The Effect of Performance Measurement Systems on Productive Performance: An Empirical Study of Italian Manufacturing Firms

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Abstract:

Performance Measurement Systems (PMS) are widely used, yet the evidence for their effect on productivity is still limited. We gather survey data describing the use of PMS by 246 manufacturing firms in Italy and match it with financial data for the study period 2003-2012. We develop a PMS score to aggregate the survey information and quantify how well a firm implemented and used PMS. We find that multinational firms are more productive than firms that only operate domestically, and that overall, the Italian manufacturing industry exhibits decreasing returns-to-scale. Further, we find many mature firms in the industry and that endogenous growth will likely lead to reduce productivity. We conclude that higher quality PMS positively and significantly correlates with higher productivity.

Keywords: Performance Measurement System (PMS); Productivity Analysis; Italian Manufacturing

1. Introduction

Performance Measurement Systems (PMSs) help an organization align its goals, strategic plans, and overall vision (Neely et al. 1995). PMS is widely believed to have two functions: acting as a catalyst to increase performance, and then maintaining overall performance (Gunasekaran and Kobu 2007).

The research on PMS spans a wide variety of fields, such as manufacturing (Stede et al. 2006, Bendoly et al 2007), marketing (Homburg et al. 2012), and product development (Mallick and Schroeder 2005). Much of the literature has focused on design and implementation (Neely 2005), particularly the identification of metrics for a PMS that characterizes a firm's strategy (Bourne et al. 2000, Kaplan and Norton 1992, Stede et al. 2006, Micheli and Manzoni 2010, Choi et al. 2013, de Lima et al. 2013). While many researchers have stressed the importance of identifying the best metrics and methods to implement PMS (Melnyk et al. 2004), there is little evidence that PMS quantifies and predicts operational improvements or productivity gains. While there is considerable theory to motivate the relationship between PMS and an organization's overall performance, the lack of empirical research analyzing the relationship has made it difficult to justify increased investment in PMS (Neely 2005).

Nonetheless, there are several interesting related studies. For example, Koufteros et al (2014) uses Resource Orchestration Theory to investigate the effects of PMS on organizational capabilities and performance. Bendoly et al (2007) focus on providing evidence that links three multilevel performance metrics: tactical level metrics, strategic level metrics, and financial performance metrics. Tung et al. (2011) analyze various factors that influence the effective implementation and maintenance of PMS. Jain et al. (2011) develop a PMS using data envelopment analysis (DEA) for target setting in manufacturing systems. Crabtree and DeBusk (2008) study balanced scorecard, a type of PMS, to quantify the effect on shareholder returns.

The research described in this paper is motivated by the need for a "more robust empirical and theoretical analysis of performance measurement frameworks and methodologies" (Neely 2005). Therefore, we hypothesize that PMS has a positive and significant effect on an organization's productive performance. We gather survey data describing the use of PMS by 246 manufacturing firms in Italy and match it with financial data for the study period 2003-2012.We implement two methods to test our hypothesis: 1. Constructing an aggregate PMS score from survey data characterizing the quality and use of PMS; 2. Proposing empirical models to analyze the relationship between output production and the use of PMS. We use a variety of different methods to aggregate the survey data and different specifications and estimation techniques for the empirical model which allows us to investigate the robustness of our results.

Our paper provides evidence for the positive effect of PMS on productivity in manufacturing, a result that is robust to the method used to aggregate the survey data, the specification of the model, and the estimation technique. We find that multinational manufacturing firms have higher productivity than firms that only operate domestically. We find that firms with a quality focus strategy tend to be more productive; however, this result is sensitive to the model specification or other modeling assumptions.

The remainder of the paper is organized as follows. Section 2 discusses the theoretical motivations for the relationship between performance measurement systems and productivity, describes the survey data, and the calculation of the PMS score. Section 3 describes the empirical models. Section 4 analyzes the results of the models. Section 5 summarizes the findings and discusses the use of PMS in fields other than manufacturing.

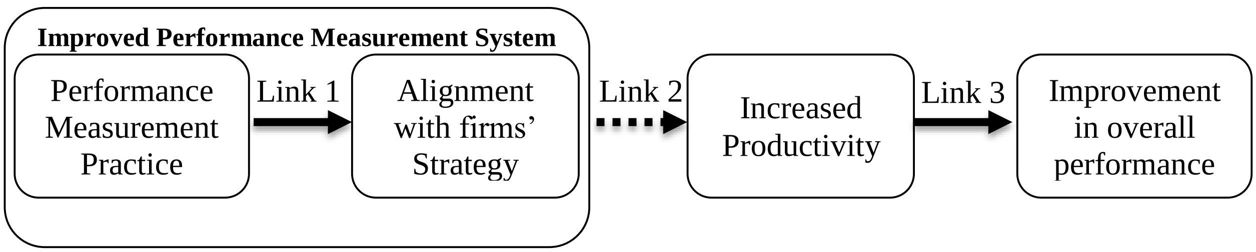
2. Measuring PMS Practices Using Survey Data

To investigate the effect of PMS, we construct a robust measure of PMS. We start by gathering survey data and then aggregate the data's dimension for empirical testing. In this section we present the theoretical motivation for a relationship between PMS and productivity, describe the survey and data gathered, the methods for calculating a PMS score, and the additional control variables available in the survey data.

2.1 Theoretical Motivation for the Relationship between Performance Measurement Systems and Productivity

A survey of the performance measurement literature suggests that PMS improves overall performance by aligning firm's practices with their strategy and vision (Melnyk et al. 2004, Neely et al. 1995). Our research model describes the process which improved performance measurement systems leads to improvement in overall firm performance.

Figure 1: Research Model



Notes: The dotted arrow in link 2 represents a lack of literature and empirical evidence in connecting superior PMS practices to increased productivity.

Currently there is extensive research on Link 1, between good performance measurement practices and aligns with firms' strategy, in the PMS literature (Lynch and Cross. 1992, Kaplan and Norton 1992, Franco and Bourne 2003). In fact, the majority of the literatures have focused on finding metrics that best align firms' operation to their strategy. In the early research focused primarily on financial measures as a criteria for PMS (Kennerley and Neely 2003). However, Johnson and Kaplan (1987) argue that firms are missing the big picture if they focus on financial measures only. Also, Dixon et al. (1990) suggests that financial measures have a significant lag in reporting and thus represent the result of past performance and are not a good indicators potential improvement. Kennerley and Neely (2003) states that as the complexity and competitiveness of the market increases, firms cannot rely solely on financial based PMS. Faced with this criticism, multidimensional PMS models, that takes in to account both financial and non-financial aspect, are developed (Sinclair and Zairi 2000). Kaplan and Norton (1992) proposed the Balanced Scorecard method to financial and non-financial criteria and more effectively align of the firm's practices to the firm's strategies. Other multidimensional approaches to PMS include: Performance Prism (Neely and Adams 2000, Neely et al. 2002) and Performance Pyramid (Lynch and Cross 1992). In summary the role of PMS is to "maintaining alignment and coordination" (Melnyk et al. 2004)

However, Link 2 that connects the bubble containing both performance measurement practice and alignment with firms' strategy to increase productivity is dashed to indicate the lack of empirical research focusing on this link. This is problematic because a significant proportion of PMS literature focus on the strategic aspect and assumes that a well implemented PMS will lead to better performance (Koufteros et al 2014). Pavlov and Bourne (2011) state that the link between PMS and its effect on performance has not received enough attention leading to a gap in the literature. Thus, it is hard to justify that PMS has a positive effect on firm performance without closing this gap with empirical research showing the improved alignment of operations with firm strategy, the primary result of a well implemented PMS, translates into better productivity that will positively influence overall performance. Our research focuses on closing this gap using performance and survey data from Italian manufacturing firms.

