Measuring Management Practices

Abstract

Good management practices are remarkably difficult to robustly measure, especially when unique data on firms and their managers are not available. We propose a new model estimated with Bayesian techniques that requires only the usual accounting data on inputs and outputs and thus can be applied to any firm. We show that our management practices estimates are more than 90% correlated with existing state-of-the-art measures from a very specialized data set by Bloom and Van Reenen (2007). We also obtain very high correlations when conducting an extensive Monte Carlo analysis. Finally, we show that frontier-based methods previously used to estimate management practices do not provide good approximations.

Keywords: Management practices; Productivity; Cost efficiency; Bayesian methods.

1 Introduction

The robust quantification of good management practices (also termed managerial quality, skill, ability, or simply management) is an indispensable tool of empirical research in management, economics, finance, and other social sciences. Measuring management practices poses well-known difficulty, mainly due to the scarcity of relevant disaggregated data and the mere nature of the concept, and the relevant literature goes back to Mundlak (1961), Lucas (1978), and Rosen (1981), who note that differences in firm productivity must be related to the so-called firm fixed effect of managerial quality. In more recent endeavors, Bloom and Van Reenen (2007; 2010) use survey data to assess good management practices of firms, while Demerjian et al. (2012; 2013) and Bonsal IV et al. (2016) use data envelopment analysis (DEA)-based methods. Other studies use either measures of inventory buffers of manufacturing firms (e.g., Lieberman et al., 2005) or corporate governance characteristics related to experience (e.g., Custódio et al., 2017).

Relative to this literature, the contribution of our study is twofold. First, we propose a new method to thoroughly measure *general management practices* and show, through several validation methods, that we have come the closest yet to their approximation. Second, our method can be applied to any firm without posing restrictions on data availability, besides the usual output and inputs of production that can be derived from simple financial statements. This is highly important because our approach can be applied to all firms for which conventional accounting data are available.

Our method relies on the estimation of a simple cost efficiency model, where management is an input of production. This approach is consistent with a broad definition of management practices, which includes human and intellectual capital, conceptual and technical skills, and entrepreneurial and human-resource abilities that lead to better management of the traditional inputs and superior productivity (Katz, 1974; Bloom et al., 2017). Thus, this broad set of management practices encompasses virtually all other inputs, besides labor and capital, used by firms to achieve their objectives. The novel element of our research is that management is an unobserved (latent) variable (input of production) to be estimated from the data. The drawback of our approach is the somewhat more involved statistical procedure, as we must use Bayesian econometrics due to the presence of several latent variables in our model.

Our model yields a system of five equations to be simultaneously estimated. The first two equations are a translog cost function and one of the share equations that is related to unobserved management practices. The share equation is used to allow identification of management from the cost-share system. The third and fourth equations estimate the determinants of the unobserved managerial price (compensation) and management practices, respectively. These latent variables are approximated only by firm size, a time trend, and priors (used for Bayesian estimation). Finally, the fifth equation models technical efficiency, which is allowed to depend on latent management. This is important from a theoretical viewpoint because management quality must be a significant part of technical efficiency.

We systematically explore the internal validity of our model using (i) a unique data set previously employed to robustly measure management practices and (ii) 1,000 simulated data sets generated from a production function. First, in a series of milestone papers for the measurement of management practices, BVR (2007; 2010) and Bloom et al. (2012) use a rigorous interview-based evaluation tool that examines the basic managerial practices covering all relevant processes of firms. This yielded the World Management Survey (WMS), which is an international research initiative to measure the differences in management practices across organizations and countries. In summary, the WMS's methodology is to obtain and conduct interviews with senior managers across a number of dimensions in firm performance, ensure the collection of accurate responses through several procedures, and evaluate management practices across operations management, performance monitoring, target setting, leadership management, and talent management.[1] To the best of our knowledge, the WMS produces the most detailed and scientifically-based measure of management practices, albeit for a limited number of medium-sized firms.

In addition to the measurement of management practices, BVR report data on the usual inputs (capital and labor) and output (sales) of firms. This data set allows us to conduct an experiment to validate our estimates. We first estimate our model using data only on firms' output and inputs from BVR (2007) and obtain estimates for management practices. Subsequently, using a simple bivariate regression, we compare our estimates with the BVR scores and find that our estimates explain about 92% of the BVR scores.

In turn, we examine whether this high correlation holds in other samples by conducting a Monte Carlo study. To make the environment relatively unfavorable to our model and more favorable to existing frontier-based methods for the measurement of management practices, we generate panels from a production function with simulated information on inputs and their prices, output, and management practices. We use different sizes of the cross-sectional dimension (firms) and a constant time dimension, as well as different assumptions regarding availability of data for the input prices. We show that as the cross-sectional dimension of the sample increases (eventually reaching a maximum of 2,500 firms over 10 years), the rank correlations between our model's estimates and simulated management scores are between 0.83 and 0.91, depending on whether information on the two input prices is available (larger values observed when data on both input prices are available). Thus, our two validation procedures show that we have come very close to a robust measure of management practices.

As a final exercise, we check how the measurement of management practices from Data Envelopment

[1] For more details, see http://worldmanagementsurvey.org/.

Analysis (DEA) fares when applied to the data set of BVR (2007). The application of a DEA-based method to measure management is currently the most common approach in the literature (e.g., Demerjian et al., 2012). The premise of that literature is that management is part of the efficiency component, which is estimated using DEA. Management can then be derived as a residual from the regression of DEA scores on variables that managers cannot affect (e.g., firm size, market share, firm age, etc.). This technique has gained momentum despite the fact that it involves regressing the DEA scores on covariates, a practice that biases results in unknown magnitude and direction (as highlighted in the seminal paper of Simar and Wilson, 2007).

We first apply the usual DEA approach (Demerjian et al., 2012; 2013; Bonsal IV et al., 2016) to the same output and inputs from BVR (2007) and use as management practices either these scores or the residuals from the regression of the DEA scores on firm size, firm age, etc., as management practices. Subsequently, we compare the DEA-based management scores with those from BVR. We find that DEA-based measures are statistically significant determinants of the BVR scores but never explain more than 5% of these scores.

Besides the work by BVR (2007; 2010) and Bloom et al. (2012; 2017), our paper relates to several strands of literature in a multidisciplinary context. The common aim of these strands is to identify sources of productivity differences of firms and sources of managerial quality (e.g., Sáenz-Royo and Salas-Fumás, 2014) and, to this end, it is important to have a robust measure of management practices that can be applied to any firm. Unless there is access to unique and specialized data, the unobserved (stochastic) nature of management unavoidably leads to some sort of econometric/mathematical analysis.

The literature (predominantly the management literature) stresses quite graphically the importance of validation of any new measure of management practices. Only indicatively, Schriesheim et al. (1993) identify deficiencies in the measurement of management practices and suggest that any new method requires some sort of validation based on good benchmark data. Schilke and Goerzen (2010) conceptualize and operationalize alliance management capability, and contribute to the performance effects of alliance structures and alliance experience based on survey data from 204 firms. Richard et al. (2009) focus on measuring organizational performance and conclude with a call for research that examines triangulation using multiple measures, longitudinal data, and alternative methodological formulations as methods of appropriately aligning research contexts with the measurement of organizational performance." Even more recently, Hermalin and Weisbach (2017) discuss the importance of managerial ability and its assessment in firms' corporate governance.

Our paper proceeds as follows. In Section 2 we present our model and estimation approach. In Section 3 we discuss our validation approaches. In Section 4 we conclude the paper and provide directions for future research.

2 Unobserved management

2.1 Model

We consider a production model of the firm in which management practices, x_J^*, is an unobserved (latent) input of production. The recent work of Bloom et al. (2017) motivates the modeling of management as a factor of production. We aim to model x_J^* using a cost-share system, plus two equations that allow the identification of management practices and their price, respectively, from their latent dynamics and other observed variables. We also add a fourth equation to the model to allow for a firm inefficiency component and its dependence on management and other variables (e.g., Sáenz-Royo and Salas-Fumás, 2014).

An important question is whether management is the only unobserved input of production. If it is not, then x_J^* will capture other inputs unrelated to management *per se*. There are two main reasons backing our assumption, the first theoretical and the second driven by our empirical results. First, management science broadly defines management practices to include human and intellectual capital, conceptual and technical skills, and entrepreneurial and human-resource abilities leading to better management of the traditional inputs and superior firm productivity (Katz, 1974; many others since then). Indeed, the coordination of the rest of the inputs involves precisely these broadly defined skills to gather, allocate, and distribute economic resources or consumer products to individuals and other businesses in the economy. This definition is also fully aligned with standard microeconomic theory, which assumes that there is a third factor of production besides labor and capital (including land). Specifically, all modern economic textbooks list human capital, entrepreneurship, or a similar notion as a factor of production (e.g., Samuelson and Nordhaus, 2009). Management practices, as defined here, encompass all of these notions and, thus, it should be only this "best management practices" component missing from the list of firms' inputs in the estimation of production relations.

Second, our empirical results essentially back our assumption that management is the main (if not the only) unobserved input of production. Our key validation approach compares our estimates from the model below to the state of the art measure of management practices developed by BVR (2007). The approach of this study is to obtain unique survey data on a specific sample of firms for which best management practices are well-defined and measured. This approach has nothing to do with the estimation of a production relation, so that identifying a close relation between our estimates of management practices and those of BVR constitutes a strong indication that what we indeed measure is management and not some other unobserved input(s) of production.

