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Abstract

We revisit the production frontier of a firm, and we examine the effects that the firm's management has on output. In order to estimate these effects using a cross-sectional sample while avoiding the costly requirement of obtaining data on management as a production factor, we develop a two-tier stochastic frontier model where management is treated as a latent variable. The model is consistent with the microeconomic theory of the firm, and it can estimate the effect of management on the output of a firm in monetary terms from different angles, separately from inefficiency. The approach can thus contribute to the cost–benefit analysis related to the management system of a company, and it can facilitate research related to management pay and be used in studies of the determinants of management performance. We also present an empirical application, where we find that the estimates from our latent-variable model align with the results obtained when we use the World Management Survey scores that provide a measure of management.

Keywords Management · Two-tier stochastic frontier · Efficiency · Endogeneity · Copula

JEL Classification: D24 · C21

1 Introduction

It is a widely circulated maxim in the business world that, in order to manage something, you must be able to measure it. It is therefore a bit ironic that management itself has for a long period of time resisted quantification, a situation helped by the fact that

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the very definition of management appears to remain unsettled, since it is a multi-dimensional ensemble of planning designs, processes, monitoring, decision making, hardware, software, and people.

In economics, we know how to measure such complex entities—we do it by using their monetary value, with the most prominent example being the capital production factor. So, in principle, we could collect all the costs related to management in a company (like salaries of positions with supervising duties, monitoring software costs, etc.) and use it as a quantitative measure of the management factor. The problem is that such a decomposition of costs is not usually done by many companies, and in any case it is not available to outside researchers. Faced with such hurdles, scholars that were determined to do quantitative research on management have experimented with many different methods, which we can group into three main approaches: one that uses other variables as proxies for management, another that attempts to obtain a measure of management through the quantification of survey responses, and a third that treats management as a latent variable and focuses mainly on measuring its effects.[1]

Many different variables have been used over the years to proxy the management factor: some scholars used financial performance variables like unit costs or profit margins (see, e.g., Dawson and Hubbard 1987), others a quantitative measure of productivity like crop yield (e.g., Patrick and Eisgruber 1968). But the validity of such proxies is compromised by the reverse causality that arises when the dependent variable in a regression setting is a measure of output or a financial variable, and it usually belongs in these categories. Other studies have used "informational" or "knowledge" variables to proxy management. For example, Müller (1974) used fees paid for services obtained from professional organizations, while Massell (1967b) included in his agricultural regression a variable indicating whether the farmer had undergone a training program offered by the government. A related and frequent occurrence is the use of "human capital" variables, usually education, experience, and industry and/or firm tenure (e.g., Page 1980; Sumner and Leiby 1987; Dawson and Dobson 2002; Rahman et al. 2020). But the empirical studies of many different industries and from different countries mostly show that such proxy variables are rather weakly linked to the effects that management has on a firm. Nevertheless, human capital variables may play a complementary role to a quantitative measure of management, representing the "quality" (namely the diligence) with which the designed management system and practices are actually implemented.[2]

Measuring management directly has always been based on responses to survey questionnaires. Starting early in the twentieth century, the content of these surveys has evolved from being strongly focused on behavioral traits of the "head of operations" (targeting mainly small enterprises in the agricultural sector), to the current wave of national/international surveys of management practices, to which we now turn.

The World Management Survey project (WMS) started in 2002. As stated in the project's website, the goal was to "see if one could 'measure one of the unmeasurable' parts of the production function residual." Led by Nicholas Bloom, John Van

[1] We draw here also from Papadopoulos (2020b) that surveys 70 years of related empirical research.

[2] Such a link between human capital and management quality has been found in Bender et al. (2018). Brea-Solís et al. (2015) stress the distinction between the designed management system and its implementation, or "how the levers are pulled" in their words.

Reenen and associates (who introduced the project and its first results to the world in Bloom and Van Reenen 2007), the core task of the project is to collect survey data on "management practices" across countries and industries, and construct a "management score" for each firm (or plant), which we will call the WMS score. The methodology was originally based on telephone interviews to obtain answers from middle managers (plant/shop-floor) to 18 open-ended questions that were subsequently graded by the interviewer on a Likert scale. These questions concerned management practices in four main areas (operations, monitoring, targets, incentives, with "operations" being subsumed in later incarnations to "monitoring"). This initial WMS score was an attempt to measure a quality management index, and it was validated through its correlation with the financial performance of the firms involved.

The method has since been implemented by its creators using various other data sets, mainly focused on the manufacturing sector and on large firms. Indicatively, Bloom et al. (2012a) used it on nearly 10,000 observations from 20 countries. Bloom et al. (2012b) adapted the questionnaire and examined management practices in transition economies from Eastern Europe and also countries in Asia that used to be part of the USSR. Bloom et al. (2013b) investigated management practices in the Indian textile industry. Bloom et al. (2016) used it with a data sample from 34 countries and more than 10,000 observations, while Bloom et al. (2017) applied it on US data to investigate differences at the plant level. This last paper contained a change in the methodology: here the goal was to obtain a measure of how "structured" is the management system of the firm.[3] The responses to the survey's questionnaire were graded according to this criterion in the [0,1] interval, with "1" corresponding to the "most structured" and "0" to the "least structured." This change can be seen as a movement towards a more quantitative measurement, which is certainly a methodological improvement.

