provides evidence that the non-neutral effects of management matter. When looking at the individual coefficients for the SPSC model we see that better managed firm have lower total factor productivity and lower capital productivity but higher labour productivity.

The gaps between the OLS and SPSC coefficient estimates also show that for certain levels of management OLS under- or over-estimates the productivities of the conventional inputs. This effect is most obvious for labour where for high (low) levels of management the OLS coefficient underestimates (overestimates) labour productivity. Generally, these results underline

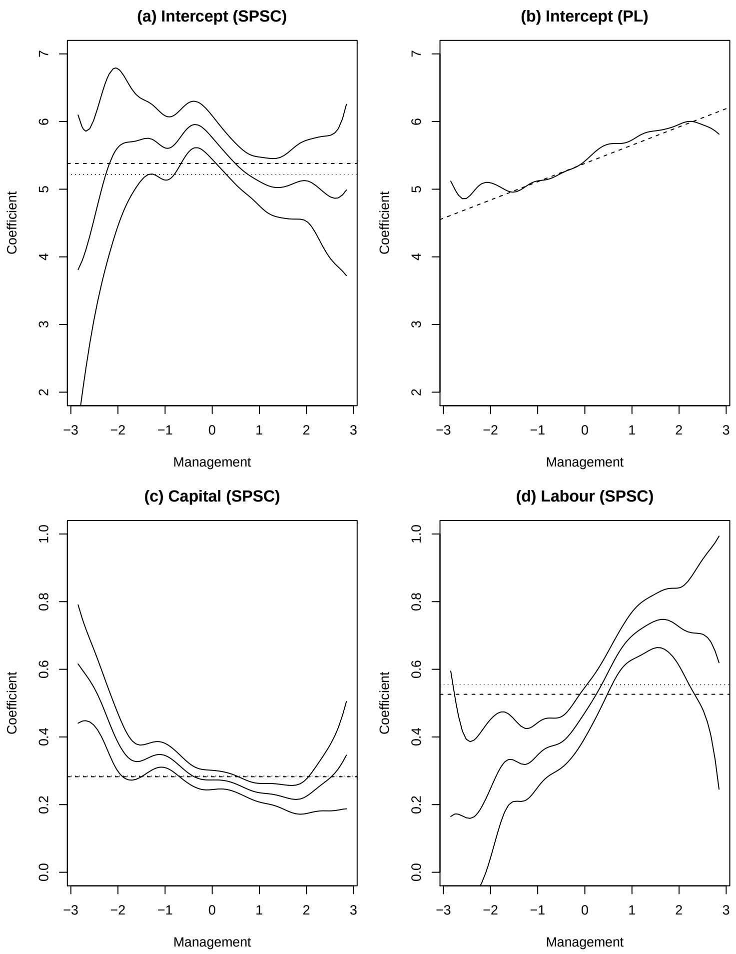

Figure 3: This graph plots the coefficients against management practices for the SPSC-CD and PL-CD models (solid lines). It also gives the coefficients for the OLS-CD model including management (dashed lines) and excluding management (dotted lines). The upper and lower solid lines for the SPSC-CD model are the 95 percent bootstrapped confidence intervals.

that labour and capital productivities are heterogenous across firms when taking into account management something that OLS estimates cannot capture. But this does not invalidate the OLS estimates because these show the effects for the sample mean firm only. Actually, that we get the same qualitative results for the interaction between the conventional input factors and management from the SPSC model and the interaction terms in the parametric translog model validates the semiparametric model.

For any well behaved production technology the labour and capital productivities depend on each other because of substitution/complementary effects. To highlight this relationship we plot management against capital productivity *and* labour productivity in a three dimensional space in Figure 4. Whereas capital coefficients are plotted along the length of the graph,

