How much does management affect productive performance? New insights from a semi-nonparametric analysis of the World Management Survey

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Abstract

It remains a challenge to demonstrate the effects of management for improving performance beyond simply relying on case studies and anecdotal evidence. The World Management Survey presents a unique opportunity to look more closely at the relationship between management and performance. This paper critiques prior research and offers alternative semi-nonparametric estimation techniques. Findings reveal that the effect of management vary significantly across countries, that some management practices are more important than others, and that management has a significant effect on output, even in a cross-sectional analysis.

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JEL Classification Codes: L2, M2, O32, O33

1. Introduction

News headlines about the salaries of CEOs, Gabaix and Landier (2008) and the latest scandals point to the continuing debate concerning the role of management in global society. But how much does “management” really matter to the world at large? The World Management Survey described in Bloom and Van Reenen (2007) is the first data set to include survey information for multiple countries across multiple sectors extensive enough to allow researchers to begin quantifying the effects of management. [1]

Since its inception in 2004, the World Management Survey (WMS) has gathered data through direct interviews with company managers. The survey is executed by a management consulting firm under guidance from Nicholas Bloom and John Van Reenen. A double blind approach is used to minimize bias in data collection. The survey focuses on four specific areas: operations (3 questions), monitoring (5 questions), targets (5 questions), and incentives (5 questions). The survey questions are weighted equally, standardized and aggregated to a single management score. While perhaps adding to the robustness of the measure of management, aggregation also contributes to the loss of information. Therefore, this paper investigates the disaggregated management survey results to determine if further insights can be gained. While the survey information gathered has the potential to provide ground-breaking empirical evidence that management matters, a careful investigation of more plausible model specifications using semi-nonparametric estimators has the potential to strengthen the credibility of the survey results.

This paper examines the 2004 World Management Survey (hereafter WMS) to assess the robustness of Bloom and Van Reenen’s conclusion that better management is associated with higher output. Specifically, we investigate four issues: 1) the assumption of constant practices over time based on survey results gathered in 2004 and performance information from 1994-2004; 2) the assumption of constant management effects over countries while allowing the productivity of other input resources to change; 3) the use of a Cobb-Douglas functional form that imposes the elasticity of substitution among inputs and between inputs and management to be 1; and 4) the use of an aggregate measure of management. Our analytical objective is to determine if better management leads to higher output condition on input resources and the effect

[1] We focus on the 2004 survey data results. Bloom et al. (2012) present an extended data set including surveys taken in 2006 and 2009; however even in this extended data, the ratio of interviews to firms is 10,161 /8,117 = 1.25, which indicates that the majority of firms were only interviewed once. Thus, the economic and econometric concerns we raise also apply to this larger data set.

of competition. We discuss these four modeling and estimation issues which we pose as premises below.

Our first premise is that if management matters, then changes in management over time should lead to differences in performance. Thus, we need to measure management and performance at the same time. If there is a lag in measuring management, then it may be possible to attribute the poor performance resulting from prior poor management to current management that has adopted, better, or best, management practices. Thus, we consider a cross-sectional analysis in which we only analyze the performance data for 2003.

Our second premise is that the effectiveness of management practices depends upon the environment in which they are applied. For example, the Japanese culture is often cited as a reason for the superiority of Toyota's manufacturing system or lean manufacturing principles Hino (2005). While Bloom and Van Reenen's original analysis of the WMS data allows the effects of inputs to vary across countries by estimating country specific slope parameters for the Cobb-Douglas production function, the authors' estimation of a common effect of management across countries implies that the effects of labor, capital or raw materials may differ across countries, but the effect of management is modeled as constant across countries. Thus, we consider country specific management effects in order to compare the effects of management across countries.

Our third premise is the possible misspecification of the functional form for the production function. Clearly, the variables quantifying management and inputs could be correlated if more effective managers are found in larger firms; however if the functional form of the production function is also misspecified, this would lead to the effects of the inputs being attributed to the management variables, thus overstating the effect of management. Further, the Cobb-Douglas production function in Bloom and Van Reenen has the very restrictive properties that the elasticity of substitution between inputs is equal to one for all input pairs and the elasticity of substitution between management and inputs is also one. Relative to a less restrictive assumption, it is not clear if the restriction on the elasticity of substitution would bias the analyst toward over or under estimating the effect of management.

Our fourth premise is that certain dimensions of management may matter more. Thus, we consider the disaggregate WMS results.