The WMS project has become the base for mail-in national surveys on management practices in USA (see Buffington et al. 2017) but also in other countries (see Brouillette and Ershov 2014 for Canada and Broszeit et al. 2019 for Germany). Moreover, the availability of the WMS scores has started to be exploited in studies not directly associated with the WMS project, like Tsionas (2015), Sickles et al. (2020) and Triebs and Kumbhakar (2018), the last one offering a particularly important finding. The authors set out to test whether productivity estimates are good proxies for the unobserved management, and whether management does indeed operate as a technology, i.e., a production multiplier, in a neutral and monotonic way. They used data from the original Bloom and Van Reenen (2007) study. The results are somehow mixed: productivity estimates correlate positively with the management score, but weakly. So it may be valid to use them in order to rank firms in terms of their management, but not for quantifying the latter. Moreover, using semi-parametric techniques, they find that management is not just a neutral shifter of the production function: the coefficients characterizing the production function changed at different levels of management.

It certainly appears that the WMS approach is becoming a new scientific paradigm to measure management across industries and countries. In light of this, we must note that the basic WMS questionnaire is not a universal tool for all firms and all aspects of management. First, it mainly targets manufacturing firms and it must be adapted when

[3] Bloom et al. (2013a, p.21) define "more structured" as "more specific, formal, frequent or explicit."

one wants to examine commercial enterprises or the Services sector (as its creators did when they applied it to Healthcare, see Bloom et al. 2014b). Second, it has in mind mainly large firms and not small-and-medium enterprises. But SMEs are a large part of an economy. Indicatively, for 2016 in the European Union, SMEs accounted for 2/3 of employment and 56% of total valued added.[4] Third, the WMS approach is mainly concerned with the "human resources" aspects of management. While supervising and coordinating personnel is certainly a crucial function of management, it is not the only important one. Assets management (procurement, maintenance, security, replacement) is a big part of management practices, especially after we remember that "assets" do not include only fixed tangible assets, but also inventory and customer receivables (and firms know painfully well how mismanagement of commercial credit may decimate a business). Dealing with the outside world (contractors, vendors, customers, regulatory authorities, public agencies, competitors) is also a heavy part of management, more so because here management cannot exert the degree of control that it can when operating inside the boundaries of the firm. And for both of these areas of management activity, the business world has developed many guidelines and structured management practices.

Apart from these issues, measuring anything through surveys incurs considerable costs. In Bloom et al. (2014a), the average cost per interview (i.e., per observation) is estimated at 400 USD (including fixed costs). In a personal communication with the author in December 2017, professor Bloom increased the estimate to USD 500. In other words, a data set of 2500 observations costs anywhere between 1 to 1.25 million USD. While transforming the WMS approach into a mail-in national survey conducted by a public agency certainly reduces costs, it also makes the obtained data not so easily available (since many such data sets are not accessible to researchers in other countries). And in any case, not all, not even many countries will instigate such surveys. Finally, research will be tied to the specific data sets created.

These very practical issues make worthwhile those research approaches that attempt to estimate the effects of management without having available a measure of it, and it is in this category that our research belongs. We present the latent-variable modeling approach in Sect. 2. In Sect. 3, we discuss the various methodological issues that must be decided upon as one undertakes the task of modeling management. In Sect. 4, we develop our model first as a deterministic production function that includes management, and then as a two-tier stochastic frontier. Section 5 contains an empirical study where we implement the model on a sample for which WMS scores are available, and we examine also whether the obtained results align with them. Section 6 discusses extensions of the basic model as topics of future research. "Appendix" includes mathematical derivations.

[4] See EU's "Annual report on European SMEs 2016/2017" https://doi.org/10.2873/742338. For a UK survey that targets management practices in SMEs, see Forth and Bryson (2019).

2 Modeling management as a latent variable

Early on scholars were aware that management affects output and were thinking about it as an omitted variable in output regressions. For example, in Yaron (1960) we find the following remark (p. 66): "Hardcopf has suggested that the residuals from an empirically estimated production function may be considered as representing the share of the management factor in output and an error term."[5] In fact Hoch (1955) had implemented an approach to extract the management factor from the Ordinary Least Squares (OLS) residuals, that later fueled the seminal Mundlak (1961) paper that pioneered the panel data "individual effects" model. Mundlak showed how, if a $T = 2$ panel data set was available, one could obtain an estimated series for the management variable (in mean deviation form), and separately its output elasticity, using the Least-Square Dummy Variables estimator and the assumption of constant returns to scale over production factors including management.