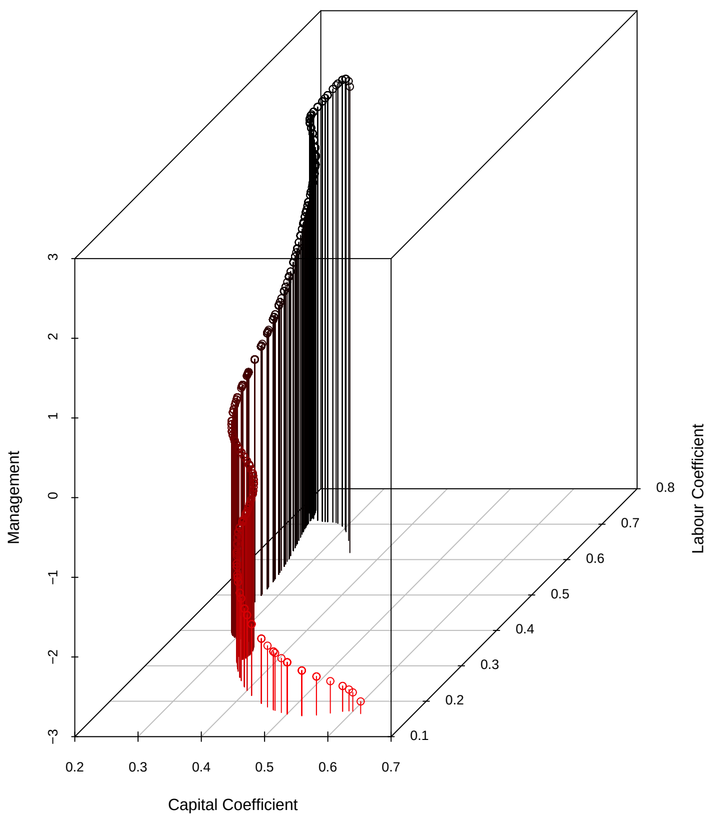

Figure 4: This graph plots the coefficient estimates for capital and labour against management for the SPSC-CD model.

labour coefficients are plotted along the widths and management is plotted along the heights. We observe that capital and labour productivities are negatively correlated (i.e., substitutes) everywhere, that the combined labour and capital productivity increases monotonically in management, and that the best managed firms have again high labour productivities and low capital productivities. This might reflect the bias towards labour effectiveness in the way management is measured or it might provide evidence that capital productivity does not much depend on management practice.

Having investigated the individual factor productivities and their correlations with management we now look at the overall management productivity (16). We compare productivity with respect to management for the fully parametric and semiparametric models, viz., parametric Cobb-Douglas (OLS-CD), parametric Translog (OLS-TL), and the two SPSC specifications

(SPSC-CD and SPSC-TL). We plot a LOWESS smooth of these derivatives against management in Figure 5. The solid line is the constant estimate for the parametric Cobb-Douglas model. Next we have the flexible parametric Translog model which intersects with the Cobb-Douglas model at the mean of the management variable but shows a monotonic decrease in management productivity. Then, we have two semiparametric models which both give an inverted U-shape relation between management and its productivity. At the mean the semiparametric estimates are greater than the estimates from the parametric models. But the difference between the parametric and the non-parametric models is greater away from the mean underlining again that semiparametric model add value when we are not only interested in estimates at the sample mean. What is important here is that even the more flexible parametric model leads to results that are qualitatively different from the semiparametric models. And again there is evidence for decreasing returns to management.

Also the SPSC models produce a number of negative estimates for the overall impact of management on output which is somewhat surprising. To see what might drive this we separate the observations by sign and and plot kernel density estimates for the two separate groups over some other variable that might explain the difference (Henderson, 2010). We test several potential drivers like the level of management, output or the capital-labour ratio. We find that the distributions differ only for the level of management as depicted in Figure 6. We plot the two distributions for both functional forms. In particular for the Translog form (right panel) it seems that firms that have a negative marginal impact of management have management levels either below or above the mean for the firms that have positive marginal effects. The mode for relatively high levels of management suggests that there are negative returns to management beyond some level of management. This provides evidence that management does not always improve output. We can think of several reasons why this might be the case. Management practices could be highly context specific. Or there could be a crowding effect in the sense that even without also taking into account the costs of better management efforts to improve management can be disruptive or introduce inefficiencies. Stated practices might not reflect the quality of their implementation. That is, the negative marginal effects might represent bad implementation of otherwise well intended practices. Looking at workplace practices Black and Lynch (2001) find that if wrongly implemented, these practices can reduce productivity. Last, as the labour input is measured as labour expenses it should reflect the increased cost of better management which certainly for the labour channel would imply decreasing marginal returns beyond some point. It is less clear why there is a group of firms that have relatively poor management practices and a negative marginal impact.