Our paper unfolds as follows. Section 2 models a production function and the effects of management and other controls, such as competition, by using the Convex Nonparametric Least Squares (CNLS). Section 3 discusses the empirical results of applying the model we develop. Section 4 suggests alternative conclusions drawn from investigating the WMS and why management matters.

2. Modeling and estimators

We consider the joint estimation of a production function aggregating multiple inputs and the effect of management variables and competition in a cross-sectional production model using the following semi-nonparametric, partial log-linear equation

$$\ln Y_i = \ln f(L_i, K_i, N_i) + \boldsymbol{\delta}'\mathbf{M}_i + \boldsymbol{\gamma}'\mathbf{Z}_i + \varepsilon_i \qquad (1)$$

where Y_i denotes the output of firm i, L_i = labor, K_i = capital and N_i = intermediate inputs (materials) collectively are the inputs to the production function, $\phi : \Re_+^m \to \Re_+$ is a classic (increasing and concave) production function, $\mathbf{M}_i \in \Re^r$ denotes a row vector of contextual variables that characterize the measured management, and $\mathbf{Z}_i \in \Re^t$ denotes a row vector of controls. The vector $\boldsymbol{\delta} = (\delta_1 ... \delta_r)'$ is a column vector of unknown parameters (to be estimated) representing the average effect of the management variables $\mathbf{M}_i$ on performance, the vector $\boldsymbol{\gamma} = (\boldsymbol{\gamma}_1, ..., \boldsymbol{\gamma}_t)$ is a column vector of unknown parameters representing the average effect of the control variables $\mathbf{Z}_i$ on performance, and ε_i is a random disturbance term representing the effects of omitted factors, measurement errors, and other stochastic noise. Here, we assume variable ε_i is an independently distributed random variable that is uncorrelated with the input variables $\mathbf{X}_i = (L_i, K_i, N_i)$, the management variables $\mathbf{M}_i$, and the control variables $\mathbf{Z}_i$.

We characterize the empirical data of a sample of n firm by the output vector **Y**, $n \times m$ input matrix **X**, $n \times r$ matrix of management variables **M**, $n \times t$ matrix of control variables **Z**, and use $\mathbf{0} = (0 \dots 0)'$ and $\mathbf{1} = (1 \dots 1)'$ with appropriate dimensions. Denoting $\mathbf{B} = \begin{bmatrix} \mathbf{X} & \mathbf{M} & \mathbf{Z} \end{bmatrix}$, we assume that matrix **B** has full column rank. However, we allow any two columns of **B** to be correlated.

For the parametric part of the model (i.e. $\boldsymbol{\delta}'\mathbf{M}_i + \boldsymbol{\gamma}'\mathbf{Z}_i$) we assume a linear functional form, noting that the elements of $\mathbf{M}_i$ and $\mathbf{Z}_i$ can first be transformed by using suitable data transformation (e.g., exponential or logarithmic). Further, vectors $\mathbf{M}_i$ and $\mathbf{Z}_i$ may well include quadratic, cubic or higher-order polynomial transformations of the original management data or controls data. The elements of $\mathbf{M}_i$ in the WMS are primarily binary dummy variables representing categorical and/or ordinal data describing management practices.

The joint estimation of the production function and the effect of management variables is critical. Often the relationship between productivity and management or other control variables is investigated via two-stage methods. In the first stage a production function is estimated and the residual is used to represent total factor productivity. And in the second stage productivity is regressed on management scores, Black and Lynch (2001) and Bloom and Van Reenen (2007). Simar and Wilson (2007) discuss the limitations of two-stage methods, emphasizing the separability assumptions necessary. Specifically, if management does affect the output level and it is excluded from the first stage production function estimation, then the first stage suffers from an omitted variable bias. We propose to avoid this issue by jointly estimating the production function and the effect of management as stated in model (1).

2.1.Semi-Nonparametric Estimators with Management Variables

We estimate (1) via *convex nonparemetric least squares* (CNLS), Hildreth (1954) and Kuosmanen (2008). We note that CNLS is particularly suited for production analysis because the typical functions of interest have axiomatic properties, such as monotonicity, convexity, or homogeneity, that are easy to impose in a CNLS formulation.