In our research model, we focus on the effect of PMS on productive performance rather than the effect on overall performance. Majority of the studies have assumed a direct relationship between better PMS practices to overall firm performance (Crabtree and DeBusk 2008, Davis and Albright 2004). Within the few empirical papers that exist, most of the literature focus on explaining the effect on financial performance. Thus, our research is unique because it focuses on the effect of PMS on productive performance. Ideally the measurement for productive performance should be physical quantity of output, but often physical output is proxied for by value added (Aigner and Chu 1968, Bloom and Van Reenen 2007, Stevenson 1980). After establishing Link 2 there is extensive theoretical and empirical evidence linking improvement in productivity to improvement in overall performance; see for example the literature review of Syverson (2011).

From a production economics and productivity analysis perspective, our research provides empirical evidence for PMS as a potential driver of productivity differences. In this regard our research provides additional insights to answer two of Syverson's (2011) ten questions for productivity analysis researchers: Which productivity drivers matter most? How do management and managers impact productivity?

2.2 Survey Data

We gather survey data via mail from 246 manufacturing firms in Italy between 2009 and 2012 (Table 1). Koufteros et al (2014) uses data from this same survey looking at a wide variety of industries including services focusing on nomological networks. The demographic data consisted of firm respondent's job title, firm multinationality, firm age, and strategy type (Tables 2, 3, 4, and 5). Around 47% of respondents were controllers and the others were managers or other high-ranking officers. All firms were located in Italy, with nearly 55% of respondents from multinational firms and 45% from domestic firms. Since Italy has a long history of manufacturing, 33% of the firms were more than 51 years old, while 9% were less than 10 years old and 56% were between 10 and 50 years old. Regarding strategy types, the firms were asked to select 1 of 4 possible types: quality focused, expansionistic, strategic adaptation, or status quo. The strategies are described in section 2.3. The survey consisted of 173 questions to measure the overall characteristics of PMS. The questions were categorized into seven categories with 19 sub-categories of performance measurement aspects as shown in Table 6. The financial data was taken from the Bureau Van Dijk Amadeus Financial database of financial information for public and private firms across Europe.

Table 1: Distribution of Survey Received by Year

Survey Received Year	# of Firms	Percentage
2009	81	32%
2010	44	17%
2011	117	47%
2012	4	1.6%
Sum	246	100%

Table 2: Firm Respondent's Job Title

Job Title	# of Firms	Percentage
CEO	12	4.8 %
CFO	40	16 %
HR Manager	12	4.8 %
MD	22	8.9 %
Operation Manager	43	17 %
Controller	117	47 %
Sum	246	100%

Table 3: Firm Multinational or Domestic

Multinationality	# of Firms	Percentage
Domestic	112	45%
Multinational	134	54%
Sum	246	100%

Table 4: Firm Age

Bin for Firm Age (Year)	# of Firms	Percentage
Age≤10	22	8.9%
11≤ Age≤20	38	15%
21≤ Age≤30	26	10%
31≤ Age≤40	35	14%
41≤ Age≤50	39	15%
51≤Age	82	33%
Missing Values	4	1.6%
Sum	246	100%

Table 5: Strategy Type and Distribution

Strategy Type	Quality	Expansionistic	Strategic Adaptation	Status Quo	Missing Data
Frequency	42	109	67	11	17
Percentage	17%	44%	27%	4.4%	6.9%

Table 6: Explanation of Survey Categories

Category Number	PMS Measurement Category	Category Explanation	Sub-Category Number	Sub-Category (Number of Questions)	Sub-Category Explanation
1	Purpose of Measuring Performance	Asks for reasons why performance is measured	1	Purpose of Measuring Performance (27)	Why does your firm measure performance?
2	Nature of Performance Measurement's Use	Measures how well top management uses the performance measurement as part of its managerial support tool	2.1	Monitoring (4)	How well is PMS used to monitor results for a better progress toward the goal?
			2.2	Focus Attention (7)	How well is PMS used to keep the focus of the organization together?
			2.3	Strategic Decision Making (6)	How well is PMS used to support strategic decision making?
			2.4	Legitimization of Support Decision (9)	How well is PMS used to support decision or actions taken?
3	Diversity of Measures	Asks about the criteria PMS measures and if the use of PMS meets the target	3	Diversity of PMS measurement (20)	What criteria are measured and does your organization meet the target set using PMS?
4	Organizational Learning	Measures how well information and knowledge is shared throughout organization	4	Organizational Learning (4)	Does your organization have a good organizational learning environment that will help management to implement and use PMS effectively?
5	Effects of PMS on Business performance	How does PMS affect various aspects of the organization?	5.1	Effects on Strategic Management (7)	How well does PMS affect strategic management by focusing people on key issues and giving feedback?
			5.2	Effects on Organizational Capabilities (5)	How well does PMS help increase organizational capabilities? Does it stimulate debates and help vertical and/or horizontal communications?
			5.3	Effects on Organizational Behavior and Employee Issues (17)	How well does PMS help stimulate organizational growth by focusing on employee motivation, satisfaction, and other O.B. factors?
			5.4	Effects on Operations and Tactical Issues (5)	Does PMS promote operational improvements?
			5.5	External Effects (4)	Does PMS help the organization improve relationship with suppliers, customers, regulators? Does it improve overall organization's leadership in the market?
			5.6	Negative Effects (10)	What are some of the downsides of PMS?
6	Factors Influencing the Effects of PMS	Asks about the factors that may influence the effects of PMS	6.1	Employee Involvement and Participation (3)	To what extent do employees participate in performance measurement?
			6.2	Organizational Principles (4)	What are the principles and values that your organization is based on?
			6.3	Top and Middle Management Commitment (16)	How committed are top and middle management in using PMS?
7	Performance Review	How well does your organization use PMS to review performance?	7.1	Frequency of Performance Reviews (6)	How often does your organization assess, review, and monitor performance?
			7.2	Review Policies (7)	Are there specific guidelines when reviewing performance? How well are the used?
			7.3	Performance Management Leadership (12)	How well does performance measurement managers (leaders) do their job in your organization?

We construct two datasets using the survey and financial data. The first, which is used in our primary analysis, matches the survey information with the ten years of financial data, assuming the characteristics of the PMSs did not change during the study period. The resulting dataset, which this paper refers to as the *pooled dataset*, had approximately 1,500 observations. Pooled datasets are common in the economic analysis of survey data, see for example Bloom and Van Reenen (2007). The second analysis, used as a robustness check for the analysis of the pooled dataset, links the financial data only to the corresponding year the survey data was received. In the resulting dataset, which this paper refers to as the *cross-section dataset,* each firm appeared once, thus approximately 160 observations.