Hoch (1962) presented more fully the panel data model with both "firm-specific" and "time" effects, and he also allowed for the possibility that the firm may not be strictly profit-maximizing. In this paper, the author called the "firm-specific" effect an indicator of "technical efficiency," in line with the terminology adopted in efficiency analysis. Massell (1967a) applied the same econometric technique, but with a cross-sectional sample of multi-product firms (thus having again a two-dimensional sample). Alvarez and Arias (2003) combine approaches. Using panel data, they modeled management as a fixed individual effect for each firm, but estimated it as a handicap from the most efficient firm in the data, essentially creating a proxy for management that was then used as a regressor in a cost-function estimation. Siebert and Zubanov (2010) did not equate the individual effect with management, but they treated it as function of the latter, examining a single large UK-based clothing retailer with the intent to estimate the store-manager effects on store sales.[6] Wolff et al. (2013) examined the "skipper effect" on the French purse-seine fleet harvesting tuna in the Indian Ocean, using a three-dimensional panel data set that identified vessel and vessel captain per observation.

A second approach to estimate the effects of management on output while having no measure of it is by a structural latent-variables model. Here management is treated as the causal force behind the observable variables (the "reflective" variant of this methodology). The observables now are not used as proxies for management but as "intermediaries" to eventually estimate the effects of management through a structural model and maximum likelihood. This approach has been used by Ford and Shonkwiler (1994), Kalaitzandonakes and Dunn (1995), Mäkinen (2013). It appears to be a more promising way to use any available management-related information, than treat such covariates as regressors and direct proxies for management.

Although ostensibly a stochastic frontier model, in reality Delis and Tsionas (2018) develop a structural latent-variable model to indirectly estimate management using standard cost and production data on firms, and robustly show in different ways that

[5] The author was referring to an unpublished MS thesis by R.W. Hardcopf in 1956 at Iowa State University. I take here the opportunity to thank Jeffrey Kushkowski, Business and Economics Librarian at the Iowa State University, for his assistance regarding obscure documents in his library.

[6] The single-firm focus has the flavor of Insider econometrics.

their estimated management scores explain 90% of the WMS scores, that are available for the sample they use. The authors essentially trade-off the cost of creating data sets containing management scores with estimation complexity, since their Bayesian econometric methods are rather involved.

Turning to studies from the efficiency and productivity analysis field, which is served predominantly by two methodological approaches, data envelopment analysis (DEA) and stochastic frontier analysis (SFA), Gathon and Pestieau (1995) stressed the importance of the regulatory environment on the achieved efficiency, especially for public enterprises. They framed this effect as constraints on managerial autonomy. Examining 19 European railways, they used first a stochastic frontier model to obtain the "gross" efficiency score (relative to the best score in the sample). Subsequently, through a detailed questionnaire answered by the management of each company, they obtained three "autonomy indices" (for hiring, pricing and commercial autonomy), as well as an aggregate autonomy index. Using the latter, they then decomposed the relative gross efficiency scores into a management and a regulatory efficiency score. In another decomposition exercise, Fried et al. (2002), combined DEA and SFA methods and separated the inefficiency coming from external factors. What was left was named by the authors "management inefficiency." Alvarez et al. (2005), in the context of a single-tier SF production model, treat also management as a latent input in production. The authors specify a technically optimal value for management, defined as the value of management that leads to maximum output given the other inputs, and in this way they establish a relation between technical inefficiency and the distance of management from this optimal level. They arrive at a random coefficients model to be estimated with simulated maximum likelihood. Looking at their empirical results of interest is the fact that similarly to Triebs and Kumbhakar (2018), they too find evidence that management is not neutral to the structure of the conventional production function. Their model has been subsequently applied by Marques and Barros (2010) on European Airports, and by Barros et al. (2014) in a study of efficiency in Portuguese football. Liu and Sickles (2020), among other research goals, merge the "agency problem" coming from the separation of ownership from management with a cost stochastic frontier model in order to identify separately managerial inefficiency from inefficiency attributable to other factors. They equate the level of managerial "shirking" (the consequence of the agency problem), with an inefficiency factor that increases costs above minimum, a reasonable way to model the actual monetary effects of the agency problem.

...and that's about it. In the very large literature on efficiency and productivity analysis, these were all the papers that we were able to find that model explicitly the management factor. This may appear strange, because this field puts management at the heart of efficiency and efficiency is the carrier of causal forces that affect both the level of output and the productivity measures of the conventional production inputs.[7] To invoke a well-known quote, Farrell (1957) stated that "technical efficiency indicates the gain that can be achieved by simply gingering up the management." It appears that, even when we acknowledge that the inefficiency of a firm is also due to external factors, we treat management as accountable for any inefficiency and as responsible for reducing it. Fried (2008, p. viii), writing "Ultimate responsibility for performance

[7] See Sickles and Zelenyuk (2019, ch.4) for the relations between these concepts.

rests with management. We believe that inefficiency arises from the varying abilities of managers...," could not express this stance more concisely. The (unintended?) consequence was that too few studies deal with management directly, while in almost all cases, the inefficiency term is called "managerial inefficiency." The field acknowledged the great importance of management for its object of study, efficiency/productivity, and then equated it with these concepts, effectively making it disappear from sight.