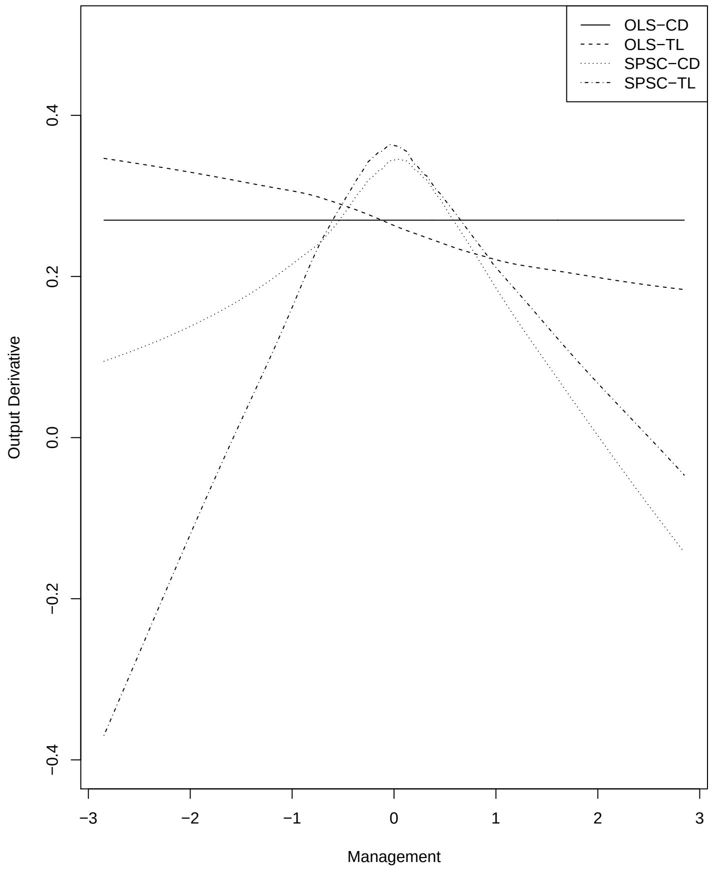

Figure 5: This graph plots the overall derivative with respect to management againt the level of management.

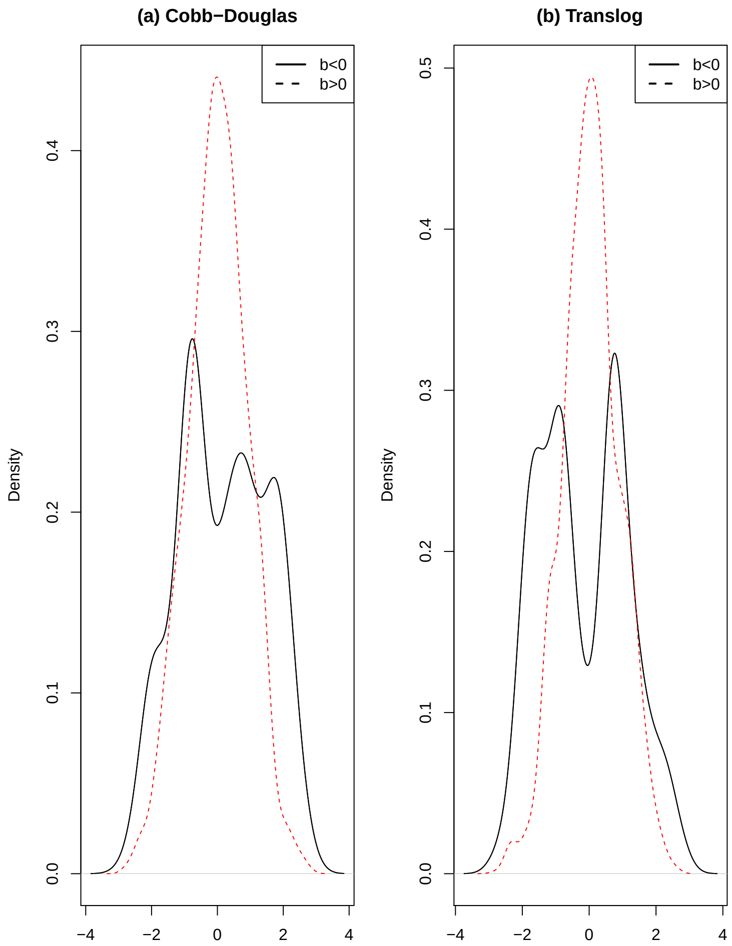

Figure 6: This graphs plots kernel densities for the total marginal effects of management for the two SPSC specifications over the level of management. The solid lines are for all the observations where the marginal effect is negative and the dotted lines are for the observations that have a positive effect.