2.3 Calculating a PMS Score

The survey includes 173 questions that need to be aggregated for analysis purposes. Aggregation significantly reduces the risk of overfitting and improves model interpretation (James et al. 2013). Since the aggregation method chosen can bias the measure of PMS quality and use, we use three different aggregation techniques: uniform weighting, uniform weighting within category, and principal component analysis. Table 6 categorizes the questions, and the following sub-sections give the details.

Initially, all survey respondents answered each question using a six point scale (1= "Not at all", 2= "To a very little extent"… 6= "To a very great extent"). The majority of questions asked about positive characteristics, i.e. a score of 6 indicated high quality and proper usage of the PMS, but ten questions asked about undesirable characteristics, i.e. a score of 6 indicated lower quality and incomplete usage of the PMS. For scaling consistency, the scales in questions asking about undesirable characteristics were reversed, i.e. a higher score represented less of the undesirable characteristics. The following describes the three aggregation techniques used.

Uniform Weighting: We create a PMS score by averaging the responses to each of the 173 questions with equal weight consistent with Bloom and Van Reenen (2007) and Bloom et al. (2014). We assume that every survey question has equal importance in representing the quality of the PMS used by a firm. Therefore, we normalize the response of each question and then calculate the unweighted average.

Uniform Weighting within Category: Assuming each category is equally important to high quality and proper PMS usage, we map questions to categories and calculate a uniform weighted average by category. We perform a similar analysis using sub-categories instead of categories.

Principal Component Analysis (PCA): We calculate the unweighted average score for each survey question category and then calculate the principal components for the matrix of data summarizing the survey question category scores for each firm. Using Horn's (1965) criteria, we calculate the number of principal components to include in the model. We test the robustness of our results to the number of principal components and to the use of sub-category data instead of the categorical data.

2.4 Strategy Type

We include several control variables, such as company age, multinationality, and strategy type that can affect productive performance, to adjust for the differences between firms. The survey asked firm respondents about the firm's strategy type that are described below.

Quality Focused: This strategy characterizes firms that want to locate and maintain a secure niche in a relatively stable product or service area. The firms tend to offer a more limited range of products or services than their competitors, and try to protect their domain by offering higher quality, superior service, lower prices, and so forth. The firms are not necessarily at the forefront of developments in the industry and tend to ignore industry changes that have no direct influence on current areas of operations.

Expansionistic: This strategy characterizes firms that typically operate within a broad product-market domain that undergoes periodic redefinition. The firms value "first in" in new product and market areas even if some efforts do not prove highly profitable. The firms respond rapidly to early signals concerning areas of opportunity, and their responses often lead to a new round of competitive actions. However, the firms may not maintain market strength in all areas of entry.

Strategic Adaptation: This strategy type characterizes firms that want to maintain a stable, limited line of products or services while at the same time adjusting quickly to follow a carefully selected set of the more promising new developments in the industry. The firms are seldom "first in" with new products or services, yet by carefully monitoring the actions of major competitors in areas compatible with its stable product-market base, often firms can be "second-in" with a more cost-efficient product or service.

Status Quo: This strategy type characterizes firms that do not appear to have a consistent product-market orientation. They are usually not as aggressive in maintaining established products and markets or willing to take as many risks as their competitors. Rather, they respond when forced by environmental pressures.

3. Parametric and Semi-nonparametric Models

This section describes the empirical models we develop to test the effects of PMS on productive performance. We also statistically test the axiomatic properties of the production function.

Our model relates the observed output for firm i in period t, Y_{it}, to the inputs, labor (L_{it}) and capital(K_{it}) via an unobserved production function, f. The effects of PMS, other control variables, and the residuals are multiplicative. A function, g, describes how information regarding the PMS is aggregated, and a separate function, h, describes how the effects of the control variables are aggregated resulting in equation (1).

$$Y_{it} = f(L_{it}, K_{it})\, e^{g(P_i)+h(Z_i)+U_{it}} , \qquad (1)$$

Note this formulation allows for heteroscedasticity of the residuals which is typical feature of a value-added production function, Hsieh and Klenow (2009).

First, we jointly estimate a log-linear Cobb-Douglas production function and the effects of PMS and control variables. The equation that will be estimated in our primary analysis is shown in equation (2).

$$\ln(Y_{it}) = \alpha_0 + \alpha_l \ln(L_{it}) + \alpha_k \ln(K_{it}) + \beta P_i + \gamma Z_i + U_{it} , \qquad (2)$$

where we use value-added output measured in euros (€),Y_{it}, number of employees, L_{it} , and capital employed measured in €, K_{it}, taken from the financial data. P_i, in our primary specification, is the normalized uniformly weighted aggregate PMS score for firm i. The coefficient, β, is the parameter of interest indicating the effect of PMS on log output. We include a linear function of control variables, Z, such as company age, strategy types, and dummy variable for multinational firms. The disturbance term, U_{it}, represents omitted variables, measurement errors, and all other effects that cannot be explained by the above variables.

Throughout our analysis we use a heteroskedastic model, because the result from White's test for heteroskedasticity using both the pooled dataset and the cross-section dataset results in p-values of nearly zero, thus rejecting the null hypothesis of *homoskedasticity*.

To investigate the robustness of our results from the parametric log-linear Cobb-Douglas model, we investigate generalizations of the parametric model. First, we use a nonparametric test, Sen and Meyer (2013), to determine if the data is consistent with a linear function indicating constant returns-to-scale versus the alternative of a concave function corresponding to decreasing returns-to-scale. We use the sum of squared errors values from a linear regression and a concave nonparametric regression to construct a test statistic that is compared to a p-value generated from simulation results. Section 4 gives the details.

If we find evidence of a concave production function, we use one of several available estimators to estimate a concave production function nonparametrically to investigate the robustness of the results from the parametric log-linear Cobb-Douglas model. We estimate a production function jointly with the effects of the contextual variable and control dummies by using the nonparametric shape constrained methods proposed by Johnson and Kuosmanen (2011). When both the parametric and nonparametric estimates indicate that PMS has a positive and significant effect on productive performance, it provides robust evidence beyond simply focusing on either the parametric or the nonparametric results.

$$\min_{\alpha,\beta,\delta,\varphi,\varepsilon} \sum_{i=1}^{n} (\varepsilon_i^{CNLS})^2 \tag{3}$$

Subject to:

$$\ln y_i = \ln \varphi_i + \delta' P_i + \gamma' Z_i + \varepsilon_i^{CNLS} \quad \forall i \tag{3a}$$

$$\varphi_i = \alpha_i + \beta'_i x_i \quad \forall i \tag{3b}$$

$$\alpha_i + \beta'_i x_i \leq \alpha_h + \beta'_h x_i \quad \forall i, h \tag{3c}$$

$$\beta_i \geq 0 \quad \forall i \tag{3d}$$

In this model, Y = output, X = input for production function (Labor and Capital), Z = control variables, and P = the contextual variable (PMS Score) with i and h representing the firm index. Equation (3a) shows that log output will be a linear function of log aggregate input, the control and contextual variables. Equation (3b) defines that tangent hyperplanes with slope β_i and intercept α_i will be used to approximate the true monotonic and concave function. Equation (3c) is the Afriat inequalities imposing concavity, and equation (3d) given (3c) imposes monotonicity (Afriat 1967, 1972). Note the estimator (3) is a sieve estimator where the dimensionality of parameters $(\alpha, \beta, \delta, \varphi, \varepsilon)$ grows in the number of observations and is thus classified as a nonparametric estimator, Chen (2007). We use the two-step method described in Kuosmanen et al. (2015) to perform inference.