We begin with a cost function of the form:

$$C = C\left(w_1, ..., w_{J-1}, w_J^*, y\right) = \min_{x \in \mathbb{R}_+^J} : w'x, \text{ s.t. } F(x, y) = 1, \tag{1}$$

where $w = [w_1, ..., w_{J-1}, w_J^*]'$ is the vector of input prices, y is the vector of outputs, x is the vector of inputs, and F is a transformation function. Here, we consider the case of one output (the log of sales), and two observed inputs, namely labor (the log of employees) and capital (the log of capital stock) as, for example, in Bloom and Van Reenen (2007) and Chen et al. (2015). The choice of a cost function is in line with the premise that managers seek to achieve a given level of output by minimizing costs. Also, w_J^* is the (usually) unobserved (latent) management price (average managerial compensation across firms) of management practices, x_J^*, and $C = w_1x_1 + ... + w_{J-1}x_{J-1} + w_J^*x_J^* \equiv TC^x + w_J^*x_J^*$, where TC^x denotes the input cost excluding management cost (cost of labor and capital). For simplicity, let $\mathbf{w} = [w_1, ..., w_{J-1}]'$ be the vector of input prices besides management price (i.e., the prices of labor and capital). We treat all input prices as parameters of inputs to be estimated and thus constant across firms.[2]

We have the following share equations and, as in similar modeling frameworks (e.g., McElroy, 1987; Hijzen et al., 2005), we can drop the second one:

$$\begin{aligned} \frac{w_j x_j}{TC^x + w_J^* x_J^*} &= \frac{\partial \log C(\mathbf{w}, w_J^*, y)}{\partial \log w_j}, \ \forall j = 1..., J-1, \\ \frac{w_J^* x_J^*}{TC^x + w_J^* x_J^*} &= \frac{\partial \log C(\mathbf{w}, w_J^*, y)}{\partial \log w_J}. \end{aligned} \tag{2}$$

For simplicity, and without loss of generality, let us consider the case of one output and two inputs ($J = 2$), the second of which is management practices. Using a translog specification, which is the preferred in many empirical exercises due to its flexibility and linearity in parameters (Greene, 2008), we have:

$$\begin{aligned} \log \frac{C}{w_1} = \beta_o + \beta_1 \left(\log w_2^* - \log w_1\right) + \tfrac{1}{2}\beta_2 \left(\log w_2^* - \log w_1\right)^2 + \\ +\beta_3 \log y \left(\log w_2^* - \log w_1\right) + \beta_4 \log y + \tfrac{1}{2}\beta_5 \left(\log y\right)^2. \end{aligned} \tag{3}$$

The share equation corresponding to management is:

$$S_2^* = \beta_1 + \beta_2 \left(\log w_2^* - \log w_1\right) + \beta_3 \log y. \tag{4}$$

Thus, we have $C = w_1x_1 + w_2^*x_2^*$ and $S_2^* = \frac{w_2^*x_2^*}{w_1x_1 + w_2^*x_2^*} = 1 - S_1$.

In (4) the dependent variable corresponding to managerial share will always be observed as $S_J^* = 1 - \sum_{j=1}^{J-1} S_j$. Further, w_2^* can be identified through the nonlinearity in (3) and the joint appearance

[2] Despite the fact that some databases (e.g., BoardEx) report managerial salaries or the price of capital, we are generally unaware (or can have very rough estimates) of input prices, especially across unlisted, relatively small, and non-US firms.

of w_2^* in (3) and (4). The technical problem, however, is that x_2^* appears also in C and thus we need assumptions on predetermined variables that identify x_2^* and w_2^* to be stated in additional equations below.

For all firms and time periods $J-1$, the econometric (stochastic) form of the cost function and the first share equation is as follows:

$$\begin{aligned} C_{it} &= C\left(\mathbf{w}_{it}, w^*_{J,it}, y_{it}; \boldsymbol{\beta}\right) + v_{1,it} + u_{it}, \\ \tfrac{w_{j,it}x_{j,it}}{TC^x_{it}+w^*_{J,it}x^*_{J,it}} &= \tfrac{\partial \log C\left(\mathbf{w}_{it}, w^*_{J,it}, y_{it}; \boldsymbol{\beta}\right)}{\partial \log w_{j,it}} + v_{j,it},\ \forall j = 1..., J-1, \end{aligned} \tag{5}$$

where $\boldsymbol{\beta}$ is the parameter vector to be estimated, $\mathbf{v}_{it} = [v_{1,it}, ..., v_{J+1,it}]'$ is the vector of error terms, and $u_{it} \geq 0$ represents technical inefficiency. The addition of the error terms in our model follows standard practice in the estimation of stochastic production relations (e.g., Coelli et al., 2005; Kumbhakar and Lovell, 2000). This essentially implies decomposing the stochastic term to the inefficiency component and the remainder disturbance, which captures random shocks outside the control of firms. For the error terms in (5), we assume $\mathbf{v}_{it} \sim \mathcal{N}_J\left(\mathbf{O}, \boldsymbol{\Sigma}\right),\ \forall i = 1, ..., n,\ t = 1, ..., T$. As is also standard in the same literature, $\mathbf{v}_{it}$ is independent from u_{it}, and we impose concavity in input prices and monotonicity (e.g., Kumbhakar and Lovell, 2000; Coelli et al., 2005).

Technical inefficiency comes, as usual, from the result that cost inefficiency is related to input-oriented inefficiency (Kumbhakar, 1997). To impose linear homogeneity with respect to prices, we express all prices relative to the first one. Besides the variables reflecting output and inputs, we use country and industry dummies in the cost equation, as we find that these improve the precision of our management practices estimates relative to our validation benchmarks.

For the measurement of the latent variables, we assume that

$$\log w^*_{Jt} = \mu_1\left(1-\rho_1\right) + \rho_1 \log w^*_{J,t-1} + \overline{\mathbf{x}}'_t \boldsymbol{\alpha}_1 + \varepsilon_{t1},\ \forall t = 1, ..., T, \tag{6}$$

$$\log x^*_{J,it} = \mu_{2i}\left(1-\rho_2\right) + \rho_2 \log x^*_{J,i,t-1} + \mathbf{x}'_{it} \boldsymbol{\alpha}_2 + \varepsilon_{it,2},\ \forall i = 1, ..., n,\ t = 1, ..., T. \tag{7}$$

In equations (6) and (7) μ_1, μ_2 and ρ_1, ρ_2 are, respectively, location and persistence parameters for the variables involved. If $\rho_j = 1$ then the intercept μ_j disappears. Separate identification is possible because (i) μ_2 and ρ_2 appear in the denominator of the left hand side of (7) and (ii) there is a separate first order condition (equation 7), which involves only w^*_{Jt} in the right hand side of (6). In equation (6) we keep, for simplicity, managerial compensation equal across all firms (as we do for the rest of the input prices) and only allow it to vary with time.[3] This does not affect our estimates but considerably eases estimation. In contrast, management practices in equation (7) varies with both firm and time,

[3] Allowing time variation makes this model compatible with the use of panel data.

as this is the main focus of our analysis.

Importantly, equations (6) and (7) allow the identification of our two main variables from observed characteristics and a dynamic latent variable (i.e., unobserved persistence of management practices and their price). As is usual the case with panel data, the degree of persistence is expected to be 'large'; thus we do not consider this a strong assumption. In essence, we place more structure on management practices and their price to come up with well-identified posterior measures.[4] This is also well-justified theoretically because learning-by-doing processes, personnel and director experience, labor immobility, restrictive regulations and wage stickiness, etc., create important sources of persistence in the management practices of firms.[5]

Symmetrically with w^*_{Jt}, we have $\overline{\mathbf{x}}_t = n^{-1}\sum_{i=1}^{n}\mathbf{x}_{it}$. In the vectors $\overline{\mathbf{x}}$ and $\mathbf{x}$, of equations (6) and (7), we include firm size (measured by the log of fixed assets),[6] its squared term to capture potential non-linear effects due to diseconomies of scale, the principal component of prices on labor and capital and its square, and the interaction of firm size with the principal component. We allow management and managerial compensation to depend on these variables and especially the principal component of the price of labor and capital because part of an effective management is to determine the right input prices. Of course, the alternative would be to have both prices in each specification. Unfortunately, adding more latent variables in the model yields convergence problems. With the principal component, the model runs and yields the results reported in the paper. Of course, the "success" of our analysis is outcome-driven: we use this approach because results are closer to Bloom and Van Reenen and the ones produced in our Monte Carlo exercise.

For the error terms in (6) and (7), we assume $\varepsilon_{t1} \sim \mathcal{N}\left(0, \sigma^2_{\varepsilon_1}\right), \varepsilon_{it,2} \sim \mathcal{N}\left(0, \sigma^2_{\varepsilon_2}\right), \forall i = 1, ..., n,\ t = 1, ..., T$. The multivariate normality assumptions, along with the relevant ones in equation (5), are standard practice in the econometric literature (e.g., Coelli et al., 2005; Kumbhakar and Lovell, 2000).