In SPSC, unlike in a standard regression framework, it is not possible to obtain confidence intervals analytically as some variables enter nonparametrically. Figure 7 gives evidence on the statistical significance for the overall management productivity using bootstrapped confidence intervals for the SPSC-CD model with 200 replications. First, we plot the estimates of productivity against themselves shown by the 45° line. Then we plot the confidence intervals for all estimates. The dots above the 45° line are upper bounds and the dots below are lower bounds. If the horizontal line at zero passes through any given confidence interval then the management effect is not significantly different from zero. Looking at the vertical dimension if the lower (upper) bound lies above (below) zero then the effect is statistically larger (smaller) than zero. The graph shows that there are both statistically significant negative and positive estimates as well as estimates that are insignificantly different from zero. As the positive estimates clearly dominate we obtain a positive mean values as shown above. The point to note, however, is that the overall management effect is quite heterogeneous which can not be inferred from the OLS estimates.

Lastly, we investigated the impact of management on standard economic quantities like allocative efficiency and economies of scale. Note that even a Cobb-Douglas specification now allows firm-specific values for such quantities because the coefficients that are used for their construction vary with management. First, we wanted to see whether management changes the level of allocative efficiency for inputs. One hypothesis could be that the marginal rate of transformation approaches the input price ratio as management practices improve. Since the physical capital and labour inputs are measured in terms of costs, the implied price ratio is unity. Asserting profit maximization the ratio of the marginal products should equal the price ratio. It turns out that the estimated marginal rate of transformation is far below 1 and that from a visual inspection (graph not shown) it appears that there is no distinct pattern in the relationship between the marginal rate of transformation and management. Reasons for this might be that the assumptions of profit maximization and common prices are too strong. For economies of scale it is less obvious what the hypothesis should be but again it makes sense to hypothesize that better management practices should correlate with efficient scale size (unitary returns to scale). For the SPSC-CD specification Figure 8 shows that returns to scale approach unity as management practice improves (we obtain the same result for the translog form). It seems that poorly managed firms are too large.

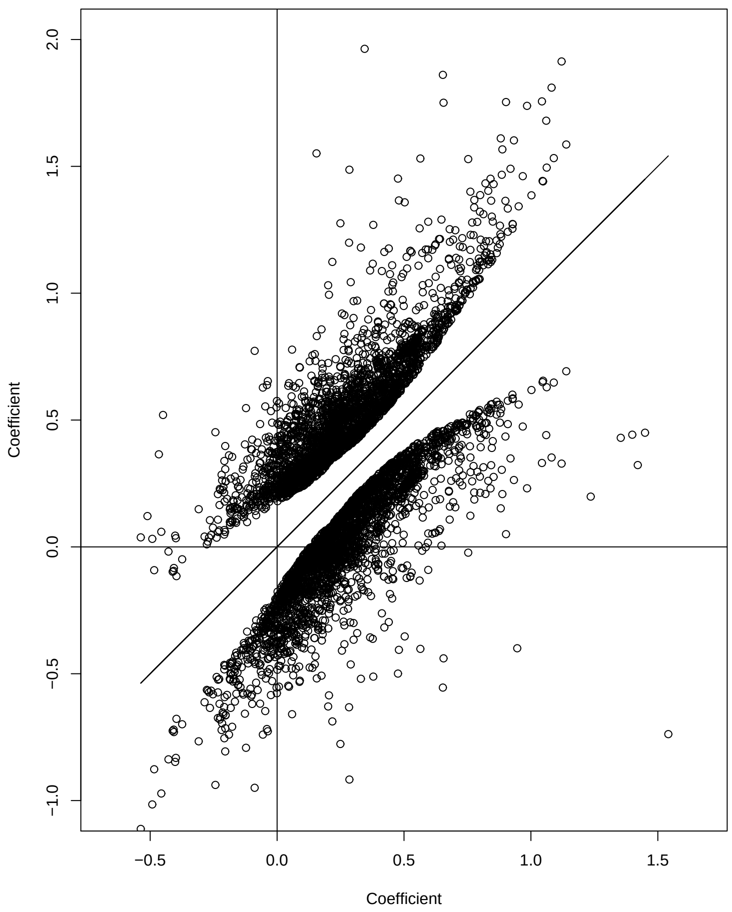

Figure 7: This graph plots the derivative with respect to management and its 95 percent confidence interval for the SPSC-CD model.