The Convex Nonparametric Least Squares (CNLS) estimator in (3) is semi-nonparametric and does not require a priori assumptions regarding the functional form of the production function. Because it is computationally difficult to solve, we use the computational improvements by Lee et al. (2013) which allows us to use CNLS estimator for our cross-section dataset with approximately 200 firms depending on the exact specification. The CNLS estimator optimizes the fit of the production function to the observed data; however, non-linear optimization routines do not scale well in large datasets, thus we use the Multivariate Bayesian Convex Regression with contextual variables (Z-MBCR) developed by Preciado Arreola and Johnson (2015) for the pooled dataset.

The multiplicative error Z-MBCR algorithm, a special case of the MBCR-I algorithm (Preciado Arreola and Johnson, 2015) and an extension of the MBCR algorithm (Hannah and Dunson, 2011), estimates a set of hyperplanes the lower envelop of which constructs a monotonic and concave functional estimate. It is computationally less demanding than optimization methods, as it relies on adaptive partitioning and simulation. Further, the use of standard Bayesian inference provides confidence intervals on parameter estimates.

Z-MBCR considers partitions of the data and fits each partitioned dataset separately with linear functions (hyperplanes). For each iteration of the algorithm, Z-MBCR proposes to keep the same number of partitions, further partitions the dataset, or merges two of the existing partitions. For each proposed partition, Z-MBCR draws a slope and an intercept parameter from a prior distribution. The Metropolis-Hastings acceptance probability for the best specification of the chosen type of move is then computed. Finally, the proposed partition is accepted or rejected based on a likelihood calculation.

For every accepted piecewise-linear description of the production function, Z-MBCR draws environmental variable effects from their posterior probability distributions. Finally, Z-MBCR loops through these two parameter estimation procedures (dataset partitioning/hyperplane estimation and environmental variable effects estimation) until the algorithm reaches stationarity parameter estimates. We note that stationarity is guaranteed by the Metropolis–Hastings nature of Z-MBCR.

4. Data Analysis Result

Table 7 summarizes the results of analyzing the pooled dataset (Columns 1-4) and the cross-sectional dataset (Columns 5-8). The primary result in Table 7 is the coefficients of PMS scores. In the analysis of the pooled dataset, the coefficients are positive, ranging from 11.5% to 18.8%, and significant at the 5% level, for all model specifications. In the analysis of the cross-sectional dataset, the effect of the PMS scores is positive, ranging from 20.9% to 26.5%, and significant at the 5% level. These findings support our hypothesis.

Further, the coefficients for the dummy variable for multinational firms are positive and significant at the 1% level. The coefficients ranging from 19% for the analysis of the pooled dataset to 24% for the analysis of the cross-sectional dataset indicate that multinational firms outperform domestic firms by producing approximately 20% more output. This finding aligns with a variety of international trade results that consistently indicate multinational firms are more efficient than firms that only operate domestically (Caves 1974; Kogut and Zander 1993).

Table 7: Estimates of Performance Measurement System

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimation Method	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Dependent Variable	$\ln(Y_{it})$	$\ln(Y_{it})$	$\ln(Y_{it})$	$\ln(Y_{it})$	$\ln(Y_{it})$	$\ln(Y_{it})$	$\ln(Y_{it})$	$\ln(Y_{it})$
	ValueAdded	ValueAdded	ValueAdded	ValueAdded	ValueAdded	ValueAdded	ValueAdded	ValueAdded
PMS z-score	0.1883 ***	0.1550 ***	0.1149 **	0.1162 **	0.2645 ***	0.2543 ***	0.2086 **	0.2165 **
	(0.0562)	(0.0564)	(0.0565)	(0.0575)	(0.0892)	(0.0952)	(0.0950)	(0.0969)
$\ln(L_{it})$	0.5363 ***	0.5269 ***	0.5121 ***	0.5108 ***	0.5513 ***	0.5390 ***	0.5209 ***	0.5105 ***
Labor	(0.0569)	(0.0599)	(0.0597)	(0.0599)	(0.0492)	(0.0514)	(0.0509)	(0.0515)
$\ln(K_{it})$	0.4336 ***	0.4426 ***	0.4381 ***	0.4362 ***	0.4065 ***	0.4040 ***	0.4029 ***	0.4059 ***
Capital	(0.0452)	(0.0481)	(0.0486)	(0.0488)	(0.0440)	(0.0454)	(0.0446)	(0.0448)
Expansionistic		-0.0146	-0.0445	-0.0453		-0.0153	-0.0489	-0.0518
Strategy Dummy		(0.0649)	(0.0625)	(0.0655)		(0.1100)	(0.1087)	(0.1108)
Strategic		-0.0737	-0.0995	-0.1029		-0.1534	-0.1916	-0.1980
Strategy Dummy		(0.0726)	(0.0725)	(0.0748)		(0.1195)	(0.1182)	(0.1200)
Status Quo		-0.0980	-0.1721	-0.1657		-0.0092	-0.1279	-0.1244
Strategy Dummy		(0.1387)	(0.1397)	(0.1427)		(0.2069)	(0.2080)	(0.2088)
Multinational			0.1921 ***	0.1979 ***			0.2255 ***	0.2409 ***
Dummies			(0.0499)	(0.0502)			(0.0855)	(0.0865)
Year Dummies	Yes	Yes	Yes	Yes	Not Applicable	Not Applicable	Not Applicable	Not Applicable
Controls Var.	No	No	No	Yes	No	No	No	Yes
Adjusted R-Squared	0.8542	0.8586	0.8634	0.8635	0.8342	0.8315	0.8377	0.8390
# of Firms	224	208	208	205	175	163	163	160
# of Observations	1564	1462	1462	1439	175	163	163	160
Dataset	Pooled	Pooled	Pooled	Pooled	Cross-Section	Cross-Section	Cross-Section	Cross-Section
*** p<0.01, ** p<0.05, * p<0.1	(Value inside parentheses are the standard errors. For pooled analysis, cluster-robust standard errors are reported.)							

Notes: The number of observations in the pooled dataset, Columns (1) to (4), are less than 2,460 (246 firms with 10 years of data each) because some observations were omitted in the regression due to missing values and outlier correction. The same reason applies to the cross-section dataset, Columns (5) to (8), which has less than 246 observations. See Table 16 in Appendix IV for estimates including outliers.