A final key element of our model is that we allow the technical inefficiency component to depend on management practices, as follows:

$$u_{it} \sim \mathcal{N}_+\left(a_0 + a_1 x^*_{Jt} + a_2 u_{i,t-1} + \mathbf{a}'\mathbf{z}_{it},\ \sigma^2_u\right), \forall i = 1, ..., n,\ t = 1, ..., T. \quad (8)$$

[4]Surely, we have distributional and parametric assumptions, which, however, we believe are reasonable based on prior grounds. Also, their validity should be considered in light of the evidence we provide. If the validation procedures showed that our estimates of management practices were questionable, we would have had to think again about the entire specification. For example, non-persistent managerial ability estimates would make us wonder why this is so and our attention would turn to the specification of the model. As the results on persistence are highly significant and our management scores are a very good fit to the scores of BVR and the scores from the Monte Carlo simulations, we proceed with the simplest assumptions possible that are also in line with existing literature.

[5]Bloom and Van Reenen (2010) show that management practices persist and attribute this persistence to the reasons we highlight. For implications of persistence of managerial quality within a framework of innovation, see Custódio et al. (2017). Wage stickiness and its causes is analyzed in a big economics literature (e.g., Goette et al., 2007; references therein).

[6]For firm size, we would optimally require the total firms' assets, but as these are not available, we use fixed assets. However, at the end this is marginally important, given the strong correlation identified between our estimates and BVR's estimates.

Equation (8) is a fundamental model in efficiency and productivity analysis, since at least the work of Kumbhakar et al. (1991) and Battese and Coelli (1995), who consider the role of external determinants of inefficiency. From a theoretical viewpoint, Bloom et al. (2017) discuss the role of efficiency in the production function, noting the role of dynamics in this component. The dependency of the inefficiency component on management practices is intuitive from a theoretical viewpoint as management is considered to be part of the overall firm efficiency (e.g., Demerjian et al., 2012; 2013; Koester et al., 2016). The difference here is that management quality is a (latent) variable to be estimated and thus the relation between management and inefficiency is testable in our context (i.e., whether a_1 is significant). In the vector, $\mathbf{z}$, which denotes the variables affecting firm inefficiency, we include firm size and its square, a time trend and its square to capture trends in efficiency, as well as interactions of size with trend and $u_{i,t-1}$. Note that we also allow for dynamic inefficiency, which is important given the high persistence of inefficiency within firms for reasons similar to persistence in management practices and compensation (also see, Bloom et al., 2017).

In a nutshell, our complete model to be estimated includes equations (5) to (8). As in the inefficiency literature, we also provide definitions of managerial and cost-inefficiency elasticities (even though these are not strictly part of the model). We define managerial elasticity as:

$$\vartheta_{it} = \frac{\partial \log C\left(\mathbf{w}_{it}, w^*_{J,it}, y_{it}\right)}{\partial \log w^*_{J,it}}, \ \forall i = 1, ..., n, \ t = 1, ..., T, \tag{9}$$

which represents the responsiveness of total costs to a change in management price. We also define the elasticity of cost inefficiency with respect to management practices (i.e., the responsiveness of cost inefficiency to a change in management practices) as:

$$\eta_{it} = \frac{\partial \log E\left(u_{it} | \mathcal{D}_{it}\right)}{\partial \log x^*_{J,it}}, \ \forall i = 1, ..., n, \ t = 1, ..., T, \tag{10}$$

where $\mathcal{D}_{it}$ denotes all data and $E\left(u_{it} | \mathcal{D}_{it}\right)$ is the usual measure of technical inefficiency (Jondrow et al., 1982). This elasticity can be computed using numerical derivatives. The rest of the variables are as in the equations (5) to (8).

2.2 Estimation using Bayesian techniques

We use a Bayesian technique based on Sequential Monte Carlo/Particle-Filtering (SMC/PF), the theoretical details of which are described in the appendix.[7] The reason we use this approach is that we must include dynamic latent variables in our model. We introduce the dynamics because we believe that persistence is an important part of variables like management practices and their price. When

[7]Of course, all the modules are available for estimation and replication purposes.

dynamic latent variables are present, the likelihood is not available in closed form because of the presence of multivariate integrals with respect to the latent variables. There are no reliable procedures for approximating multivariate integrals and thus the likelihood cannot be accurately approximated. SMC/PF techniques precisely deal with this problem and they offer unbiased and consistent (in the number of simulations) estimates of the likelihood and posterior.

Our prior for the translog parameters and those in associated share equations is the "vague prior", $\boldsymbol{\beta} \sim N\left(\mathbf{0},\, 10^4\mathbf{I}\right)$. We adopt the same prior for $\boldsymbol{\alpha}_1$, $\boldsymbol{\alpha}_2$, a_0, a_1, and $\mathbf{a}$. For μ_1 and μ_{2i}, we assume $\mu_1 \sim \mathcal{N}\left(0,\, 1\right), \mu_{2i} \sim \mathcal{N}(\underline{\mu},\, \sigma_\mu^2)$, $\forall i = 1, ..., n$, where $\underline{\mu} \sim \mathcal{N}(0,\, 1)$. For ρ_1 and ρ_2, we assume a uniform prior $\mathcal{U}\left(-1, 1\right)$. For $\boldsymbol{\Sigma}$, we assume $p\left(\boldsymbol{\Sigma}\right) \propto |\boldsymbol{\Sigma}|^{-(\underline{m}+1)} \exp\left(-\frac{1}{2}\mathrm{tr}\underline{\mathbf{A}}\boldsymbol{\Sigma}^{-1}\right)$, with $\underline{m} = 1$ and $\underline{\mathbf{A}} = 10^{-4}\mathbf{I}$. All scale parameters $\sigma_{\varepsilon_1}^2$, $\sigma_{\varepsilon_2}^2$, σ_u^2, and ω^2 follow proper but vague priors of the form $p\left(\sigma\right) \propto \sigma^{-(\underline{n}+1)}\exp\left(-\frac{\underline{q}}{2\sigma^2}\right)$, and we set $\underline{n} = 1$, $\underline{q} = 10^{-4}$. For notational simplicity we let $\boldsymbol{\theta} = [\boldsymbol{\beta}', \boldsymbol{\alpha}_1', \boldsymbol{\alpha}_2', \mathbf{a}, \mu_1, \underline{\mu}]'$,

First, we write (5) as follows:

$$\mathcal{F}(\mathbf{w}_{it}, w^*_{J,it}; y_{it}, \boldsymbol{\beta}) = \mathbf{v}_{it} + u_{it}\boldsymbol{\iota}, \tag{11}$$

where $\boldsymbol{\iota} = [1, 0, ..., 0]'$, $\mathbf{v}_{it} \sim \mathcal{N}(0, \boldsymbol{\Sigma})$. The posterior distribution is given by:

$$\begin{aligned}
p(\boldsymbol{\beta}, \boldsymbol{\theta}, \underline{\mu}, \sigma_{\varepsilon 1}, \sigma_{\varepsilon 2}, \sigma_u, \sigma_\mu, \boldsymbol{\Sigma}, \{u_{it}\}, \{\log w^*_{J,t-1}\}, \{\log x^*_{J,i,t-1}\}|\mathcal{D}) \propto |\boldsymbol{\Sigma}|^{-(J+\underline{m}+1)} \exp\left\{-\tfrac{1}{2}\mathrm{tr}\left(\underline{\mathbf{A}} + \mathbf{S}\right)\boldsymbol{\Sigma}^{-1}\right\} \cdot \\
\sigma_{\varepsilon 1}^{-(nT+1)} \exp\left\{-\tfrac{1}{2\sigma_{\varepsilon_1}^2} \textstyle\sum_{i=1}\sum_{t=1}^T \left(\log w^*_{Jt} - \mu_1\left(1-\rho_1\right) - \rho_1 \log w^*_{J,t-1} + \overline{\mathbf{x}}_t'\boldsymbol{\alpha}_1\right)^2\right\} \cdot \\
\sigma_{\varepsilon 2}^{-(nT+1)} \exp\left\{-\tfrac{1}{2\sigma_{\varepsilon_1}^2} \textstyle\sum_{i=1}\sum_{t=1}^T \left(\log x^*_{J,it} - \mu_{2i}\left(1-\rho_2\right) - \rho_2 \log x^*_{J,i,t-1} - \mathbf{x}_{it}'\boldsymbol{\alpha}_2\right)^2\right\} \cdot \\
\sigma_u^{-(nT+1)} \exp\left\{-\tfrac{1}{2\sigma_u^2} \textstyle\sum_{i=1}\sum_{t=1}^T \left(u_{it} - a_0 - a_1 x^*_{Jt} - a_2 u_{i,t-1} - \mathbf{a}'\mathbf{z}_{it}\right)^2\right\} \cdot \\
\textstyle\prod_{i=1}^n \prod_{t=1}^T \Phi\left\{\dfrac{a_0 + a_1 x^*_{Jt} + a_2 u_{i,t-1} + \mathbf{a}'\mathbf{z}_{it}}{\sigma_u}\right\}^{-1} \cdot \\
\sigma_\mu^{-(n+1)} \exp\left\{-\tfrac{1}{2\sigma_\mu^2} \textstyle\sum_{i=1}^n \left(\mu_{2i} - \underline{\mu}\right)^2\right\} \cdot p\left(\boldsymbol{\beta}, \boldsymbol{\theta}, \underline{\mu}, \sigma_{\varepsilon 1}, \sigma_{\varepsilon 2}, \sigma_u, \boldsymbol{\Sigma}\right),
\end{aligned} \tag{12}$$

where $\mathbf{S} = \sum_{i=1}\sum_{t=1}^T V_{it}(\mathbf{w}_{it}, w_{J,it}; y_{it}, \boldsymbol{\beta})$,

$$\begin{aligned}
V_{it}(\mathbf{w}_{it}, w_{J,it}; y_{it}, \boldsymbol{\beta}) \equiv \mathcal{F}(\mathbf{w}_{it}, w^*_{J,it}; y_{it}, \boldsymbol{\beta}) = \\
\left[C_{it} - C\left(\mathbf{w}_{it}, w^*_{J,it}, y_{it}; \boldsymbol{\beta}\right) - u_{it}, \left\{\frac{w_{j,it}x_{j,it}}{TC^x_{it} + w^*_{J,it}x^*_{J,it}} - \frac{\partial \log C\left(\mathbf{w}_{it}, w^*_{J,it}, y_{it}; \boldsymbol{\beta}\right)}{\partial \log w_{j,it}}\right\}_{j=2}^J\right]',
\end{aligned} \tag{13}$$

and the prior appears in the last line of (12).