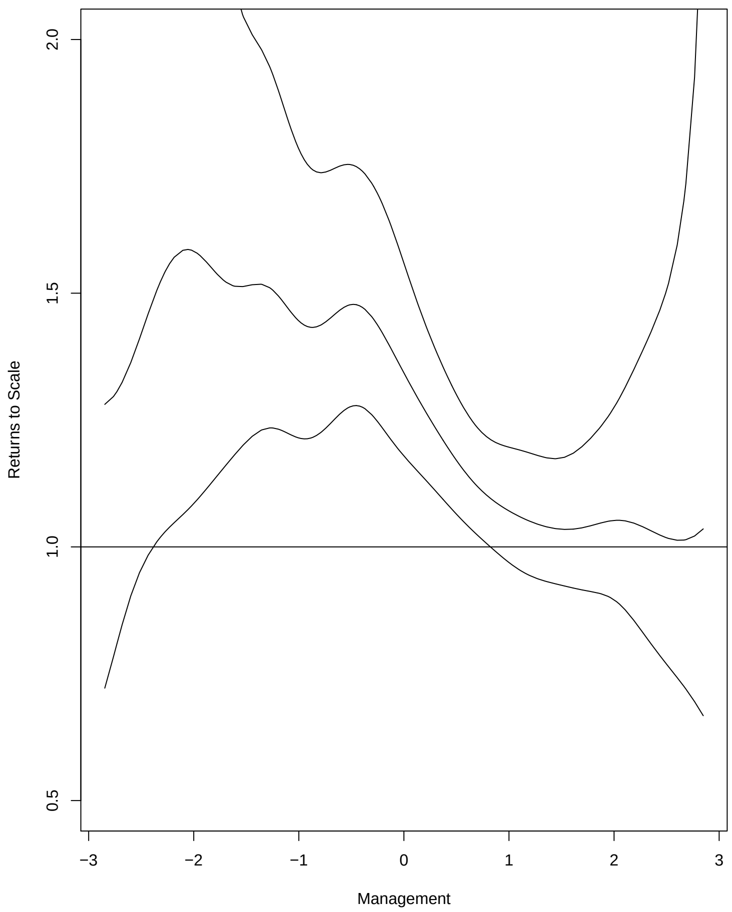

Figure 8: This graph plots returns to scale for the SPSC-CD against management including the 95 per cent bootstrapped confidence interval.

6 Conclusion

A production function model that allows observed management practices to enter in a fully flexible way improves our understanding of how management practices affect productivity. First, our results suggest that estimates of unobserved efficiency do not correlate highly with observed measures of management. Many businesses and policy makers use efficiency estimates to assess possible performance improvements through better management. The scope for such improvement might be much smaller than indicated by inefficiency estimates from stochastic frontier models.

Second, our results suggest that the impact of management on productivity is unlikely to be neutral or linear. Management affects output both in a neutral fashion and non-neutrally through the conventional inputs. And it does so in a non-linear fashion.

Third, of our three channels - intercept (neutral), capital, and labour - the latter seems to be the most important channel for management to affect output. Traditionally, management is associated with the labour input (e.g., Taylorism). But it is not clear whether management inherently relates more to labour than capital or whether management commonly focuses on labour possibly neglecting the management of capital. As already mentionned it is also possible that our management measure is biassed towards labour implying that this result might be an artifact of the way management is measured. It is less likely that there is an industry bias as our sample is for manufacturing firms that are rather more capital intensive than other industries.

Fourth, our results give more support to some theories of management than others. We find that management has decreasing and for some firms even negative returns. Decreasing returns to management beyond some level of management suggest that management should be treated as a standard input and not as a technology parameter where more is always better. Negative returns also provide support for the contingency theory which suggests that the impact of management depends on the firm environment.

Current debates on firm size, management compensation, and industry regulation require a better understanding of how management works. In this paper we showed that more flexible models can improve this understanding.

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