The coefficients on the strategy type dummy variables present mixed results. Tables 8 and 12 show negative and significant coefficients for dummy variables associated with strategies focused on strategic adaption or status quo when using CNLS and ZMBCR, which implies that firms with these strategies perform better than firms with a strategy focused on strategic adaptation or status quo. The parametric estimation in Table 7, however, shows statistically insignificant coefficients for strategy type coefficients. Overall, our findings on the effect of strategy type align with Stede et al. (2006), who found that "regardless of strategy, firms with more extensive PMS have higher performance."

The parameter estimates of the production function are consistent with economic theory. In Table 7, the coefficients of labor and capital (Rows 4 and 5) are both positive and significant regardless of the dataset used or the model specification, which implies that capital and labor are important inputs and significant predictors of output levels. Table 18 in Appendix VI estimates a model with year and firm fixed effects and also shows positive and significant coefficient for capital and labor. Regardless of the dataset and the number of explanatory variables, manufacturing firms in Italy display decreasing returns-to-scale, indicated by the coefficients of labor and capital summing to a value between 0.916 and 0.969. This finding aligns with our results from the Sen and Meyer null hypothesis test, i.e. the null hypothesis of a linear function is rejected with a p-value of nearly zero in favor of a concave production function.

While parametric methods provide more structure on the production model, there is a risk of misspecification. Therefore, we re-estimate the production functions and the effect of PMS using semi-nonparametric estimators as a robustness check. We use the CNLS estimator for the cross-sectional dataset and Z-MBCR for the pooled dataset. Table 8 shows the results.

Table 8: Estimation of PMS using Concave Shape Restricted Nonparametric Methods

	(1)	(2)	(3)	(4)
Estimation Method	CNLS	CNLS	ZMBCR	ZMBCR
Error Term	Heteroskedastic	Heteroskedastic	Heteroskedastic	Heteroskedastic
PMS z-score	0.1070***	0.0931 ***	0.0749***	0.0480***
	(0.0351)	(0.0357)	(0.0121)	(0.0125)
Expansionistic		-0.0583		-0.0472
Strategy Dummy		(0.0885)		(0.0324)
Strategic		-0.2104 **		-0.1124***
Strategy Dummy		(0.0964)		(0.0346)
Status Quo		-0.1674		-0.2129***
Strategy Dummy		(0.1736)		(0.0590)
Multinational		0.2404 ***		0.2101***
Dummies		(0.0698)		(0.0230)
Mean Squared Error	0.1461	0.1284	0.0259	0.1730
Percentage RMSE	0.7177	0.6729	0.8528	0.8211
Year Dummies	Not Applicable	Not Applicable	Yes	Yes
Controls Var.	No	Yes	No	Yes
# of Firms	160	160	205	205
# of Observations	160	160	1439	1439
Dataset	Cross-Section	Cross-Section	Pooled	Pooled
(Values inside parentheses are the standard errors)	*** p<0.01, ** p<0.05, * p<0.1 (Inference for CNLS)		(Inference for ZMBCR) Significant at: * 90% credible interval ** 95% credible interval *** 99% credible interval	

Notes: Input and output data for this estimation are done in scales, where values are divided by their standard deviations. One firm is omitted in both CNLS and Z-MBCR estimations as an outlier. See Appendix III for analysis of omitted outliers. Even including the outlier, the statistical inference does not change and the values are still significant and positive. See Table 12 in Appendix II.

We use scaled data for the CNLS and ZMBCR estimators where the values are divided by their standard deviations, for efficient calculations. Thus, rescaling the parameter estimates of the effect of PMS (in row 3 columns 2 and 4 of Table 8, 0.0931 and 0.0480) gives coefficient estimations of 0.211 and 0.106 respectively.

Estimation using CNLS and Z-MBCR both result in a positive coefficient associated with the PMS score. For the CNLS estimator, the coefficient is significant at the 1% level. Also, for the Z-MBCR estimator, using a credible interval, the coefficient is significant at the 99% credible interval. Overall, both parametric and nonparametric estimators with heteroskedastic error terms consistently indicate that PMS has a positive and significant effect on productive performance.

To further test the robustness of our aggregation of the survey questions, we aggregate at the category and sub-category levels and estimate model (2) with seven PMS variables (the unweighted average of questions in the category level) and 19 PMS variables (the unweighted average of questions in the sub-category level), respectively. Table 9 shows firms that monitoring results, implementing organizational learning processes, sharing information, reviewing policies, and disseminating good practices tend to have higher productivity levels. This finding characterizes the essential contribution of PMS, where firms strive to become better by measuring and analyzing performance continuously to both identify strengths and weaknesses and to communicate with stakeholders (Melnyk et al. 2004; Neely et al. 1995).

On the other hand, some categories, such as legitimization of support decision, external effects of PMS, and negative effects of PMS have a negative effect on performance, although the negative relationship between these variables and productivity is not robust. For example, Table 17 in Appendix V, which only includes a single individual category or sub-category score in model (2), shows these characteristics of PMS to be insignificant in explaining productivity. The other results in Table 17 generally align with Table 9.

Table 9:
OLS Regression Coefficient of PMS Scores by Survey Category

	PMS Measurement Category	Regression Coefficients		Sub-Category	Regression Coefficients
1	Purpose of Measuring Performance	-0.0595 (0.0673)	1	Purpose of Measuring Performance	-0.0932 (0.0669)
2	Nature of Performance Measurement's Use	0.0209 (0.0596)	2.1	Monitoring	0.0929 ** (0.0466)
			2.2	Focus Attention	0.0199 (0.0415)
			2.3	Strategic Decision Making	-0.0090 (0.0396)
			2.4	Legitimization of Support Decision	-0.0941 * (0.0515)
3	Diversity of Measures	0.0007 (0.0496)	3	Diversity of PMS Measurement	0.0328 (0.0511)
4	Organizational Learning	0.1083 *** (0.0344)	4	Organizational Learning	0.0755 ** (0.0361)
5	Effects of PMS on Business Performance	-0.0393 (0.0721)	5.1	Effects on Strategic Management	-0.0019 (0.0531)
			5.2	Effects on Organizational Capabilities	-0.0020 (0.0429)
			5.3	Effects on Organizational Behavior and Employee Issues	0.0298 (0.0555)
			5.4	Effects on Operations and Tactical Issues	0.0050 (0.0479)
			5.5	External Effects	-0.0821 ** (0.0349)
			5.6	Negative Effects	-0.0681 * (0.0372)
6	Factors Influencing the Effects of PMS	0.0299 (0.0547)	6.1	Employee Involvement and Participation	-0.0096 (0.0440)
			6.2	Organizational Principles	0.0238 (0.0500)
			6.3	Top and Middle Management Commitment	0.0334 (0.0596)
7	Performance Review	0.0405 (0.0531)	7.1	Frequency of Performance Reviews	-0.0021 (0.0265)
			7.2	Review Policies	0.1088 ** (0.0503)
			7.3	Performance Management Leadership	-0.0386 (0.0391)
Adjusted R-Squared		0.8663	Adjusted R-Squared		0.8712
*** p<0.01, ** p<0.05, * p<0.1			(Values inside parentheses are the cluster-robust standard errors)		

Notes: The model specification used in this analysis is similar to the analysis of the pooled dataset with full control variables in Column 4 of Table 7. Two OLS estimations were done, one with seven category level PMS measures as contextual variables and the other with 19 sub-category level PMS measures as contextual variables.