To implement Markov Chain Monte Carlo we draw from the following conditional distributions of scale parameters, which are in standard form:

$$\frac{\underline{q} + \sum_{i=1}\sum_{t=1}^T \left(\log w^*_{Jt} - \mu_1\left(1-\rho_1\right) - \rho_1 \log w^*_{J,t-1} + \overline{\mathbf{x}}_t'\boldsymbol{\alpha}_1\right)^2}{\sigma_{\varepsilon 1}^2} \sim \chi^2_{nT+\underline{n}}, \tag{14}$$

$$\frac{\underline{q}+\sum_{i=1}\sum_{t=1}^{T}\left(\log x_{J,it}^{*}-\mu_{2i}\left(1-\rho_2\right)-\rho_2\log x_{J,i,t-1}^{*}-\mathbf{x}_{it}'\boldsymbol{\alpha}_2\right)^2}{\sigma_{\varepsilon 2}^2}\sim\chi_{nT+\underline{n}}^2, \tag{15}$$

$$\frac{\underline{q}+\sum_{i=1}^{n}\left(\mu_{2i}-\underline{\mu}\right)^2}{\sigma_{\mu}^2}\sim\chi_{n+\underline{n}}^2. \tag{16}$$

For σ_u^2 we draw a candidate:

$$\frac{\underline{q}+\sum_{i=1}\sum_{t=1}^{T}\left(a_0+a_1x_{Jt}^{*}+a_2u_{i,t-1}+\mathbf{a}'\mathbf{z}_{it}\right)^2}{\sigma_u^2}\sim\chi_{nT+\underline{n}}^2, \tag{17}$$

and we accept the candidate with probability: $\prod_{i=1}^{n}\prod_{t=1}^{T}\Phi\left\{\frac{a_0+a_1x_{Jt}^{*}+a_2u_{i,t-1}+\mathbf{a}'\mathbf{z}_{it}}{\sigma_u}\right\}^{-1}$ as given in the fifth line of (12). Moreover, we draw $\underline{\mu}$ using:

$$\underline{\mu}\sim\mathcal{N}\left(n^{-1}\sum_{i=1}^{n}\mu_{2i},\ n^{-1}\sigma_{\mu}^2\right). \tag{18}$$

To facilitate SMC/PF, we integrate $\mathbf{\Sigma}$ out of the posterior *analytically* (see Zellner, 1971, p. 355).[8] The only difference is that the first line of the posterior in (12) now becomes: $\left\{\det\left(\underline{\mathbf{A}}+\mathbf{S}\right)\right\}^{-(nT+\underline{m}+1)/2}$. We use 120,000 iterations of the SMC/PF algorithm, discarding the first 20,000 to mitigate possible start up effects (starting values are generated randomly from the prior). We use 10^6 particles per iteration. To integrate out the latent variables $\{u_{it}\},\{\log w_{J,t-1}^{*}\},\{\log x_{J,i,t-1}^{*}\}$ and draw parameters we use the following procedure:

- Step 1: Integrate out the latent variables using Part A2 in Appendix A.
- Step 2: Draw parameters $\boldsymbol{\beta}$ using Part A1 in Appendix A.

The Appendix contains also introductory and supporting material for implementing these steps, in some detail.

3 Validation

3.1 Comparison with the scores from the World Management Survey

Our first and most important validation approach is to compare our management estimates with those of BVR, obtained from the WMS data. Here we refer mostly to BVR (2007), who use a sample covering 6,267 observations (panel data). In our estimations, we use 6,049 observations given data availability

[8] The result is as follows. If the posterior is $p\left(\boldsymbol{\beta},\mathbf{\Sigma}|\mathcal{D}\right)\propto|\mathbf{\Sigma}|^{-(N+1)/2}\exp\left\{-\frac{1}{2}\mathrm{tr}\mathbf{A}\left(\beta\right)\mathbf{\Sigma}^{-1}\right\}$, then $p\left(\boldsymbol{\beta}|\mathcal{D}\right)=\int p\left(\boldsymbol{\beta},\mathbf{\Sigma}|\mathcal{D}\right)d\Sigma=|\mathbf{A}\left(\beta\right)|^{-(N+1)/2}$, where $\boldsymbol{\beta}$ is the parameter vector, $\mathcal{D}$ denotes the data, integration is with respect to the different elements of $\mathbf{\Sigma}$, $N=nT+\underline{m}$, and $\mathbf{A}\left(\beta\right)=\underline{\mathbf{A}}+\sum_{i,t}\mathbf{v}_{it}\left(\beta\right)\mathbf{v}_{it}\left(\beta\right)'$, where $\mathbf{v}_{it}\left(\beta\right)$denotes residuals from (5).

on required variables.[9] Importantly, BVR provide information on accounting data that are employed as inputs and output in our model and for the variables included in the vectors $\overline{\mathbf{x}}$, $\mathbf{x}$, and $\mathbf{z}$. Thus, by using these variables, we can estimate the system of equations (5) to (8) and then compare our management practices estimates with the BVR scores.[10] This forms an ideal experiment to validate our results.

Table 1 reports summary statistics for the output/inputs. The log of sales (output) has a mean value equal to 11.83 and a standard deviation of 1.44. The log of capital (input 1) has a mean of 10.11 and a standard deviation of 1.68, while the respective values for the log of employees (input 2) are 6.73 and 1.33. All three variables are positively skewed and leptokurtic, reflecting a high clustering around the mean values (and hence a relatively low standard deviation).

Reporting results for the all-too-many parameters from the translog system of equations is impractical; we thus only report summary statistics for our management practices estimates in Table 1 (against those of BVR) and provide a graphical representation (Kernel density) of our results in Figure 1.

[Insert Table 1 here]

[Insert Figure 1 here]

Our first step toward validation is to regress our estimated scores against those of BVR. From doing this, we obtain the results in Table 2. We run regressions separately for firms in France, Germany, UK, and U.S., as well as for all countries jointly (full sample). We note that we estimate our model of equations (5) to (8) only once to take full account of information and underlying heterogeneity.

[Insert Table 2 here]

As shown in Table 2, the correlation of our estimates with the BVR scores is quite impressive despite the fact that we have used none of the extra information available in the BVR data set (like noise and general controls, college degree of manager, other attributes of the manager, etc.). The slope in all regressions is close to unity and equal to 0.98 in the regression on the full sample, indicating an almost one-to-one response of the BVR estimates to our estimates. Importantly, the R-squared of the regressions is also higher than 0.9 in all samples but the German one, reaching a value of 0.92 in the full sample. Further, in Figure 2, we provide a graphical comparison of our scores versus those of BVR. The fit is remarkably good with very few outliers. In a nutshell, our estimates of management practices almost perfectly predict those of BVR.

[9] This data set is freely available here: http://worldmanagementsurvey.org/survey-data/download-data/download-survey-data.

[10] It is important to note that BVR do not use inputs/outputs or econometric estimations to derive their scores.

[Insert Figure 2 here]

Even though our validation so far is made via one database, we cannot really attribute the fit to luck. Of course, our results are still an approximation to BVR (which are also subject to small error), but this approximation is surprisingly accurate and the BVR data are perhaps the best approximation of management practices in the literature. *Thus, we must conclude that our method produces very good estimates of management practices, while having the great advantage that can be applied to any data set with accounting information only on inputs/outputs and firm size.*

3.2 Monte Carlo simulation

In this section, we conduct further validation tests using repeated random sampling. The main reason we conduct this validation is to examine the fit of our results in samples outsides that of BVR. To make the environment relatively unfavorable to our model and more favorable to existing frontier-based methods for the measurement of management practices, we do not consider a cost function, but rather a production function of the form $Y = F(K, L, E) = K^{\alpha} L^{\beta} E^{\gamma} \exp(\nu - u)$, where K, L, and E stand for capital, labor, and intermediate inputs, whose relative prices are w_K, w_L, and w_E. We set $\alpha = 0.20$, $\beta = 0.60$, and $\gamma = 0.15$. Moreover, ν is the error term and u is technical inefficiency. We assume $u = 1 - M$, where M is management practices. The maximum value of M is 1, so that when $M = 0$ we have $u = 1$ and when $M = 1$ we have $u = 0$. The elasticity of inefficiency with respect to management is $-\frac{M}{u} = \frac{M}{M-1} \leq 0$.