Kuosmanen (2008) has shown that the set of functions satisfying the set of production function axioms (continuous, monotonic increasing and globally concave) can be equivalently represented by a family of piece-wise linear functions that are characterized using the Afriat inequalities (Afriat, 1967, 1972). Therefore, we state the Afriat inequalities for a monotonic concave function mapping multiple regressors $\mathbf{X}_\mathbf{i}$ to a single output Y_i as

$$\begin{aligned}
&Y_i = \alpha_i + \boldsymbol{\beta}_i'\mathbf{X}_i + \varepsilon_i \quad \forall i \\
&\alpha_i + \boldsymbol{\beta}_i'\mathbf{X}_i \le \alpha_h + \boldsymbol{\beta}_h'\mathbf{X}_i \quad \forall h,i \\
&\boldsymbol{\beta}_i \ge 0 \ \forall i
\end{aligned} \tag{2}$$

where α_i and $\boldsymbol{\beta}_i$ define the intercept and slope parameters of the tangent hyperplanes that characterize the estimated production function. Symbol ε_i denotes the CNLS residual. Note that in (2) the Greek letters are variables and the Latin letters are parameters (i.e., ($\mathbf{X}_i$, Y_i) is observed data).

We impose the Afriat constraints on a standard least squares regression estimation, where rearranging (1) allows us to state the residual as

$$\varepsilon_i = \ln Y_i - \left(\ln f(\mathbf{X}_\mathbf{i}) + \boldsymbol{\delta}'\mathbf{M}_i + \boldsymbol{\gamma}'\mathbf{Z}_i\right) \tag{3}$$

Conveniently, the variables $\mathbf{M}_i$ and $\mathbf{Z}_i$ appear only in the residual which will appear in the objective function of CNLS regression, with no effect on Afriat inequalities.

We use the a variant of the estimator described in Johnson and Kuosmanen (2011) which we will refer to as *CNLS-M* to estimate model (1)

$$\begin{aligned}
&\min_{\boldsymbol{\alpha},\boldsymbol{\beta},\boldsymbol{\delta},\boldsymbol{\gamma},\hat{\phi}} \sum_{i=1}^{n} (\ln Y_i - \ln \hat{\phi}_i - \boldsymbol{\delta}'\mathbf{M}_i - \boldsymbol{\gamma}'\mathbf{Z}_i)^2 \\
&s.t. \\
&\hat{\phi}_i = \alpha_i + \boldsymbol{\beta}_i'\mathbf{X}_i \ \ \forall i = 1,...,n \\
&\alpha_i + \boldsymbol{\beta}_i'\mathbf{X}_i \le \alpha_h + \boldsymbol{\beta}_h'\mathbf{X}_i \ \ \forall h,i \\
&\boldsymbol{\beta}_i \ge 0 \ \forall i
\end{aligned} \tag{4}$$

where again α_i and $\boldsymbol{\beta}_i$ define the intercept and slope parameters of tangent hyperplanes that characterize the estimated piece-wise linear frontier (note that $\boldsymbol{\beta}_i'\mathbf{x}_i = \beta_{iL}L_i + \beta_{iK}K_i + \beta_{iN}N_i$). Symbol $\hat{\phi}_i$ is the estimated output level associated with input level $\mathbf{X}_i$. Because (4) is a nonlinear programming (NLP) problem having a nonlinear objective function and a system of linear inequality constraints, we solve it by using standard NLP algorithms and solvers such as MINOS, CONOPT, KNITRO or PATHNLP.

In problem (4), parameter vector $\boldsymbol{\delta}$ and $\boldsymbol{\gamma}$ are common to all observations. The CNLS-M estimator can be seen as a restricted special case of the models presented in Kuosmanen and Johnson (2010) and Kuosmanen and Kortelainen (2012), where **Z** and **M** are subsets of **X** for which $\boldsymbol{\beta}_i = \boldsymbol{\beta}_j \ \forall i, j = 1,...,n$.

The CNLS-M estimator (4) has several desirable statistical properties. Johnson and Kuosmanen (2011), who examined the statistical properties of this estimator in detail, have shown its unbiasedness, consistency, and asymptotic efficiency. Most important for our analysis, these results imply that conventional methods of statistical inference from linear regression analysis (e.g., t-tests, confidence intervals) can be used for asymptotic inferences regarding coefficients $\boldsymbol{\delta}$ and $\boldsymbol{\gamma}$. In other words, the standard result of asymptotic normality of the OLS coefficients extends to the CNLS-M estimator of management and competition variables. We note that even though estimator (4) includes a nonparametric function in addition to a linear regression function, the presence of the nonparametric function does not affect the limiting distribution of the parameter estimator in the linear part. Johnson and Kuosmanen (2011) have shown that the estimates of $\boldsymbol{\delta}$ and $\boldsymbol{\gamma}$ converge at the standard parametric rate despite the presence of the nonparametric production function in the regression equation.