This can be understood as a way to deal with the absence of measures of management, but the fact remains that accountability and responsibility are contractual concepts (formal or implicit), not causal. And both the decomposition exercises that we presented above, and also the results from Triebs and Kumbhakar (2018) mentioned earlier, provide quantitative evidence that inefficiency is a composite result due to many factors, not just management—a conclusion that should be considered plausible on reflection alone.

This does not mean that we question the socioeconomic arrangement that the ultimate responsibility for performance rests with management, quite the contrary. And to achieve performance, one must indeed pursue efficiency. Viewing management as the efficiency standard bearer strengthens the motivation for it to be analyzed from an economic point of view, and not just equate it with the end result. It is also fortunate that efficiency is an overarching goal, consistent with any short-term or long-term financial, operational or other objective a firm may have, be it profit-maximization, acquisition of market share, firm-value maximization, quality excellence, a combination of them, or something else. All are served when efficiency increases, all hurt when there are efficiency losses. Therefore analyzing, modeling and eventually measuring management and its effects should receive equal weight as measuring inefficiency.

The model that we will develop takes a step towards this direction. But before presenting it, we must examine a number of important methodological choices and modeling decisions as regards management that are not always transparently spelled out.

3 Methodological choices in modeling management

Bloom and Van Reenen (2007) viewed "management practices" as "... more than the attributes of the top managers: they are part of the organizational structure and behavior of the firm, typically evolving slowly over time even as CEOs and CFOs come and go." Theirs was a deliberate decision to exclude the higher echelons of management, and so also the aspects of mid-term strategy and direction ("leadership"), concentrating instead on the middle management level, the everyday machinery of running a company. For our purposes, the control system of a business is indeed the natural object to study when efficiency in production is examined, while leadership could be more pertinent if we looked at the overall financial success of a company in a dynamic model.[8]

[8] For a fascinating account of how leadership and the business model of a firm contributed to its long-term success, see the case study in Brea-Solís et al. (2015).

Moreover, casual observation but also scholarly research has established that management practices vary widely even in the same country, in the same industry and in the same period.[9] Such variability is good news as regards the prospects of econometric identification and estimation of the effects of management. But it also implies that we should treat management as a variable, even in a cross-sectional setting.

Further, as Triebs and Kumbhakar (2013) comment, "business scholars have long maintained that management is an important factor in production. And it is often perceived to be qualitatively different from conventional input factors and attracts special attention." But "qualitatively different" how?

In Bloom et al. (2016), the authors discuss three different ways to perceive and model management: management as capital, management as technology, and the "management as design" approach developed in the organizational economics field, where management is contingent, something over which firms optimize given their situation.[10]

In economics, the word "capital" is used for something that accumulates and depreciates. Related to management, learning curves and maturity of systems and procedures appear to be natural cases of "value accumulation" over time, while personnel turnover and internal re-organizations could obviously be mapped to depreciation and investment. Moreover, Delis and Tsionas (2018) offer a convincing argument (p. 66) that management can be seen as incorporating and representing all other resources that have been proposed as influencing production (like human capital, intellectual capital, organizational capital, etc.)—and it is not by accident that all these other concepts come with the word "capital" attached. But in a cross-sectional, i.e., static model, as the one we focus on here, this dynamic aspect cannot enter the picture, much like it holds for physical capital.

At the same time management can naturally be seen as "technology," even if only because what management does is to dictate and monitor how the other inputs must be combined. Management is a technology, a "soft" technology if you like, the "way of doing business," which may also explain why it is so variable across firms. It is a "recipe," changing all the time and from cook to cook, as cooking recipes do.[11] But an important difference arises: from a technical point of view, management is not a necessary condition for production. Production requires input factors, knowledge, and will. But "knowledge and will" do not reside solely in management but are spread to one or the other degree to all sentient participants in the production process. On the other hand, input factors are a necessary condition for production. Management with zero inputs cannot produce anything. Positive inputs without a management system in place will produce something, through some degree of self-organization and coordination, although in an inefficient way. In other words, we argue that the worst management can do is to "be absent" and leave production "unmanaged," but strictly positive.

[9] See Bloom and Van Reenen (2007, 2010) and Bloom et al. (2014a) for discussions about the heterogeneity of management practices across firms.

[10] Analogous is the "contingency model" in Management science.

[11] Technology as a recipe is not a new metaphor, see for example O'Donnell (2016), Kerstens et al. (2019).