We normalize the price of output to unity and we generate relative prices of capital, labor, and intermediate inputs as uniform numbers in the interval (1, 10), (0.1, 1), and (0.1, 5), respectively. We generate technical inefficiency as $u \sim N_{+}(0, \sigma_u^2)$, where $\sigma_u = 0.3$ and $v \sim \mathcal{N}_{+}(0, \sigma_v^2)$ where $\sigma_v = 0.3$, so that the signal-to-noise ratio $\lambda = \frac{\sigma_u}{\sigma_v} = 1$. Then, we generate values for M from $u = 1 - M$. The unobserved management price w_M^* is a positive function of management $w_M^* = 10M \exp(\varepsilon_M)$, where $\varepsilon_M \sim \mathcal{N}(0,\ 0.1^2)$.

Evidently, in our Monte Carlo setup, management is part of the inefficiency component and not directly an input of production as in our baseline model. The reason for this choice is to make the Monte Carlo environment less favorable to our model and more favorable to the literature that estimates management practices using standard frontier efficiency methods. In this way, we actually give an initial advantage to the frontier approaches. Please note, however, that our Monte Carlo setup is consistent with the modeling of management practices as an input. The reason is that M still enters the Monte Carlo production function as a multiple of the standard inputs via the inefficiency component u.

The first order conditions of profit maximization are as follows:

$$K = \frac{\alpha Y}{w_K},\ L = \frac{\beta Y}{w_L},\ E = \frac{\gamma Y}{w_E}. \tag{19}$$

For management practices the first order condition is:

$$K^{\alpha} L^{\beta} E^{\gamma} \exp(\nu - u) = w_M^*. \tag{20}$$

Substituting the first order conditions in the production function, we can generate output as:

$$Y = \left\{ \left(\frac{\alpha}{w_K}\right)^{\alpha} \left(\frac{\beta}{w_L}\right)^{\beta} \left(\frac{\gamma}{w_E}\right)^{\gamma} \exp\left(v - u\right) \right\}^{1-(\alpha+\beta+\gamma)}. \tag{21}$$

Then, we can generate input values from equation (12). For realism, we consider error terms so inputs are generated in stochastic form as follows:

$$K = \frac{\alpha Y}{w_K} \exp(\varepsilon_K),\ L = \frac{\beta Y}{w_L} \exp(\varepsilon_L),\ E = \frac{\gamma Y}{w_E} \exp(\varepsilon_E), \tag{22}$$

where $\varepsilon_K, \varepsilon_L, \varepsilon_E \sim \mathcal{N}\left(0, \sigma^2_{inp}\right)$, $\sigma^2_{inp} = 0.1$ The unobserved management price can be generated from equation (13) with the following minor modification:

$$K^{\alpha} L^{\beta} E^{\gamma} \exp(\nu - u) = w_M^* \exp\left(\varepsilon_{w_M^*}\right), \tag{23}$$

where $\varepsilon_{w_M^*} \sim \mathcal{N}\left(0, \sigma^2_{w_M^*}\right)$,$\sigma^2_{w_M^*} = 0.1$. We use 1,000 replications. In all cases the time periods are set to $T = 10$, but the number of firms n varies as shown in the results reported in Tables 3 and 4.

Subsequently, we re-estimate our model of equations (5) to (8) using the simulated data. We consider four different estimations (cases) based on whether input prices w are observed or not. In the first case, we assume that all input prices are observed, in the second that w_L is latent, in the third that w_L and w_K are latent, and in the fourth that all w_L, w_K, and w_E are latent. In Table 3, we report summary statistics for the simulated and estimated management scores and for the different sample sizes. Evidently, the values of means and standard deviations of the estimated management practices are very close to the simulated ones, especially as the sample size increases and some of the input prices are observed.

Importantly, in Table 4 we report rank correlations of simulated and estimated management practices (first row of each sample size n and in bold), rank correlations of simulated and estimated managerial elasticity (second row of each sample size) and rank correlations of simulated and estimated managerial price (third row of each sample size). We also report results from four different assumptions regarding the availability of input prices (all input prices are observed, missing w_L, missing w_L, and

w_K, and missing all three prices).

[Insert Tables 3&4 here]

The results show that as the number of firms increases, we obtain higher values for the rank correlations between the simulated and estimated management practices. Where all prices are observed and n = 2,500, the correlation reaches 0.91; where all prices are missing, the respective correlation is still as high as 0.83. These results hold despite the fact that our simulated samples are drawn from a production function (results would be even more favorable if we drew samples from a cost function). In a nutshell, and following validation via the sample of BVR, the Monte Carlo study also suggests a very good fit of our model's estimates to simulated management practices scores. This should hold in most real samples, given that most sample sizes from databases such as Orbis and Compustat will be higher than n = 2,500 x 10 years, especially with respect to the cross-sectional dimension.

3.3 DEA methods against robust existing measures

Most existing studies on the measurement of management practices use the implications of the large frontier efficiency literature to draw implications. The premise of this literature is that good management is part of technical efficiency of firms, at least as far as the reach of managers goes to affect managerial operations. Most of the management literature uses DEA techniques, a set of inputs and outputs, and some transformation of the end technical efficiency DEA scores to estimate management practices. Subsequently, these estimated management practices scores are used to examine relations between management practices and other variables (e.g., Demerjian et al., 2013). Unfortunately, these two-stage techniques are rarely validated using rigorous statistical methods and, as research has shown, are prone to significant error. Importantly, Simar and Wilson (2007; 2011) demonstrate that when DEA efficiency scores are simply regressed on covariates, inference is biased and inconsistent.[11]

Without aiming to condemn existing studies in their entirety, we carry out validation of a DEA-based approach against the sample of BVR. DEA efficiency is usually defined as the ratio of outputs over inputs. The particular DEA method we use is the same as in Demerjian et al. (2012). Specifically, we solve the following optimization problem:

$$max\theta = y * (\upsilon_{\kappa} x)^{-1}, \tag{24}$$

subject to $\theta \leq 1$,$\kappa = 2$ inputs, and $\upsilon > 0$ is a parameter denoting the relative weight of the inputs in

[11] Many studies discuss this problem and propose solutions. For reviews, see Bădin and Daraio (2011) and Olesen and Petersen (2016).

production. We use DEA on the same firms as in our previous exercise and the same output (sales) and inputs (capital and labor). Given that firms do not usually operate at optimal scale (because of regulations, imperfect competition, credit constraints, etc.), we resort to a variable-returns-to-scale model. This implies that we add a convexity constraint to the DEA model (see e.g., Coelli et al., 2005, pp. 172). Finally, to be consistent with our previous analysis in answering by how much can input quantities be proportionally reduced without changing the output quantity, we use an input-oriented DEA model. We run all DEA models using the standard software of Coelli (1996).

We first use three different DEA scores: (i) DEA applied once to the full sample, (ii) DEA applied four times by country, and (iii) DEA applied numerous times according to the 2-digit industry SIC code. In column (1) of Table 5 we use the first of these scores to predict the management practices scores of BVR. The slope is highly statistically significant, but the fit of the regression is less than 1%. In column (2) we use the country-specific DEA scores, which increase the R-squared to 2.5%. In column (3), we use the industry-specific DEA scores and this further improves the R-squared to 5.1%.

[Insert Table 5 here]

In column (4), we use a procedure similar to that of Demerjian et al. (2012). We first estimate DEA by industry and then regress DEA on firm size, firm age, a dummy reflecting whether the firm is public or not, and a dummy reflecting whether the CEO is the founder. These potential correlates of firm efficiency are variables beyond the control of managers and might need to be cleaned out to receive better estimates of management practices. In turn, we use the residuals as management practices. We find that the slope is still highly significant, but the R-squared is again as low as 4%. Also, the fit of this regression to the management practices estimates of BVR is relatively loose (Figure 3). Of course, the management practices estimates are correlated with firm performance measures like Tobin's q, etc., and in this respect the validation tests by Demerjian et al. (2012) are well done. What we suggest here is that DEA-based scores can at best be viewed as correlates of management practices and not as good estimates of management practices.

[Insert Figure 3 here]

Of course, there is a big list of DEA models that can be applied to measure management practices and, undoubtedly, some of them will provide a better fit to the BVR scores. We especially expect that stochastic DEA methods will provide better results, because these methods at least partially overcome the problem raised by Simar and Wilson (2007). Our objective in this paper, however, is to compare our method with existing methods. As our method yields good results, we leave the examination of additional DEA methods for future research.

4 Concluding remarks and directions for future research

Measuring management practices has been at the center of research in management and economics for many years. In our research, we estimate a simple model of the firm, that is completely aligned with microeconomic theory, where management practices is an unobserved (latent) variable (input of production). The use of latent variables requires estimation via an admittedly involved Bayesian method. The rents are, however, quite satisfactory: using data only on inputs (labor and capital), output (sales), and firm size, we are able to predict by approximately 92% the "actual" managerial quality scores of Bloom and Van Reenen (2007). The latter scores are a quite accurate reflection of management practices, as they have been drawn from a very careful analysis of survey data. We also validate our estimates using simulated data drawn from a production function and show that the estimates of management practices still closely predict the actual management practices scores, especially as the sample size increases. Finally, we show that DEA-based methods, currently the predominant way of estimating management practices, provide a much poorer fit.

We view our findings as particularly important in two dimensions. First, to the best of our knowledge, we have come the closest yet to the robust measurement of general management practices. By general here we mean the full spectrum of firm managerial processes that affect firm productivity, efficiency, and performance. Thus, we view our method as an advancement to the frontier-based methods that decompose the firm inefficiency component to a management component and a residual. Given that the fit of our method is better according to an extensive set of validation techniques, we suggest that our model allows better future research on multiple fields, especially in economics and management, but also in finance, accounting, even in sociology, psychology, and other social and applied sciences. Second, the model presented in this paper can be used for closely approximating management practices in panels or cross sections of firms without the need of detailed data: simple accounting ratios are sufficient. Thus, our method can be applied to all firms in the world, for which simple accounting data are available.