Since performing statistical inference on $\boldsymbol{\delta}$ and $\boldsymbol{\gamma}$ may not appear obvious due to the complexity of the NLP formulation (4), Kuosmanen et al. (2014) have proposed to run an OLS regression, $\ln Y_i - \ln(\hat{\phi}_i + 1) = \boldsymbol{\delta}'\mathbf{M}_i + \boldsymbol{\gamma}'\mathbf{Z}_i + \varepsilon_i$, in order to yield the same coefficients $\hat{\boldsymbol{\delta}}$ obtained as the optimal solution to problem (4). Running such a regression also returns the standard errors and other standard diagnostic statistics, such as t-ratios, p-values, and confidence intervals.

3. Empirical Results

To validate that management effects output, we apply the CNLS-M estimator to the WMS 2004 data.[2] The survey data was gathered via a preliminary interview and a first and second interview from 709 medium-sized public manufacturing firms excluding clients of the partnering consultancy described in more detail in Bloom and Van Reenen (2007). The performance data was gathered from Amadeus for European firms and Compustat for U.S. firms. We estimate (1) separately for each country using a cross-sectional analysis including the survey data and 2003 performance data.[3] The interviews were double blind and included 20 survey questions whereby the respondent could evaluate the firm as best practice (5) or worst practice (1). The 20 survey questions and their mapping to variable names and performance areas are summarized in table 1.

[2] http://worldmanagementsurvey.org/

[3] For the U.S. 2004 is used, for Germany 2003 is used, and for U.K. and France 2002 is used.

Table 1: Mapping of survey questions to areas and variable names

Survey Questions Summary	Area	Variables
Modern manufacturing, introduction	Operations	alean1
Modern manufacturing, rationale	Operations	alean2
Success of modern manufacturing techniques		alean3
Process documentation	Operations	aperf1
Performance tracking	Monitoring	aperf2
Performance review	Monitoring	aperf3
Performance dialogue	Monitoring	aperf4
Consequence management	Monitoring	aperf5
Target breadth	Targets	aperf6
Target interconnection	Targets	aperf7
Target time horizon	Targets	aperf8
Stretch targets	Targets	aperf9
Performance clarity and comparability	Monitoring	aperf10
Instilling a talent mindset		atalent1
Managing human capital	Targets	atalent2
Rewarding high performance	Incentives	atalent3
Removing poor performers	Incentives	atalent4
Promoting high performers	Incentives	atalent5
Attracting human capital	Incentives	atalent6
Retaining human capital	Incentives	atalent7

Table 2 presents some descriptive statistics of the inputs, outputs, and competition variables for the four countries in 2003 along with the aggregate management indicator.

Table 2: Descriptive statistics of the outputs, inputs, management and competition variables

	Sales	Labor	Capital	Materials	Aggregate management indicator	Imperfect competition dummy
USA						
Mean	513,114	2,372	131,997	294,096	0.119	0.433
St. Dev.	648,556	2,697	218,593	416,194	0.666	0.496
Skewness	1.993	1,590	3.294	2.448	0.003	0.272
Min	8,765	61	708	2,075	-1.470	0
Max	3,995,902	16,000	1,522,006	2,913,280	1.373	1
UK						
Mean	173,904	822	37,638	161,259	-0.149	0.415
St. Dev.	417,782	1193	75,535	793,810	0.762	0.495
Skewness	7.262	3.255	5.260	8.802	-0.200	0.348
Min	7,854	57	983	660	-1.646	0
Max	4,048,836	7,642	640,171	7,942,749	1.373	1
GER						
Mean	513,482	2,262	103,994	206,751	0.086	0.605
St. Dev.	627,211	2,380	128,579	325,331	0.534	0.492
Skewness	2.106	1.698	2.274	3.656	-0.209	-0.439
Min	18,164	72	2,522	5,745	-1.219	0
Max	2,936,797	10,065	606,142	2,150,347	1.355	1
FRA						
Mean	146,661	627	23,495	63,572	-0.076	0.687
St. Dev.	217,794	957	55,095	89,654	0.807	0.466
Skewness	4.510	5.796	7.190	2.796	-0.104	-0.817
Min	17,456	106	469	150	-1.646	0
Max	1,717,843	8,706	527,029	488,507	1.373	1