Empirical analysis using the first principal component derived from the PMS data aggregated at the category level as the contextual variable in an analysis with a Cobb-Douglas production shows results similar to using the unweighted average. Comparing Rows 1 and 2 in Table 10 to Columns 4 and 8 in Table 7 shows that the coefficients of the contextual variables continue to be statistically significant and positive. Further, the production function continues to exhibit decreasing returns-to-scale; the coefficients of Labor and Capital sum to values between 0.915 and 0.946 consistent with the range shown in Table 7. Table 10 also shows the coefficients of multinational dummies are significant and positive, with values between 0.190 and 0.232 consistent with our primary analysis. Table 11 in Appendix I shows the results of model (2) estimated using the principal component calculated from the sub-category information as the measure of PMS and the estimates align with those in Table 10.

Table 10:
Estimates of Performance Measurement System using Principal Components

	$\ln(L_{it})$ Labor	$\ln(K_{it})$ Capital	Principal Component	Multinational Dummies	Year Dummies	Controls Var.	Adjusted R-Squared	Number of Firms	Number of Observations	Dataset
(1)	0.5105***	0.4361***	0.0528 **	0.1906***	Yes	Yes	0.8642	205	1439	Pooled
	(0.0595)	(0.0484)	(0.0216)	(0.0500)						
(2)	0.5117***	0.4041***	0.0906**	0.2322**	Not Applicable	Yes	0.8405	160	160	Cross Section
	(0.0513)	(0.0446)	(0.0357)	(0.0864)						

Notes: Cluster-robust standard errors are reported for pooled analysis.

5. Conclusion

This paper, which focused on manufacturing, where output and thus productivity is more easily measurable, hypothesized that PMS has a positive effect on firms' productive performance. An empirical model jointly estimated a Cobb-Douglas production function and the effect of PMS. PMS survey data was gathered from 246 manufacturing firms operating in Italy between 2003 and 2012. The coefficients of the PMS scores were positive and significant for analyses of both pooled and cross-section datasets. The production function estimates and hypothesis testing on the functional form of the production function indicated that overall, the Italian manufacturing industry exhibited decreasing returns-to-scale consistent with Italy's largely mature manufacturing sector. The use of nonparametric estimators with heteroskedastic error terms and contextual variables confirmed the findings of the OLS estimation. The finding that multinational firms outperformed domestic firms in terms of output by approximately 20% aligned with the international trade literature.

Analyzing the effect of four types of strategy (quality focused, expansionistic, strategic adaptation, and status quo) employed by the firms in the dataset indicated that a quality focused strategy outperformed the other strategies in both the CNLS and Z-MBCR estimations, whereas the differences were insignificant in the OLS estimation. The coefficient of the PMS variable indicated a positive and significant effect on productivity even with different aggregations of survey data at the category level.

The measures of output in manufacturing industries are well established and therefore we focused on this industry. Further research could look at the importance of PMS in other industry, but would require the development of output indices. Extensions to service industries, for example, are likely to encounter measurement issues in quantifying output. The presence of PMS is likely to play an important role in institutional learning. However, investigation of this issue will require extensive data collection.

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Appendix I: Principal Component Analysis

Eigenvalues represent how much each principal component can explain the variability of the data vector. Horn's (1965) parallel analysis suggests retaining principal components having higher eigenvalues than the eigenvalues resulting from random sampling. To decide which components are significant, we generate eigenvalues from 100 random samplings of the data and plot them in Figure 2 (dotted line). For the category level data, only the first principal component has a higher eigenvalue than the randomly sampled data.