One could object by arguing that management can directly harm the firm if it is incompetent enough. Such a view appears to conflate management with leadership (and we have stressed the distinction earlier): indeed the actions of the firm's leaders can in the mid- or long-term sink a company and drive it to extinction. But this does not imply that management will nullify the production capabilities of the firm as represented by its production function. Firms are taken off the map because they lose demand for their products or control over their costs. But productive capability won't be eliminated by bad management. Put in a different way, we argue that the presence of a management system itself, however inefficient it may be, is better than no management at all.

Lastly, in the "management as design" approach, it is reasonably argued that firms attempt to optimize their management structure (qualitatively but also quantitatively) contingent on their environment and goals. This is certainly based on a fundamental premise of all economic theorizing. Bloom et al. (2016) note that if we combine the "design" approach with a quantification of management, it follows that then the "management level" could have an interior optimum and not a monotonic relationship with output.

But this is nothing else than the invocation of the law of diminishing returns: in a multi-input production process, increasing one input while keeping all others fixed will eventually lead to negative marginal product for this input. Management as "quantity" can be understood as a quantification of the extent to which a firm attempts to control its production process, through the structure of decision-making and the delegation of it, and through monitoring and reporting activities. Without making any judgment as to "how well" or "how efficiently" these activities perform, we could quantify them by measuring their sheer number and frequency, the number of decision making levels, whether job descriptions exist and/or how specific and detailed they are, the proportion of managerial positions in the total headcount, etc. Eventually, we would come up with a pure quantity index, and not necessarily a relative or bounded one.

If one were to attempt such a measurement exercise, intuitively one would expect an inverted-U relationship between the quantity of management and efficiency, a "Laffer curve for management" where the production process suffers from neglect if control is "too little" while "too much" managerial supervision suffocates the business, and so an intermediate technically optimal value must exist.

But this, as said, holds for all inputs. Do we model this aspect of production processes? Most of the times we don't. Our two basic functional forms, the Generalized Cobb-Douglas and the C.E.S production functions have marginal products that are declining but everywhere positive, and tend to zero only asymptotically. Apparently, the justification for ignoring the law of diminishing returns in our models is that actual production processes are not characterized by inputs in such relative quantities that their marginal products approach zero, let alone being negative. So both for theoretical but also for empirical work, it is argued that we only really need functional forms that can represent and approximate production for "middle" regions of input values, where marginal products are positive and safely away from zero.

We conclude that in a cross-sectional model, management should be modeled as a variable and not as a constant, its zero-level should be neutral to an "unmanaged" strictly positive level of production, and it should be in a position to affect how the other inputs contribute to output.

4 A 2TSF production model of management

Bringing onto the surface the usual treatment of management in efficiency analysis, the production function can be written as

$$Q = \mathrm{AF}(\mathbf{x}) \cdot \exp\{-u(m)\}, \quad u \geq 0, \quad \partial u/\partial m < 0. \tag{1}$$

Here, A is a technology shifter, and $AF(\mathbf{x})$ represents maximum output given the inputs $\mathbf{x}$. The variable m represents management, typically "better" or "more effective," the higher its arithmetic value. It is modeled as a force reducing inefficiency u.

We detect two issues with this formulation. First, management is modeled as being a "defensive" force only, it does not contribute to maximum output at all and it exists solely in order to reduce inefficiency. But management is also an input and not only in the unavoidable sense that it has its own financial costs, but also from a more technical point of view: contemplating a produced piece of a product, it is an inseparable mix of the materials used, of intangible resources like the services of equipment or electricity consumed, and certainly of the labor hours of those that worked directly on it. But it has also absorbed the labor hours of those coordinating and supervising the direct workers: management hours (and related resources). One could argue that the estimation of A will include an "average" level of management. But as we have said already, management practices differ wildly, and to treat management as a constant common across firms appears to us too big a compromise to make (note that "hard" technology varies by much less in the cross-sectional setting).

A second issue is that the above expression does not reflect the effects that management has on the other inputs as regards their contribution to production. In the model that we develop next, we focus on mending the first problem, while in the last section we discuss how our model can be extended to deal with the second issue.

4.1 A production function with management

We consider the following maximum production function,

$$Q_{\max} = \mathrm{AF}(\mathbf{x}) \cdot \exp\{h(m)\}, \quad m \geq 0,\ h(0) = 0,\ h'(m) > 0,\ h''(m) < 0. \tag{2}$$

Here, $\exp\{h(m)\}$ is the term representing the effects of management, with $h(\cdot)$ being a transformation function. The way we model management here reflects the following methodological choices:

First, we treat management as a variable. Second, it enters the production function in a way that guarantees that for $m = 0$ management becomes "neutral." "No management" does not imply zero production, as discussed earlier. Third, the relation between management and output is monotonic. Its marginal product though is not necessarily everywhere declining: for $\partial^2 Q/\partial m^2 < 0$ we require not just $h''(m) < 0$ but the stronger condition $h''(m) + [h'(m)]^2 < 0$.