Section 2 addresses our four issues regarding previous analysis of the WMS. The first is that while the survey results were gathered in 2004, Bloom and Van Reenen associate the survey data with performance data from 1994-2004, implicitly assuming constant practices over this 11-

year time period. Clearly, it is not plausible that the firms' management practices did not change over this time. Since a cross-sectional analysis associating a firm's performance with the management practices at the particular point in time the management survey was gathered would relax this assumption, we gather the performance data for 2003 and estimate a cross-sectional model.[4]

Second, the primary specification used in Bloom and Van Reenen allows the marginal productivity of inputs to change across countries, and country specific slope parameters are included in the Cobb-Douglas specification. However, the management effect is held constant over countries. We relax this assumption and estimate (1) for each country separately which allows us to estimate the effect of management in each country. Our more flexible approach would be particularly critical if there were cultural characteristics of the country that lend themselves to benefiting more or less from the management practices measured by the WMS survey.[5]

Third, the original analysis of the WMS data uses the Cobb-Douglas functional form to define the functional relationship between inputs and output. While extensively used in a wide variety of economic applications for nearly 100 years, the Cobb-Douglas function puts considerable restrictions on the flexibility of the function, specifically the elasticity of substitution among inputs and between inputs and management to be 1. Therefore, we estimate (1) for each country using the CNLS-M estimator (4), which allows us to impose the axioms of monotonicity, convexity, and constant returns-to-scale on the production function without restricting to a specific functional form. Note that if inputs are correlated with the management variables which would be expected if improved management increased the probability that a firm continued in operations and grows, then a misspecification of the production function causes the effect of the inputs to show up in the estimates of the management parameters. Table A1 in the appendix reports the correlations between inputs and the management variables and all correlations are positive for the 2003 performance data and the WMS data. This would lead to over-estimating the effect of management.

[4] We would have preferred to use 2004 data; however, there were only 9, 2 and 21 observations for the French, German, and U.K. firms in the performance data; thus we used 2003 data. However, we report the results of the analysis of 2004 U.S. data.

[5] Bloom and Van Reenen suggest one example, i.e. that the survey may be biased toward an Anglo-Saxon definition of good management and thus countries with this cultural background might benefit more from these management practices. This is just one example, but many others are possible.

Fourth, some management practices may have a detrimental effect on output. While Bloom and Van Reenen present some limited results regarding the analysis of the aggregate data, we focus on the disaggregate data. This will allow specific advice to be given regarding the management practices that are most effective.

We begin by first estimating country specific model (1) using CNLS-M via the single aggregated management indicator reported in Table 3. The estimated management coefficients conform to the results reported by Bloom and Van Reenen (2007). Management has a positive effect on productivity in all countries. Management is statistically significant for the U.S. and France, but not for the U.K. and Germany. The three inputs (labor, capital, and materials) explain more than 95% of the variance of sales across firms, whereas the aggregated management indicator has minimal explanatory power. For the U.S. in 2003 and 2004 management predicts approximately 2% and 5% of the variation in sales respectively, but for the U.K., Germany and France it predicts less than 1% of sales.

For the U.S. firms, we estimate the effect of aggregate management indicator using the input-output data from years 2003 and 2004 as separate cross sections. In both years, the management has a significant positive effect on performance. However, we note that the coefficient is considerably larger in year 2004 (the survey year) than in 2003, even though the sample size was somewhat smaller in 2004. This supports our first issue that the results of the WMS reflect the contemporary situation in the firm, and it may be inappropriate to associate the results with historical performance of the firm.

Table 3: Estimated effects of the aggregate management indicator on sales

Country and year	**Coefficient**	**Standard error**	**p-value**	**Total R^2**	**Partial R^2 of z-variables**	***n***
USA 2004	0.034	0.010	0.001	0.994	0.051	233
USA 2003	0.020	0.010	0.038	0.994	0.017	261
UK 2003	0.026	0.031	0.400	0.957	0.007	118
GER 2003	0.012	0.041	0.777	0.973	0.001	76
FRA 2003	0.100	0.032	0.002	0.998	0.089	115

The use of CNLS-Z allows for firm specific estimates of the marginal product of inputs, while imposing convex input sets commonly assumed in production economics, Shephard (1970). The use of an axiomatic estimator allows considerably more flexibility to model how firms trade off inputs. Table 4 presents the mean of the estimated marginal products of inputs for labor, capital and material for each country and model specification. Note for the U.S., U.K., and France the marginal product of all inputs decreases when comparing the model with an aggregate management variable to the model with a disaggregate management variable.