Our model can be extended to allow for testing several theories in the fields of management (e.g., management practices and innovation as in Custódio et al., 2017; or agency problems as in Mutlu et al., 2017), finance (e.g., management practices and risk as in Bonsall IV et al., 2016; value creation in M&As as in Delis et al., 2017), economics (e.g., along the lines of the work of Bloom and Van Reenen, as already discussed; the value of management in the short- and long-run processes of firms as in Sáenz-Royo and Salas-Fumás, 2014), and accounting (e.g., management practices and earnings quality as in Demerjian et al., 2013; tax avoidance as in Koester et al., 2016). Further, a similar model including latent variables can be applied to other difficult-to-measure notions, such as corporate social responsibility (Chen and Delmas, 2011) or risk (Giglio et al., 2016). As our study already covered considerable ground, we leave these for future research.

APPENDIX

In this appendix, we discuss the theoretical details of the Bayesian estimation methodology (particle filtering) used in Section 2.2 to obtain management practices estimates. Note that this discussion is intended to provide the econometric theory behind the precise particle filtering used and allow the reader to be located with respect to that theory. The discussion here appeared previously in an unpublished mimeo entitled "Estimating management and its applications" by Tsionas (2016), which we replicate as Tsionas (2016) is not available online.

Particle filtering

The particle filter methodology can be applied to state space models of the general form:

$$y_T \sim p(y_t|x_t), \; s_t \sim p(s_t|s_{t-1}), \tag{A.1}$$

where s_t is a state variable. For general introductions, see Gordon et al. (1993), Doucet et al. (2001), and Ristic et al. (2004).

Given the data Y_t, the posterior distribution $p(s_t|Y_t)$ can be approximated by a set of (auxiliary) particles $\left\{s_t^{(i)}, i = 1, ..., .N\right\}$ with probability weights $\left\{w_t^{(i)}, i = 1, ..., N\right\}$, where $\sum_{i=1}^{N} w_t^{(i)} = 1$. The predictive density can be approximated by:

$$p(s_{t+1}|Y_t) = \int p(s_{t+1}|s_t)p(s_t|Y_t)ds_t \simeq \sum_{i=1}^{N} p(s_{t+1}|s_t^{(i)})w_t^{(i)}, \tag{A.2}$$

and the final approximation for the filtering density is:

$$p(s_{t+1}|Y_t) \propto p(y_{t+1}|s_{t+1})p(s_{t+1}|Y_t) \simeq p(y_{t+1}|s_{t+1}) \sum_{i=1}^{N} p(s_{t+1}|s_t^{(i)})w_t^{(i)}. \tag{A.3}$$

The basic mechanism of particle filtering rests on propagating $\left\{s_t^{(i)}, w_t^{(i)}, i = 1, \ldots, N\right\}$ to the next step, viz. $\left\{s_{t+1}^{(i)}, w_{t+1}^{(i)}, i = 1, \ldots, N\right\}$, but this often suffers from the weight degeneracy problem.[12] As is often the case that parameters $\theta \in \Theta \in \Re^k$ are available, we follow Liu and West (2001), where

[12]This is a problem of the weights produced by older versions of SMC/PF. Specifically, a few weights were close to one and others were practically zero, so the likelihood/posterior would be estimated with two few weights. Of course, unbiasedness and consistency (of the likelihood/posterior estimates) are not affected but accuracy is affected. In the modern version we use here, this problem is avoided.

parameter learning takes place via a mixture of multivariate normals:

$$p(\theta|Y_t) \simeq \sum_{i=1}^{N} w_t^{(i)} N(\theta|a\theta_t^{(i)} + (1-a)\bar{\theta}_t, b^2 V_t). \tag{A.4}$$

In (A.4), $\bar{\theta}_t = \sum_{i=1}^N w_t^{(i)} \theta_t^{(i)}$, and $V_t = \sum_{i=1}^N w_t^{(i)} (\theta_t^{(i)} - \bar{\theta}_t)(\theta_t^{(i)} - \bar{\theta}_t)'$. The constants a and b are related to shrinkage and are determined via a discount factor $\delta \in (0,1)$ as $a = (1-b^2)^{1/2}$ and $b^2 = 1 - [(3\delta - 1)/2\delta]^2$. On this, see also Casarin and Marin (2007).

Andrieu and Roberts (2009), Flury and Shephard (2011), and Pitt et al. (2012) provide the Particle Metropolis-Hastings (PMCMC) technique. This technique uses an unbiased estimator of the likelihood function $\hat{p}_N(Y|\theta)$, as $p(Y|\theta)$ is often not available in closed form.

Part A1. Parameter propagation

Given the current state of the parameter $\theta^{(j)}$ and the current estimate of the likelihood, say $L^j = \hat{p}_N(Y|\theta^{(j)})$, a candidate θ^c is drawn from $q(\theta^c|\theta^{(j)})$, yielding $L^c = \hat{p}_N(Y|\theta^c)$. Then, we set $\theta^{(j+1)} = \theta^c$ with the Metropolis - Hastings probability

$$A = \min \left\{ 1, \ \frac{p(\theta^c) L^c}{p(\theta^{(j)}) L^j} \frac{q(\theta^{(j)}|\theta^c}{q(\theta^c|\theta^{(j)})} \right\}. \tag{A.5}$$

Otherwise, we repeat the current draws $\left\{\theta^{(j+1)}, L^{j+1}\right\} = \left\{\theta^{(j)}, L^j\right\}$.

Hall et al. (2014) propose an auxiliary particle filter, which rests upon the idea that adaptive particle filtering (Pitt et al., 2012) used within PMCMC requires far fewer particles to approximate $p(Y|\theta)$ compared to the standard particle filtering algorithm. From Flury and Shephard (2011) we know that auxiliary particle filtering can be implemented easily once we can evaluate the state transition density $p(s_t|s_{t-1})$. When this is not possible, Hall et al. (2014) present a new approach, where $s_t = g(s_{t-1}, u_t)$ for a certain disturbance. In this case, we have:

$$p(y_t|s_{t-1}) = \int p(y_t|s_t) p(s_t|s_{t-1}) ds_t, \tag{A.6}$$

$$p(u_t|s_{t-1}; y_t) = p(y_t|s_{t-1}, u_t) p(u_t|s_{t-1}) / p(y_t|s_{t-1}). \tag{A.7}$$

If one can evaluate $p(y_t|s_{t-1})$ and simulate from $p(u_t|s_{t-1}; y_t)$, the filter would be fully adaptable (Flury and Shephard, 2011).

We can use a Gaussian approximation for the first-stage proposal $g(y_t|s_{t-1})$ by matching the first two moments of $p(y_t|s_{t-1})$. So the approximating density $p(y_t|s_{t-1}) = N\left(\mathbb{E}(y_t|s_{t-1}), \mathbb{V}(y_t|s_{t-1})\right)$. In the second stage, we know that $p(u_t|y_t, s_{t-1}) \propto p(y_t|s_{t-1}, u_t) p(u_t)$. For $p(u_t|y_t, s_{t-1})$ we guard for the possibility that it is multimodal (as it turned out so in the course of using SMS/PF) and thus we assume it has M modes with $\hat{u}_t^m$, for $m = 1, \ldots, M$. For each mode, we can use a Laplace approximation. If we let $l(u_t) = log\,[p(y_t|s_{t-1}, u_t)p(u_t)]$, from the Laplace approximation we obtain:

$$l(u_t) \simeq l(\hat{u}_t^m) + \tfrac{1}{2}(u_t - \hat{u}_t^m)'\nabla^2 l(\hat{u}_t^m)(u_t - \hat{u}_t^m). \tag{A.8}$$

Then, we can construct a mixture approximation:

$$g(u_t|x_t, s_{t-1}) = \sum_{m=1}^{M} \lambda_m (2\pi)^{-d/2}|\Sigma_m|^{-1/2} \exp\left\{\tfrac{1}{2}(u_t - \hat{u}_t^m)'\Sigma_m^{-1}(u_t - \hat{u}_t^m\right\}, \tag{A.9}$$

where $\Sigma_m = -\left[\nabla^2 l(\hat{u}_t^m)\right]^{-1}$ and $\lambda_m \propto \exp\{l(u_t^m)\}$, with $\sum_{m=1}^{M} = 1$. This is done for each particle s_t^i and is known as the Auxiliary Disturbance Particle Filter (ADPF). An alternative is the independent particle filter (IPF) of Lin et al. (2005). The IPF forms a proposal for s_t directly from the measurement density $p(y_t|s_t)$. An alternative, proposed by Hall et al. (2014) is to draw from the state equation instead. This is a valid option but, in our application, the former approach worked much better in the SMC/PF procedure.

In the standard particle filter of Gordon et al. (1993), particles are simulated through the state density $p(s_t^i|s_{t-1}^i)$ and they are re-sampled with weights determined by the measurement density, which is evaluated at the resulting particle, viz. $p(y_t|s_t^i)$.

The ADPF is simple to construct and rests upon the following steps:

For $t = 0, \ldots, T-1$ given samples $s_t^k \sim p(s_t|Y_{1:t})$ with mass π_t^k for $k = 1, ..., N$.