Figure 2: Scree Plots for Parallel Analysis for Category Data

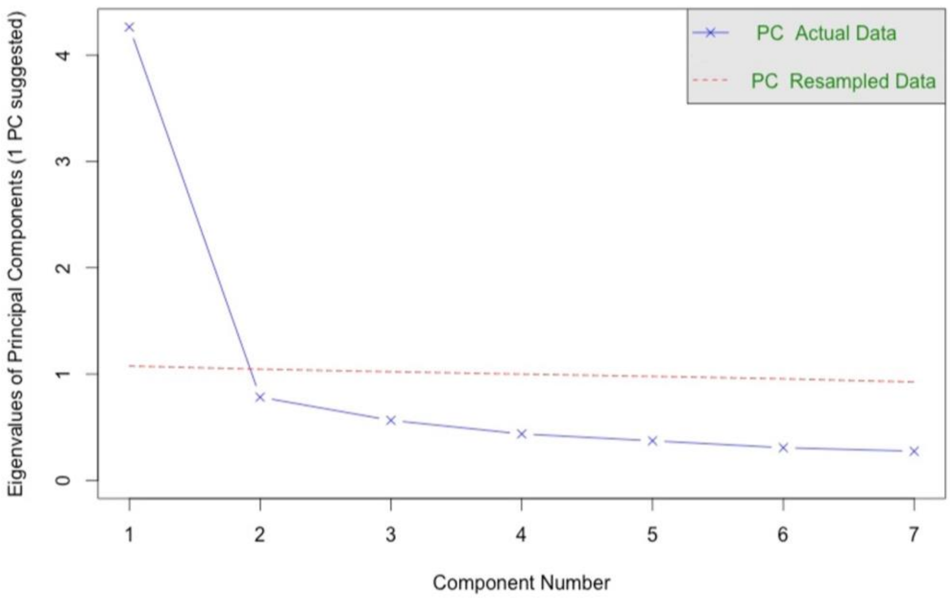

Table 11:
Estimates of Model (1) using Principal Components to Measure PMS

	(1)	(2)	(3)	(4)	(5)	(6)
Estimation Method	OLS	OLS	OLS	OLS	OLS	OLS
Dependent Variable	$\ln(Y_{it})$	$\ln(Y_{it})$	$\ln(Y_{it})$	$\ln(Y_{it})$	$\ln(Y_{it})$	$\ln(Y_{it})$
	ValueAdded	ValueAdded	ValueAdded	ValueAdded	ValueAdded	ValueAdded
Dimension Reduction Method	PCA	PCA	PCA	PCA	PCA	PCA
	(Category Data)	(Category Data)	(Subcategory Data)	(Category Data)	(Category Data)	(Subcategory Data)
$\ln(L_{it})$	0.5105 ***	0.5040 ***	0.5040 ***	0.5117 ***	0.5080 ***	0.4984 ***
Labor	(0.0595)	(0.0603)	(0.0598)	(0.0513)	(0.0518)	(0.0532)
$\ln(K_{it})$	0.4361 ***	0.4408 ***	0.4404 ***	0.4041 ***	0.4063 ***	0.4127 ***
Capital	(0.0484)	(0.0490)	(0.0487)	(0.0446)	(0.0448)	(0.0456)
Principal Component 1	0.0528 **	0.0494 **	0.0281 **	0.0906 **	0.0889 **	0.0519 **
	(0.0216)	(0.0219)	(0.0130)	(0.0357)	(0.0359)	(0.0207)
Principal Component 2		0.0911 *	0.0128		0.0497	0.0161
		(0.0538)	(0.0271)		(0.0843)	(0.0451)
Principal Component 3			-0.0474			-0.0522
			(0.0320)			(0.0585)
Multinational	0.1906 ***	0.1809 ***	0.1860 ***	0.2322 ***	0.2286 ***	0.2288 ***
Dummies	(0.0500)	(0.0273)	(0.0498)	(0.0864)	(0.0868)	(0.0870)
Adjusted R-Squared	0.8642	0.8653	0.8645	0.8405	0.8398	0.8391
Year Dummies	Yes	Yes	Yes	Not Applicable	Not Applicable	Not Applicable
Controls Var.	Yes	Yes	Yes	Yes	Yes	Yes
# of Firms	205	205	205	160	160	160
# of Observations	1439	1439	1439	160	160	160
Dataset	Pooled	Pooled	Pooled	Cross-Section	Cross-Section	Cross-Section
	*** p<0.01, ** p<0.05, * p<0.1		(Values inside parentheses are the standard errors)			

Notes: Cluster-robust standard errors are reported for pooled analysis.

Appendix II: Estimation of PMS using Nonparametric Methods in Scales

Columns 1, 3, 5, 7, and 9 in Table 12 show the results of estimating model (3) removing outlier observations. Columns 2, 4, 6, 8, and 10 show the results including all data. Note that the coefficient of the PMS score is always positive and that the statistical inference is significant in most cases.

Nonparametric estimations are done using scaled data, where values are divided by their standard deviations, for efficiency in calculations. The coefficient estimations for PMS z-score when the values are rescaled back to levels are 0.243, 0.232, 0.211, 0.195, 0.154, 0.207, 0.164, 0.152, 0.106, and 0.1048 for Columns 1 to 10.

Table 12: Estimation of PMS using Concave Shape Restricted Nonparametric Methods

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Estimation Method	CNLS	CNLS	CNLS	CNLS	ZMBCR	ZMBCR	ZMBCR	ZMBCR	ZMBCR	ZMBCR
Error Term	Heteroskedastic	Heteroskedastic	Heteroskedastic	Heteroskedastic	Heteroskedasic	Heteroskedastic	Heteroskedastic	Heteroskedastic	Heteroskedastic	Heteroskedastic
PMS z-score	0.1070 ***	0.1020 ***	0.0931 ***	0.0857 **	0.0679*	0.0910*	0.0749***	0.0693***	0.0480***	0.0475***
	(0.0351)	(0.0353)	(0.0357)	(0.0362)	(0.0364)	(0.0458)	(0.0121)	(0.0118)	(0.0125)	(0.0127)
Expansionistic			-0.0583	-0.0568	-0.0683	-0.0913			-0.0472	-0.0453
Strategy Dummy			(0.0885)	(0.0900)	(0.0843)	(0.1075)			(0.0324)	(0.0322)
Strategic			-0.2104 **	-0.1793 *	-0.2142**	-0.2239*			-0.1124***	-0.1049***
Strategy Dummy			(0.0964)	(0.0971)	(0.0921)	(0.1183)			(0.0346)	(0.0337)
Status Quo			-0.1674	-0.1651	-0.1807	-0.1356			-0.2129***	-0.21153***
Strategy Dummy			(0.1736)	(0.1766)	(0.1590)	(0.1977)			(0.0590)	(0.0601)
Multinational			0.2404 ***	0.2388 ***	0.2301***	0.1761*			0.2101***	0.2076***
Dummies			(0.0698)	(0.0706)	(0.0711)	(0.0889)			(0.0230)	(0.0244)
Mean Squared Error	0.1461	0.2621	0.1284	0.3542	0.1620	0.3319	0.0259	0.1570	0.1730	0.1495
Percentage RMSE	0.7177	2.5155	0.6729	2.9241	0.7557	2.8306	0.8528	1.6302	0.8211	1.5909
Year Dummies	Not Applicable	Not Applicable	Not Applicable	Not Applicable	Not Applicable	Not Applicable	Yes	Yes	Yes	Yes
Controls Var.	No	No	Yes	Yes	Yes	Yes	No	No	Yes	Yes
# of Firms	160	161	160	161	160	161	205	205	205	205
# of Observations	160	161	160	161	160	161	1439	1444	1439	1444
Correction for Outlier	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Dataset	Cross-Section	Cross-Section	Cross-Section	Cross-Section	Cross-Section	Cross-Section	Pooled	Pooled	Pooled	Pooled
(Values inside parentheses are the standard errors)	*** p<0.01, ** p<0.05, * p<0.1 (Inference for CNLS)				(Inference for ZMBCR) Significant at: * 90 % credible interval, ** 95% credible interval, 99% credible interval					

Notes: Input and output data for this estimation has been done in scales, where values are divided by their standard deviations.

Appendix III: Analysis of Omitted Outliers

Firm 39 is omitted in the analysis of the cross-section and the pooled datasets because the variables – value added, capital employed, and number of employees – show a large discrepancy compared to the other data. Table 13 shows the disaggregate data for firm 39. Tables 14 and 15 indicate that the three variables for Firm 39 are nearly twice as large as those in the second largest firm in the dataset. The findings suggest that Firm 39 is either operating in a unique industry, or there is an error in the data collection process. We were unable to validate Firm 39 and chose to remove it.

Table 13: Summary Statistics for Omitted Observations

Omitted Observations						
Data Set	Firm Index	Year	Value Added	Capital Employed	Number of Employees	PMS Score
Cross-Section	39	2009	12.4520	10.2595	12.0970	-0.1277
Pooled	39	2010	16.7424	20.4328	17.1785	-0.1237
Pooled	39	2009	18.5442	11.8186	16.8102	-0.1237
Pooled	39	2008	16.2543	10.9520	15.5440	-0.1237
Pooled	39	2007	14.4333	9.3696	13.6036	-0.1237
Pooled	39	2006	13.4451	7.8858	13.1292	-0.1237

Notes: The value reported is a scaled value, meaning that the data is divided by its standard deviation, i.e. representing how many standard deviations the value is away from the mean, since the mean value of inputs, output, and contextual variables is close to zero.

Note that the omitted observation (bold and underlined in Table 14) in the cross-section data has the highest values in inputs and outputs, and is also several times higher compared to the second largest value.

Table 14: Rank of Input, Output, and Contextual Variable in Decreasing Order, Cross-Section Dataset

Rank	Value Added	Capital Employed	Number of Employees	PMS Score
1	**12.4520**	**10.2595**	**12.0970**	3.6724
2	1.7159	5.7886	2.8044	2.2480
3	1.0346	3.8702	1.9387	2.2131
4	1.0293	1.9184	1.6359	1.9610
5	0.9392	1.6872	1.3709	1.7436

Similar to Table 14 the omitted observations (bold and underlined in Table 15) in the pooled data have input and output values several times higher than those of the other observations.