Table 4: Estimated marginal products of inputs; means and standard deviations by country and model specification

		Labor		Capital		Materials	
		Mean	**St. Dev**	**Mean**	**St. Dev**	**Mean**	**St. Dev**
US	z disaggregated	68.469	10.846	0.369	0.457	0.979	0.099
US	aggregate z	72.522	10.369	0.405	0.217	1.041	0.084
UK	z disaggregated	77.398	26.713	1.019	1.632	0.933	1.221
UK	aggregate z	80.231	32.834	1.169	1.879	1.016	1.564
GER	z disaggregated	91.788	57.912	1.154	0.839	1.468	0.519
GER	aggregate z	89.566	56.061	0.913	0.705	1.406	0.485
FRA	z disaggregated	74.461	48.207	1.619	2.693	0.992	0.473
FRA	aggregate z	83.937	37.281	2.186	4.804	1.094	0.419

Analyzing the disaggregate survey data provides the opportunity to identify which management practices lead to better performance. Figure 1 illustrates the size of the coefficients for each of the four countries and for each of the 20 survey questions.[6] Analyzing patterns across countries we see that for each country there is a mixture of both positive and negative coefficients. The size of the coefficients, in absolute terms, for the U.S. appears smaller compared to the other countries. Several disaggregate management variables have positive parameters for most of the countries specifically, the variable associated with the question, does your company instill a talent mind set? (atalent1), and three questions related to target setting (target breadth (aperf6), target interconnection (aperf7), and managing human capital(atalent2)) and two incentive questions (promoting high performers (atalent5) and attracting human capital(atalent6)). The coefficient associated with the target time horizon question (aperf8) generated a positive coefficient for all four countries. The results indicating these management

[6] For a detailed description of each survey question see Bloom and Van Reenen (2007).

practices are more likely to be best practices that could benefit a wide variety of firms if adopted. In contrast the coefficient associated with the variable characterizing the question related to consequence management was negative for all four countries. Also for the majority of countries, a negative coefficient is associated with the variables quantifying the response to two operations questions (the use of modern manufacturing techniques (alean1) and the success of modern manufacturing techniques (alean3)) and a particular target question (target stretching (aperf9)). These results indicate there are specific practices regarding incentives and target setting that can lead to better performance across countries. In contrast implementing modern manufacturing practices and the managements' evaluation of the success of those manufacturing practices showed little correlation with better performance.