1) For $k = 1, \ldots, N$ compute $\omega_{t|t+1}^k = g(y_{t+1}|s_t^k)\pi_t^k$, $\pi_{t|t+1}^k = \omega_{t|t+1}^k / \sum_{i=1}^N \omega_{t|t+1}^i$.

2) For $k = 1, \ldots, N$ draw $\tilde{s}_t^k \sim \sum_{i=1}^N \pi_{t|t+1}^i \delta_{s_t}^i(ds_t)$.

3) For $k = 1, \ldots, N$ draw $u_{t+1}^k \sim g(u_{t+1}|\tilde{s}_t^k, y_{t+1})$ and set $s_{t+1}^k = h(s_t^k; u_{t+1}^k)$.

4) For $k = 1, \ldots, N$ compute

$$\omega_{t+1}^k = \frac{p(y_{t+1}|s_{t+1}^k)p(u_{t+1}^k)}{g(y_{t+1}|s_t^k)g(u_{t+1}^k|\tilde{s}_t^k, y_{t+1})}, \pi_{t+1}^k = \frac{\omega_{t+1}^k}{\sum_{i=1}^N \omega_{t+1}^i}. \tag{A.10}$$

It should be mentioned that the estimate of likelihood from ADPF is:

$$p(Y_{1:T}) = \prod_{t=1}^{T} \left(\sum_{i=1}^{N} \omega_{t-1|t}^i\right)\left(N^{-1}\sum_{i=1}^{N}\omega_t^i\right). \tag{A.11}$$

Part A2. Particle Metropolis adjusted Langevin filters

Nemeth and Fearnhead (2014) provide a particle version of a Metropolis-adjusted Langevin algorithm (MALA). In sequential Monte Carlo we are interested in approximating $p(s_t|Y_{1:t},\theta)$, given that

$$p(s_t|Y_{1:t},\theta) \propto g(y_t|x_t,\theta)\int f(s_t|s_{t-1},\theta)p(s_{t-1}|y_{1:t-1},\theta)ds_{t-1}, \tag{A.12}$$

where $p(s_{t-1}|y_{1:t-1},\theta)$ is the posterior as of time $t-1$. If at time $t-1$ we have a set set of particles $\left\{s^i_{t-1}, i=1,\ldots,N\right\}$ and weights $\left\{w^i_{t-1}, i=1,\ldots N\right\}$, which form a discrete approximation for $p(s_{t-1}|y_{1:t-1},\theta)$, then we have the approximation:[13]

$$\hat{p}(s_{t-1}|y_{1:t-1},\theta) \propto \sum_{i=1}^{N} w^i_{t-1} f(s_t|s^i_{t-1},\theta). \tag{A.13}$$

From (A.13) Fearnhead (2008) makes the important observation that the joint probability of sampling particle s^i_{t-1} and state s_t is:

$$\omega_t = \frac{w^i_{t-1} g(y_t|s_t,\theta) f(s|s^i_{t-1},\theta)}{\xi^i_t q(s_t|s^i_{t-1},y_t,\theta)}, \tag{A.14}$$

where $q(s_t|s^i_{t-1},y_t,\theta)$ is a density function amenable to simulation and

$$\xi^i_t q(s_t|s^i_{t-1},y_t,\theta) \simeq c g(y_t|s_t,\theta) f(s_t|s^i_{t-1},\theta), \tag{A.15}$$

where c is the normalizing constant in (A.12).

In the MALA algorithm of Roberts and Rosenthal (1998)[14] we form a proposal:

$$\theta^c = \theta^{(s)} + \lambda z + \tfrac{\lambda^2}{2}\nabla \log p(\theta^{(s)}|Y_{1:T}), \tag{A.16}$$

where $z \sim \mathcal{N}(0,\mathbf{I})$, which should result in larger jumps and better mixing properties, plus lower autocorrelations for a certain scale parameter λ. Acceptance probabilities are:

$$a(\theta^c|\theta^{(s)}) = \min\left\{1, \frac{p(Y_{1:T}|\theta^c)q(\theta^{(s)}|\theta^c)}{p(Y_{1:T}|\theta^{(s)})q(\theta^c|\theta^{(s)})}\right\}. \tag{A.17}$$

Using particle filtering it is possible to create an approximation of the score vector using Fisher's

[13]For a review, see Andrieu et al. (2010).

[14]The benefit of MALA over Random-Walk-Metropolis arises when the number of parameters n is large. This happens because the scaling parameter λ is $O(n^{-1/2})$for Random-Walk-Metropolis but it is $O(n^{-1/6})$ for MALA, see Roberts and Rosenthal (1998)

identity:

$$\nabla \log p(Y_{1:T}|\theta) = E\left[\nabla \log p(s_{1:T}, Y_{1:T}|\theta)|Y_{1:T}, \theta\right], \tag{A.18}$$

which corresponds to the expectation of:

$$\nabla \log p(s_{1:T}, Y_{1:T}|\theta) = \nabla \log p(|s_{1:T-1}, Y_{1:T-1}|\theta) + \nabla \log g(y_T|s_T, \theta) + \nabla \log f(s_T|s|_{T-1}, \theta),$$

over the path $s_{1:T}$. The particle approximation to the score vector results from replacing $p(s_{1:T}|Y_{1:T}, \theta)$ with a particle approximation $\hat{p}(s_{1:T}|Y_{1:T}, \theta)$. With particle i at time $t-1$ we can associate a value $\alpha_{t-1}^i = \nabla \log p(s_{1:t-1}^i, Y_{1:t-1}|\theta)$, which can be updated recursively. As we sample κ_i in the APF (the index of particle at time $t-1$ that is propagated to produce the ith particle at time t) we have the update:

$$\alpha_t^i = a_{t-1}^{\kappa_i} + \nabla \log g(y_t|s_t^i, \theta) + \nabla \log f(s_t^i|s_{t-1}^i, \theta). \tag{A.19}$$

To avoid problems with increasing variance of the score estimate $\nabla \log p(Y_{1:t}|\theta)$, we can use the approximation:

$$\alpha_{t-1}^i \sim \mathcal{N}(m_{t-1}^i, V_{t-1}). \tag{A.20}$$

The mean is obtained by shrinking α_{t-1}^i towards the mean of α_{t-1} as follows:

$$m_{t-1}^i = \delta \alpha_{t-1}^i + (1-\delta) \sum_{i=1}^{N} w_{t-1}^i \alpha_{t-1}^i, \tag{A.21}$$

where $\delta \in (0,1)$ is a shrinkage parameter. Using Rao-Blackwellization one can avoid sampling α_t^i and instead use the following recursion for the means:

$$m_t^i = \delta m_{t-1}^{\kappa_i} + (1-\delta) \sum_{i=1}^{N} w_{t-1}^i m_{t-1}^i + \nabla \log g(y_t|s_t^i, \theta) + \nabla \log f(s_t^i|s_{t-1}^{\kappa_i}, \theta), \tag{A.22}$$

which yields the final score estimate:

$$\nabla \log \hat{p}(Y_{1:t}|\theta) = \sum_{i=1}^{N} w_t^i m_t^i. \tag{A.23}$$

As a rule of thumb, Nemeth and Fearnhead (2014) suggest taking $\delta = 0.95$. Furthermore, they show the important result that the algorithm should be tuned to the asymptotically optimal acceptance rate of 15.47% and the number of particles must be selected so that the variance of the estimated log-posterior is about 3. Additionally, if measures are not taken to control the error in the variance of the score vector, there is no gain over a simple random walk proposal.

Of course, the marginal likelihood is:

$$p(Y_{1:T}|\theta) = p(y_1|\theta)\prod_{t=2}^{T} p(y_t|Y_{1:t-1},\theta), \tag{A.24}$$

where

$$p(y_t|Y_{1:t-1},\theta) = \int g(y_t|s_t)\int f(s_t|s_{t-1},\theta)p(s_{t-1}|Y_{1:T-1},\theta)ds_{t-1}ds_t \tag{A.25}$$

provides, in explicit form, the predictive likelihood.

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Table 1: Summary statistics

	Obs.	Mean	Median	St.dev.	Min.	Max.	Skewness	Kurtosis
Log of sales	6,049	11.83	11.76	1.44	6.71	16.36	0.19	2.39
Log of capital	6,049	10.11	10.07	1.68	3.26	14.68	0.06	2.50
Log of employees	6,049	6.73	6.64	1.33	1.39	11.03	0.28	2.37
Management practices from BVR	6,049	3.22	3.28	0.75	1.06	4.86	-0.20	2.59
Estimated management practices	6,049	3.08	3.09	0.74	0.54	5.25	-0.16	2.66

Table 2: Comparison of estimated and BVR management practices scores

	France	Germany	UK	U.S.	Full sample
Constant	0.17	0.38	0.16	0.25	0.21
	(0.026)	(0.034)	(0.023)	(0.016)	(0.011)
Slope	0.99	0.94	0.98	0.97	0.98
	(0.008)	(0.011)	(0.008)	(0.005)	(0.004)
$\overline{R}^2$	0.93	0.88	0.94	0.92	0.92
Obs.	937	1,048	1,230	2,834	6,049

Notes: The table reports coefficient estimates and standard errors (in parentheses) from an OLS regression of our estimated management practices scores against the BVR scores. The results are provided separately for France, Germany, UK, and U.S., and for all countries jointly. We note that we get our results for management practices from the estimation of our model only once for the full sample.