The model conforms with standard microeconomic theory:[12] For the cost-minimization problem of a competitive firm, a well-defined and unique solution requires $F(\mathbf{x})$ to be jointly concave in its arguments, and that $h''(m) \leq 0$, both standard theoretical conditions. As is also the case in textbook models, for the profit maximization problem we need stronger conditions: that $F(\mathbf{x})$ is strictly jointly concave and that $\partial^2 Q/\partial m^2 < 0$. An important result here is that at the economic optimum, $h'(m^*) > 0$. Namely, that the marginal product of management should be strictly positive, even if $h(\cdot)$ were modeled in such a way so as to have an interior maximum.[13] Two other important theoretical results for the cost-minimizing firm are that at the optimum management is a complement to the conventional inputs as long as $h''(m^*) < 0$, and also that management has only scale and not allocative effects in an otherwise homothetic production function: this means that management that enters the production function as above does not affect the property of linear expansion paths that homothetic functions possess.

To be in line with microeconomic theory but also with efficiency analysis, the above production function is seen as measuring the maximum output given conventional inputs and management. This imposes one final modeling choice (although one that remains at the conceptual level): the management variable should be treated as representing a "quantity" view of management, leaving to the composition $\exp\{h(\cdot)\}$ the task of reflecting how the implemented management system translates into output terms.

4.2 The 2TSF stochastic specification

To turn eq.(2) into a stochastic frontier model and obtain an expression for actual output, we introduce a random disturbance and an inefficiency component,

$$Q = \mathrm{AF}(\mathbf{x}) \cdot \exp\{h(m)\} \exp\{v - u\}, \quad E(v) = 0, u \geq 0. \tag{3}$$

We do not consider the inefficiency component u to be a direct negative function of management. Earlier, we have argued that inefficiency is a composite construct and that many forces reside in it, apart from management. What we do here is to extract one of these forces and give it an autonomous presence in the model. One could ask why (and question whether) the component we are isolating is "management" and not something else. Our answer to this is twofold: first, that management is an omitted production input and what we are doing is to omit it no more. Second, that management is the only factor related to inefficiency that is present in all firms across countries, industries and time periods, and also it is the only one that has unambiguously beneficial effects. To provide a contrasting example, regulation may be detrimental to efficiency in some industries, but efficiency-augmenting in others.

[12] See Papadopoulos (2018, ch. 6) and its technical appendix for details.

[13] Tsionas (2015) analyzes in detail a profit-maximizing model with management and arrives at the same conclusion, namely, that economic optimization will result in a level of management below its technically optimal level, if one exists, or in general in a level that will leave some technical efficiency opportunities unrealized.

Returning to our model, we set for compactness $w \equiv h(m)$ and we take logarithms to arrive at

$$\ln Q = \ln A + \ln F(\mathbf{x}) + \varepsilon, \quad \varepsilon = v + w - u. \tag{4}$$

On account of its three-component error term, where two non-negative elements enter with opposite signs, this has the structure of a two-tier stochastic frontier model, introduced originally by Polachek and Yoon (1987) to measure the effects of incomplete information in wage determination in the labor market, but since then expanded to capture the effects of opposing forces in many different situations.[14] Note that here, the two opposing forces on output, management and inefficiency, are not identical or even similar in nature. But this does not create conceptual or practical issues, since what we will attempt to measure is their effects on output, not the magnitude of these factors themselves.

The above formulation allows us to estimate certain aspects of the effects of management on output, without having a measure of management as regressor, and using only a cross-sectional sample. This requires making distributional assumptions. In single-tier SF models, the standard assumptions are that $v \sim N(0, \sigma_v)$ and that the one-sided inefficiency component, u, follows either an Exponential or a Half-Normal distribution. While these latter choices have historically been adopted for the sake of modeling convenience, Torii (1992) has showed how one can obtain either one from fundamental assumptions as regards the sources of inefficiency. Specifically he showed that if inefficiency is due to the incompleteness of managerial control (an almost tautological assertion since either internal or externally imposed inefficiency reflects the inherent inability for complete control), then: if we assume that the "management effort" to mitigate inefficiency is correlated with the level of inefficiency, we obtain that the inefficiency component follows the Half-Normal distribution. If we assume that managerial intervention is statistically independent from the inefficiency level, then the inefficiency component follows the Exponential distribution. Both assumptions are plausible, since they relate to the "quality" of the management system of a firm, and this can be high (a competent management system that focuses intensely on containing and reducing inefficiency), or low (a less proactive and energetic management system). For the empirical study that we will conduct, we will assume that the inefficiency component follows the Exponential distribution, and the same assumption will be made for the management variable w.