Table 15: Rank of Input, Output, and Contextual Variable in Decreasing Order, Pooled Dataset

Rank	Value Added	Capital Employed	Number of Employees	PMS Score
1	**18.5442**	**20.4328**	**17.1785**	3.5570
2	**16.7424**	**11.8186**	**16.8102**	3.5570
3	**16.2543**	**10.9520**	**15.5440**	3.5570
4	**14.4333**	9.7416	**13.6036**	3.5570
5	**13.4451**	**9.3696**	**13.1292**	3.5570
6	3.9305	7.8858	4.0366	3.5570
7	3.5614	7.4670	4.0273	3.5570
8	3.5293	7.2149	4.0106	3.5570
9	3.0098	7.1774	4.0055	2.1773
10	2.7095	6.6682	3.8971	2.1773

Appendix IV

Table 16 shows the OLS estimation without outlier corrections. The results are similar to OLS estimation with outlier corrections in Table 7.

Table 16: Estimates of Performance Measurement Systems without Corrections for Outliers using OLS

	(1)	(2)
Estimation Method	OLS	OLS
Dependent Variable	$\ln(Y_{it})$ ValueAdded	$\ln(Y_{it})$ ValueAdded
PMS z-score	0.1123*	0.2036**
	(0.0575)	(0.0980)
$\ln(L_{it})$	0.5186***	0.5360***
Labor	(0.0600)	(0.0509)
$\ln(K_{it})$	0.4378***	0.4079***
Capital	(0.0492)	(0.0454)
Expansionistic	-0.0465	-0.058
Strategy Dummy	(0.0650)	(0.1122)
Strategic	-0.0929	-0.1675
Strategy Dummy	(0.0742)	(0.1208)
Status Quo	-0.1719	-0.1330
Strategy Dummy	(0.1433)	(0.2116)
Multinational	0.1959***	0.2369***
Dummies	(0.0499)	(0.0877)
Year Dummies	Yes	Not Applicable
Controls Var.	Yes	Yes
Adjusted R-Squared	0.8703	0.8513
# of Firms	205	161
# of Observations	1444	161
Dataset	Pooled	Cross-Section
	*** p<0.01, ** p<0.05, * p<0.1	
	(Values inside parentheses are the standard errors)	

Notes: Cluster-robust standard errors are reported for pooled analysis.

Appendix V

Four of the seven regressions in the PMS measurement category have a positive regression coefficient with a p-value of less than 8%. Nine of the nineteen regressions in the sub-categories have a positive regression coefficient with a p-value of less than 8%. The average regression coefficient is 0.073 in the category level and 0.047 in the sub-category level. Comparing these averages to the regression coefficient, 0.116, from the pooled analysis, the average coefficients from the category and subcategory levels are smaller, thus reflecting the higher measurement error at both levels.

Table 17:
OLS Regression Coefficient of PMS scores by Survey Category in Individual OLS Estimation

	PMS Measurement Category	Regression Coefficients		Sub-Category	Regression Coefficients
1	Purpose of Measuring Performance	0.0271 (0.0479)	1	Purpose of Measuring Performance	0.0271 (0.0479)
2	Nature of Performance Measurement's Use	0.0556 (0.0434)	2.1	Monitoring	0.0860 ** (0.0348)
			2.2	Focus Attention	0.0628 * (0.0337)
			2.3	Strategic Decision Making	0.0265 (0.0304)
			2.4	Legitimization of Support Decision	-0.0036 (0.0396)
3	Diversity of Measures	0.0645 * (0.0362)	3	Diversity of PMS Measurement	0.0645 * (0.0362)
4	Organizational Learning	0.1095 *** (0.0286)	4	Organizational Learning	0.1095 *** (0.0286)
5	Effects of PMS on Business Performance	0.0783 (0.0783)	5.1	Effects on Strategic Management	0.0480 (0.0321)
			5.2	Effects on Organizational Capabilities	0.0495 (0.0495)
			5.3	Effects on Organizational Behavior and Employee Issues	0.0697 ** (0.0321)
			5.4	Effects on Operations and Tactical Issues	0.0368 (0.0309)
			5.5	External Effects	-0.0127 (0.0301)
			5.6	Negative Effects	-0.0164 (0.0362)
6	Factors Influencing the Effects of PMS	0.0883 ** (0.0397)	6.1	Employee Involvement and Participation	0.0543 * (0.0297)
			6.2	Organizational Principles	0.0833 * (0.0445)
			6.3	Top and Middle Management Commitment	0.0693 ** (0.0340)
7	Performance Review	0.0896 ** (0.0407)	7.1	Frequency of Performance Reviews	-0.0167 (0.0295)
			7.2	Review Policies	0.1179 *** (0.0346)
			7.3	Performance Management Leadership	0.0397 (0.0251)
Unweighted Average of Coefficients		0.0733	Unweighted Average of Coefficients		0.0471
*** p<0.01, ** p<0.05, * p<0.1			(Values inside parentheses are the cluster-robust standard errors)		

Notes: Each regression coefficients represents the coefficients when the corresponding category or sub-category is used as a PMS score to run the OLS estimation for model (1). Thus, for the PMS Measurement Category the OLS estimation is run seven times for each PMS category. For the Sub-category the OLS estimation is run 19 times. A similar analysis is performed in Bloom and Van Reenen (2007).

Appendix VI

To account for the time-invariant, individual firm specific characteristics, a firm fixed effects model is estimated in Table 18. Column 1 represents estimation with only firm fixed effects and column 2 represents estimation with both firm and year fixed effects. For both cases the coefficient of Labor and Capital is positive and significant, which aligns with Table 7. For robust analysis, a Hausman test for firm random effects is carried out. The results reject the firm random effect model in favor of the fixed effect model as reported in Table 18. The F-test for no firm fixed effects in columns 1 and 2 rejects the hypothesis that there are no firm specific fixed effects.

Table 18: Year and Firm Fixed Effects Estimation of Performance Measurement Systems

	(1)	(2)
Dependend Variable	$\ln(Y_{it})$ Value Added	$\ln(Y_{it})$ Value Added
$\ln(L_{it})$	0.3302 ***	0.3177 ***
Labor	(0.1058)	(0.1059)
$\ln(K_{it})$	0.2266 ***	0.2502 ***
Capital	(0.0428)	(0.0442)
Year 2004		0.0333 (0.0506)
Year 2005		0.0153 (0.0457)
Year 2006		0.1248 ** (0.0501)
Year 2007		0.1759 *** (0.0477)
Year 2008		0.1155 ** (0.0495)
Year 2009		-0.0632 (0.0555)
Year 2010		0.1052 ** (0.0528)
Year 2011		0.0450 (0.05323)
Year 2012		0.0044 (0.0650)
Adjusted R-Squared	0.9252	0.9283
Number of Firms	224	224
Number of Observations	1564	1564
F-test for no fixed effects:	P-value 0.0000	P-value 0.0000
Hausman test for firm random effects	Rejects firm random effects model in favor of the firm fixed effect model with p-value of near zero	