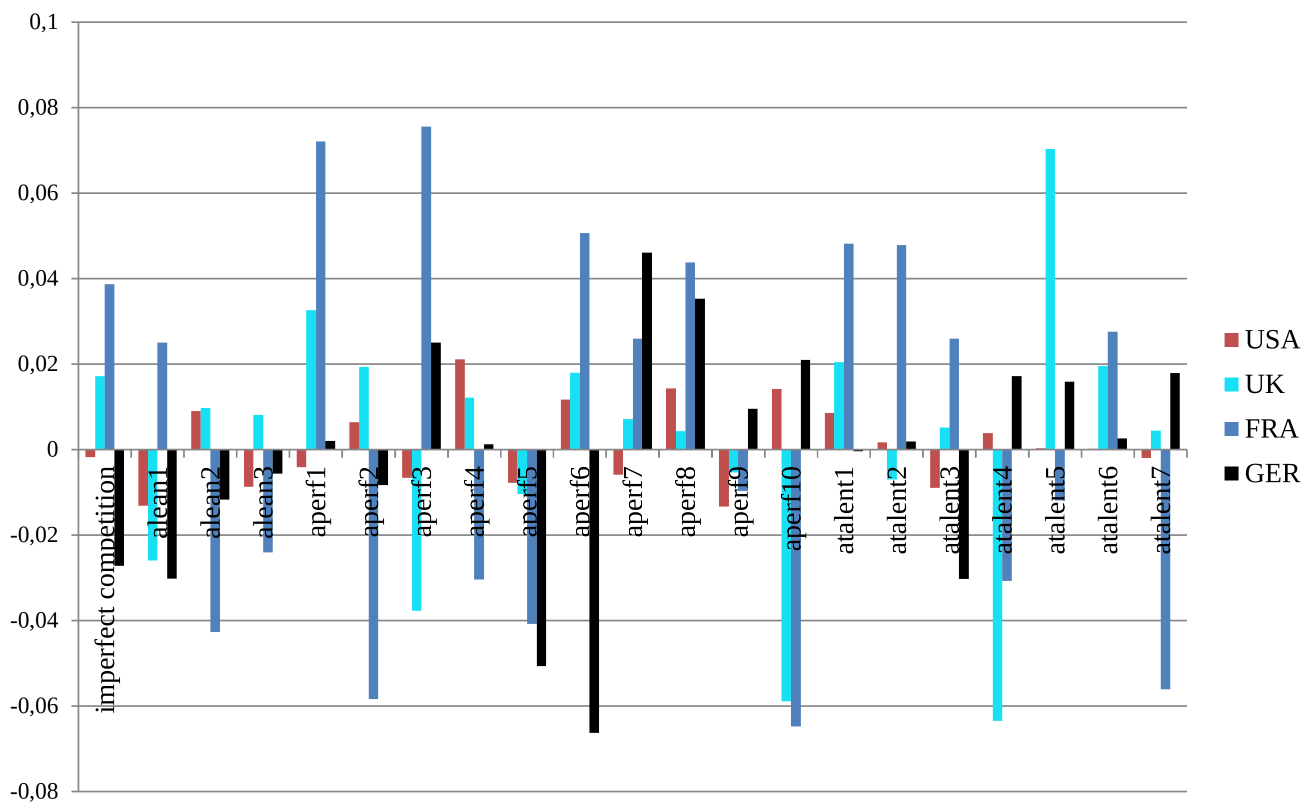

Figure 1: Estimated disaggregated management effects and the imperfect competition dummy; the bar indicates the marginal effect of the contextual variable on sales in each country

Table 4: Estimated effects of disaggregated management indicator on sales

	USA	**UK**	**GER**	**FRA**
alean1	-0.0131	-0.0260	-0.0302	0.0250
alean2	0.0090	0.0097	-0.0117	-0.0427
alean3	-0.0087	0.0081	-0.0057	-0.0241
aperf1	-0.0041	0.0326	0.0020	0.0721**
aperf2	0.0064	0.0193	-0.0083	-0.0584
aperf3	-0.0066	-0.0378	0.0250	0.0755*
aperf4	0.0211*	0.0122	0.0012	-0.0304
aperf5	-0.0078	-0.0104	-0.0506	-0.0408
aperf6	0.0117	0.0179	-0.0663**	0.0506
aperf7	-0.0059	0.0071	0.0460*	0.0259
aperf8	0.0143	0.0043	0.0353	0.0438
aperf9	-0.0133**	-0.0054	0.0095	-0.0097
aperf10	0.0142**	-0.0589**	0.0210	-0.0648**
atalent1	0.0085	0.0204	-0.0004	0.0482
atalent2	0.0017	-0.0070	0.0019	0.0478
atalent3	-0.0089	0.0052	-0.0303	0.0259
atalent4	0.0038	-0.0635**	0.0172	-0.0307
atalent5	0.0003	0.0703**	0.0159	-0.0119
atalent6	0.0002	0.0196	0.0026	0.0275
atalent7	-0.0020	0.0044	0.0179	-0.0561
imperfect competition	-0.0018	0.0172	-0.0272	0.0387
R^2 of management variables	0.118	0.205	0.191	0.349
Total R^2 of CNLS	0.995	0.965	0.978	0.946

* indicates the coefficient is statistically significant at 10% significance level

** indicates the coefficient is statistically significant at 5% significance level

*** indicates the coefficient is statistically significant at 1% significance level

Table 4 reports the coefficient values for each of the WMS questions and for each country. The significant is indicated by the number of starts next to the coefficient. Of the 84 coefficients in the table, only 11 of them are significant. Further if we look across the rows we see that for all but one question there is either no significant coefficients or the coefficient is only significant for one country indicating successful management practices do not appear to be particular robust across countries. The one question for which 3 of the 4 country coefficients are significant is performance clarity and comparability (atalent10); however, the coefficients sign is positive for the U.S. but negative for the U.K. and France. Thus, providing mixed evidence for the effectiveness of this particular practice.

4. Conclusions

The results of this paper indicate that a hard and fast conclusion that management matters is actually more subtle. Management does not seem to affect all countries equally and all management practices do not seem to lead to higher productivity. In the 2003 performance data, the primary driver of output is inputs and the effects of management are significantly smaller than the effects of inputs.