Note that we can obtain formally this last result as follows: We assume first that $h(m) = m^{\gamma},\ 0 < \gamma < 1$. This satisfies all the conditions in eq.(2). Then, if we assume that the management variable m follows a subfamily of the Generalized Gamma distribution (Stacy 1962), we obtain that $w = m^{\gamma}$ follows an Exponential distribution (see "Appendix").

The 2TSF production function model with management represents also an alternative, "omitted variables" explanation for the "wrong skewness" problem in SFA, where the OLS residuals with production data exhibit positive skew, namely a skew having the opposite sign from the one "anticipated."[15] The composite 2TSF error term may exhibit negative, positive, or even zero skewness, depending on the relative strength

[14] For a review of the 2TSF framework and its diverse applications see Papadopoulos (2020c).

[15] For a discussion of this issue and an alternative explanation see Almanidis and Sickles (2011).

of the management and the inefficiency effects. Hence, from the 2TSF view, when the OLS residuals exhibit positive skew in a production setting, it is not "wrong," but an indication that the omitted management factor is stronger than inefficiency.

4.2.1 The log-likelihood with regressor endogeneity

Given

$$v \sim \mathrm{N}\left(0,\, \sigma_v^2\right)\;,\;\; w \sim \mathrm{Exp}\left(\sigma_w\right), \quad u \sim \mathrm{Exp}\left(\sigma_u\right),$$

and assuming joint independence, the density of the composite error term $\varepsilon = v+w-u$ is

$$f_\varepsilon\left(\varepsilon\right) \;=\; \frac{\exp\left\{a_1\right\}\Phi\left(b_1\right) \;+\; \exp\left\{a_2\right\}\Phi\left(b_2\right)}{\sigma_w+\sigma_u}\;,$$

with

$$a_1 = \frac{\sigma_v^2}{2\sigma_u^2}+\frac{\varepsilon}{\sigma_u},\;\; b_1 = -\left(\frac{\varepsilon}{\sigma_v}+\frac{\sigma_v}{\sigma_u}\right),\;\; a_2 = \frac{\sigma_v^2}{2\sigma_w^2}-\frac{\varepsilon}{\sigma_w},\;\; b_2 = \frac{\varepsilon}{\sigma_v}-\frac{\sigma_v}{\sigma_w}.$$

Further, by including management in the composite error term, issues of regressor endogeneity become an even stronger possibility. In order to deal with that, we will use the Gaussian Copula method (see Tran and Tsionas 2015; Papadopoulos 2018, 2020a), that can account for endogeneity without the use of instruments. Let F_ε denote the distribution function of the composed error term, y_i the dependent variable in a linear specification, $\mathbf{x}_i$ the regressor vector, β the regression coefficients, θ the vector of parameters of the distribution of the error term. Let

$$\mathbf{q}_i = \left(\Phi^{-1}\left(\breve{x}_{1i}\right),\ldots,\Phi^{-1}\left(\breve{x}_{mi}\right),\Phi^{-1}\left(F_\varepsilon\left(y_i-\mathbf{x}_i'\beta;\theta\right)\right)\right)',$$

where

$$\breve{x}_{ji} \equiv \hat{F}_j\left(x_{ji}\right) = \frac{1}{n+1}\sum_{k=1}^{n} I\left\{x_{jk}\leq x_{ji}\right\},\quad i=1,\ldots,n,\quad j=1,\ldots,m.$$

Namely, it is the value of the empirical distribution function at each regressor value. Finally, define the correlation matrix

$$\breve{R} = \begin{bmatrix} 1 & \hat{\rho}_{12} & \cdots & \hat{\rho}_{1m} & \rho_{1\varepsilon} \\ \hat{\rho}_{12} & 1 & \cdots & \hat{\rho}_{2m} & \rho_{2\varepsilon} \\ \vdots & \vdots & \ddots & & \vdots \\ \hat{\rho}_{1m} & \vdots & & \ddots & \rho_{m\varepsilon} \\ \rho_{1\varepsilon} & \cdots & \cdots & \rho_{m\varepsilon} & 1 \end{bmatrix},$$

where $\hat{\rho}_{ji} = \operatorname{corr}\left(\Phi^{-1}\left(\breve{x}_j\right), \Phi^{-1}\left(\breve{x}_i\right)\right)$. These correlation coefficients can be estimated from the sample and be treated as fixed numbers during maximum likelihood estimation of the θ, β parameters and of the unknown correlation coefficients $\rho_{j\varepsilon} = \operatorname{corr}\left(\Phi^{-1}\left(\breve{x}_j\right), \Phi^{-1}\left(F_\varepsilon(\varepsilon)\right)\right)$.