Table 3: Summary statistics of simulated and estimated management scores

	Simulated	All w observed	Missing w_L	Missing $w_L$and w_K	All w missing
			n=100		
Mean	0.72	0.72	0.72	0.73	0.69
St.dev.	0.12	0.12	0.16	0.16	0.22
Min.	0.37	0.34	0.34	0.34	0.09
Max.	1.15	0.94	1.24	1.17	1.28
			n=200		
Mean	0.71	0.71	0.70	0.72	0.71
St.dev.	0.12	0.11	0.16	0.16	0.23
Min.	0.39	0.41	0.30	0.23	0.23
Max.	0.99	0.93	1.24	1.15	1.32
			n=500		
Mean	0.72	0.72	0.70	0.71	0.71
St.dev.	0.12	0.11	0.16	0.17	0.21
Min.	0.41	0.41	0.26	0.13	0.05
Max.	1.04	1.08	1.13	1.27	1.29
			n=1,000		
Mean	0.73	0.72	0.70	0.72	0.72
St.dev.	0.12	0.11	0.15	0.17	0.22
Min.	0.37	0.39	0.22	0.20	-0.01
Max.	1.09	1.05	1.18	1.38	1.56
			n=2,500		
Mean	0.73	0.71	0.70	0.71	0.72
St.dev.	0.12	0.11	0.15	0.17	0.21
Min.	0.32	0.37	0.20	0.08	-0.04
Max.	1.12	1.07	1.22	1.34	1.50

Notes: The table reports rank correlations from Monte Carlo simulations using different sample sizes and assumptions regarding the availability of input prices and the methodology describe in the text. The first row of each sample size reports the rank correlations of simulated and estimated management practices. The second row reports the rank correlations of simulated and estimated managerial elasticity. The third row reports the rank correlations of simulated and estimated managerial price.

Table 4: Monte Carlo results: Rank correlations between simulated and estimated management practices

	All w observed	Missing w_L	Missing $w_L$and w_K	All w missing
n=100	**0.52**	**0.50**	**0.47**	**0.44**
	0.55	0.53	0.50	0.48
	0.71	0.70	0.70	0.69
n=200	**0.66**	**0.62**	**0.59**	**0.55**
	0.71	0.68	0.65	0.62
	0.82	0.80	0.78	0.76
n=500	**0.78**	**0.75**	**0.73**	**0.71**
	0.77	0.74	0.71	0.68
	0.85	0.83	0.82	0.80
n=1,000	**0.86**	**0.82**	**0.80**	**0.68**
	0.85	0.84	0.82	0.80
	0.87	0.87	0.84	0.82
n=2,500	**0.91**	**0.89**	**0.85**	**0.83**
	0.94	0.92	0.90	0.87
	0.90	0.88	0.88	0.85

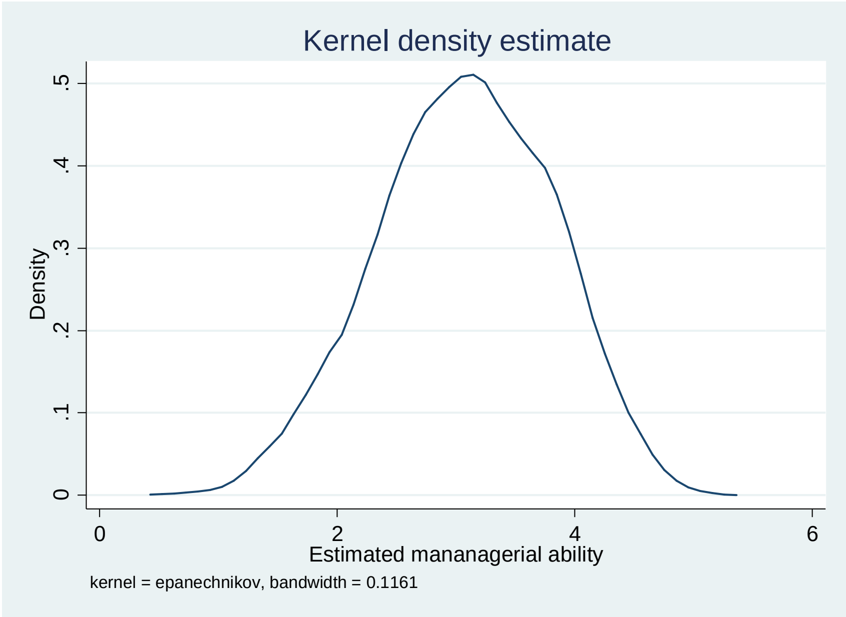
Notes: The table reports rank correlations from Monte Carlo simulations using different sample sizes and assumptions regarding the availability of input prices and the methodology describe in the text. The first row of each sample size reports the rank correlations of simulated and estimated management practices. The second row reports the rank correlations of simulated and estimated managerial elasticity. The third row reports the rank correlations of simulated and estimated managerial price.

Table 5: Comparison of DEA-based scores with BVR scores

	(1)	(2)	(3)	(4)
Constant	1.90	1.58	1.42	1.48
	(0.214)	(0.196)	(0.124)	(0.182)
Slope	1.51	1.62	1.24	1.20
	(0.245)	(0.230)	(0.122)	(0.155)
$\overline{R}^2$	0.007	0.025	0.051	0.040
Obs.	6,049	6,049	6,049	6,049

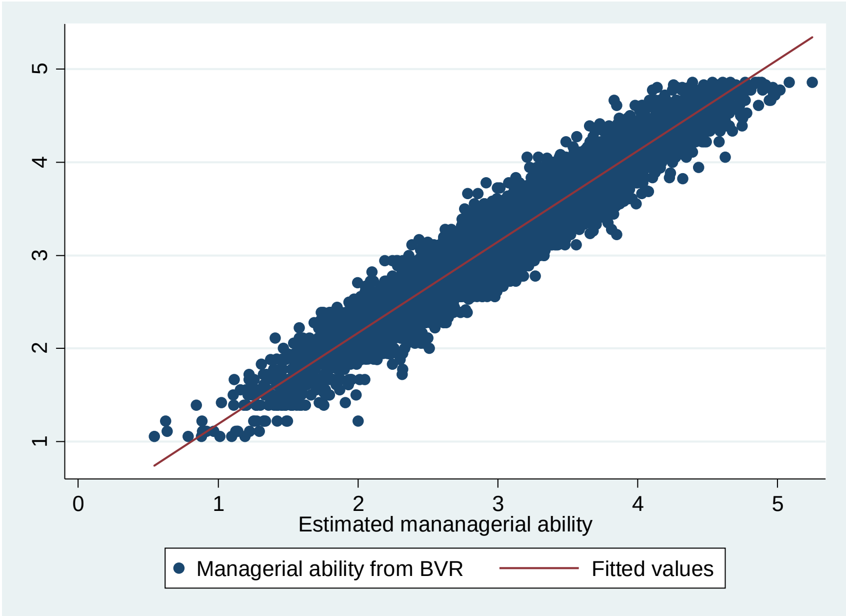
Notes: The table reports coefficient estimates and standard errors (in parentheses) from an OLS regression of estimated management practices scores using variable-returns-to-scale DEA against the BVR management practices scores. In (1) DEA is estimated once for all firms, in (2) by country, and in (3) and (4) by the 2-digit SIC code. In (4) the DEA results are first regressed on log of firm age, a dummy denoting whether the CEO is the founder, and a dummy reflecting whether the firm is public or not.

Figure A.1: Kernel density of estimated management practices



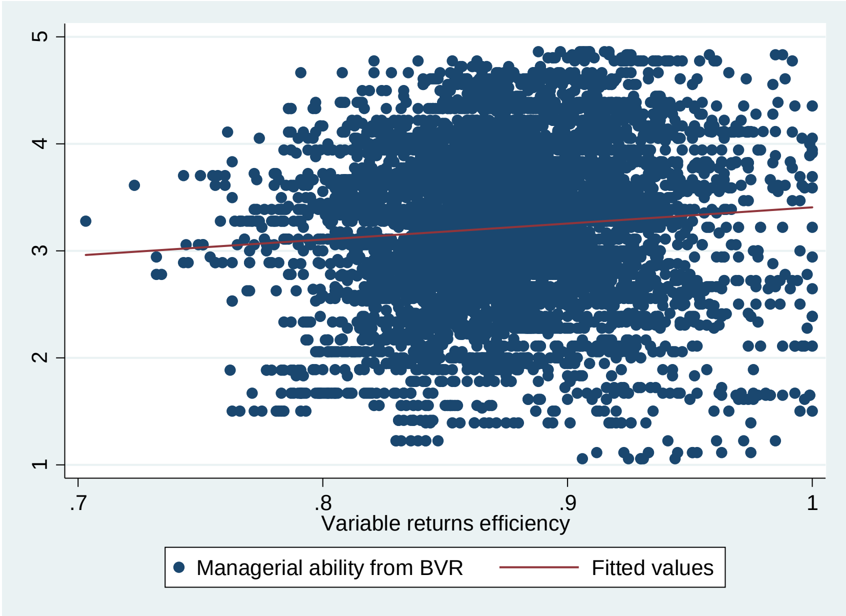
Notes: The figure presents the Kernel density of our estimated management practices scores.

Figure A.2: Comparison of our estimates with the Bloom and Van Reenen (2007) scores



Notes: The figure graphs our estimated management practices scores against those from BVR, adding a linear regression line.

Figure A.3: Comparison of DEA scores with the Bloom and Van Reenen (2007) scores



Notes: The figure graphs the DEA management practices scores (obtained from specification 4 of Table 4) against those from BVR, adding a linear regression line.