As an ongoing project, WMS provides invaluable data for understanding the connection between management and performance. We suggest that the use of panel survey data would allow dynamic effects in the changes of management practices to be observed in performance outcomes, and also would strengthen the connection between management and performance while providing clarity about the impacts of specific practices.

We recognize that there are also selection issues in play that have not been modeled. Therefore, future research on the effects of management on firms' survival should give a deeper understanding of management's effect on performance.

Table AI: Correlation between output, input, and management variables

	log sales	*log em-ployees*	*log capital*	*log materials*	*zman-agement*	*alean1*	*alean2*	*alean3*	*aperf1*	*aperf2*	*aperf3*	*aperf4*	*aperf5*	*aperf6*	*aperf7*	*aperf8*	*aperf9*	*aperf10*	*atalent1*	*atalent2*	*atalent3*	*atalent4*	*atalent5*	*atalent6*	*atalent7*
log sales	1.000																								
log employees	0.935	1.000																							
log capital	0.905	0.885	1.000																						
log materials	0.936	0.837	0.833	1.000																					
zmanagement	0.160	0.121	0.134	0.129	1.000																				
alean1	0.064	0.034	0.024	0.039	0.731	1.000																			
alean2	0.085	0.065	0.056	0.042	0.678	0.706	1.000																		
alean3	0.075	0.048	0.037	0.037	0.691	0.749	0.743	1.000																	
aperf1	0.086	0.040	0.067	0.055	0.731	0.609	0.510	0.595	1.000																
aperf2	0.066	0.035	0.053	0.034	0.712	0.584	0.508	0.533	0.579	1.000															
aperf3	0.076	0.043	0.047	0.042	0.737	0.508	0.474	0.490	0.605	0.672	1.000														
aperf4	0.110	0.075	0.078	0.069	0.746	0.501	0.477	0.513	0.578	0.567	0.726	1.000													
aperf5	0.098	0.075	0.086	0.077	0.699	0.474	0.448	0.495	0.539	0.480	0.551	0.584	1.000												
aperf6	0.207	0.164	0.182	0.166	0.693	0.494	0.422	0.427	0.432	0.449	0.485	0.528	0.452	1.000											
aperf7	0.144	0.111	0.140	0.126	0.737	0.488	0.454	0.453	0.486	0.504	0.497	0.537	0.496	0.615	1.000										
aperf8	0.116	0.085	0.117	0.074	0.677	0.469	0.439	0.466	0.479	0.450	0.461	0.476	0.454	0.557	0.586	1.000									
aperf9	0.120	0.094	0.099	0.091	0.704	0.488	0.455	0.474	0.486	0.481	0.490	0.517	0.501	0.499	0.544	0.537	1.000								
aperf10	0.132	0.120	0.122	0.138	0.670	0.488	0.437	0.455	0.440	0.487	0.491	0.467	0.408	0.497	0.500	0.455	0.434	1.000							
atalent1	0.148	0.133	0.139	0.108	0.663	0.431	0.391	0.425	0.464	0.407	0.441	0.470	0.443	0.407	0.466	0.406	0.473	0.383	1.000						
atalent2	0.136	0.089	0.111	0.140	0.458	0.295	0.274	0.302	0.338	0.257	0.288	0.266	0.278	0.294	0.268	0.280	0.297	0.309	0.416	1.000					
atalent3	0.191	0.170	0.167	0.186	0.629	0.409	0.321	0.359	0.422	0.366	0.389	0.391	0.349	0.439	0.440	0.378	0.372	0.414	0.419	0.349	1.000				
atalent4	0.056	0.052	0.045	0.062	0.575	0.375	0.346	0.325	0.367	0.303	0.347	0.342	0.491	0.338	0.395	0.318	0.345	0.360	0.366	0.322	0.363	1.000			
atalent5	0.187	0.157	0.163	0.151	0.673	0.387	0.396	0.415	0.452	0.429	0.433	0.425	0.464	0.398	0.454	0.391	0.427	0.422	0.516	0.356	0.546	0.470	1.000		
atalent6	0.100	0.070	0.099	0.099	0.624	0.349	0.352	0.386	0.399	0.342	0.366	0.423	0.371	0.356	0.442	0.373	0.412	0.384	0.448	0.464	0.412	0.362	0.484	1.000	
atalent7	0.142	0.111	0.115	0.127	0.612	0.378	0.395	0.397	0.365	0.373	0.418	0.441	0.333	0.359	0.399	0.353	0.385	0.378	0.396	0.346	0.386	0.292	0.456	0.539	1.000

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