For an i.i.d. sample, the observation log-likelihood, including a Gaussian copula density and when the endogenous regressors are continuous, is

$$\begin{aligned}\breve{\ell}_i = &-\frac{1}{2}\ln\det\left(\breve{R}\right)\\ &+\frac{1}{2}\left[\Phi^{-1}\left(F_\varepsilon\left(y_i - \mathbf{x}_i'\beta;\theta\right)\right)\right]^2\\ &-\frac{1}{2}\mathbf{q}_i'(\breve{R})^{-1}\mathbf{q}_i + \ln f_\varepsilon\left(y_i - \mathbf{x}_i'\beta;\theta\right).\end{aligned} \tag{5}$$

The distribution function of the composite error term in the 2TSF Exponential specification is

$$F_\varepsilon(\varepsilon) = \Phi\left(\frac{\varepsilon}{\sigma_v}\right) + \frac{\sigma_u}{\sigma_w + \sigma_u}\exp\{a_1\}\Phi(b_1) - \frac{\sigma_w}{\sigma_w + \sigma_u}\exp\{a_2\}\Phi(b_2). \tag{6}$$

The model is to be estimated by maximum likelihood. Identification requires that the expected value of the Hessian matrix of the sample log-likelihood is invertible (see Bowden 1973). Under the Information matrix equality, this is equivalent to the condition that the expected value of the outer product of the gradient is invertible, which requires that the elements of the gradient vector are not linearly dependent. This holds because the parameters under estimation do not enter the log-likelihood in a symmetric way.

4.3 Metrics of interest

We can approach the measurement of the effects of management on output from two distinct perspectives: Management as another production factor, and management as a structured effort to optimize the overall efficiency of a firm. Each leads to distinct metrics, which although based on the same information, are useful in answering different questions. From a statistical point of view, we treat these metrics as the random variables that they actually are. This means that they have a distribution, and therefore, we can choose not just the 1st moment (mean) but other characteristics of the distribution like the median as their most representative value, depending on the context.

4.3.1 Management as a production factor, and its contribution to output

As mentioned, management viewed as a production factor has the special property that its absence would not eliminate output. Then we can measure how much of output (in percentage terms) can be attributed to management. This can be contrasted with the costs of the management system of the company, in a cost–benefit analysis. Unmanaged output is AF $(\mathbf{x})\, e^{v} e^{-u}$ so, at the sample level we have

$$\mathrm{Mc} \equiv \frac{Q - \mathrm{AF}\,(\mathbf{x})\, e^{v} e^{-u}}{Q} = 1 - \frac{\mathrm{AF}\,(\mathbf{x})\, e^{v} e^{-u}}{\mathrm{AF}\,(\mathbf{x})\, e^{v+w-u}} = 1 - e^{-w}.$$

Note that this percentage metric is the same whether we consider maximum or actual output as the base of calculation.

Under the assumption that w follows an Exponential distribution, Mc follows a Beta distribution with parameters $\alpha = 1, \beta = 1/\sigma_w$ and mean value, median and standard deviation,

$$E(\mathrm{Mc}) = \frac{\sigma_w}{1+\sigma_w}, \quad \mathrm{med}(\mathrm{Mc}) = 1 - 2^{-\sigma_w}, \quad \mathrm{SD}(\mathrm{Mc}) = \frac{E(\mathrm{Mc})}{\sqrt{1+2\sigma_w}}.$$

Conditioning Mc on the composite error term ε, we obtain a series of conditional expected values $E(\mathrm{Mc}_i \mid \varepsilon_i)$, as an individual measure for each observation, sometimes called a "JLMS" measure from Jondrow et al. (1982) that introduced them (although the metrics for the exponentiated variables were first presented by Battese and Coelli 1988). Setting

$$\lambda = \sigma_w^{-1} + \sigma_u^{-1}, \; \chi_{2i} = \exp\{a_{2i} - a_{1i}\}\, \Phi(b_{2i}) + \Phi(b_{1i}),$$

the needed formula is

$$E\left(e^{-w_i} \mid \varepsilon_i\right) = \frac{\lambda}{(1+\lambda)\,\chi_{2i}} \left[\Phi(b_{1i}) + \exp\left\{a_{2i} - a_{1i} - b_{2i}\sigma_v + 0.5\sigma_v^2\right\} \Phi(b_{2i} - \sigma_v)\right]. \quad (7)$$

4.3.2 Management as the efficiency champion

More than being just another input, management is seen as an overall output shifter and as the efficiency champion in a firm. So we are interested in measuring how much management tends to increase output, initially ignoring and then taking into account inefficiency.

The metric that tells us how much management tends to initially increase output (to shift it multiplicatively) is simply

$$\mathrm{Ms} \equiv e^{w}.$$

This is a Pareto random variable with minimum value 1 and shape parameter $1/\sigma_w$. Its mean will exist if $\sigma_w < 1$ and its variance if $\sigma_w < 1/2$, in which case we have

$$E(\mathrm{Ms}) = \frac{1}{1-\sigma_w}, \quad \mathrm{med}(\mathrm{Ms}) = 2^{\sigma_w}, \quad \mathrm{SD}(\mathrm{Ms}) = \frac{\sigma_w E(\mathrm{Ms})}{\sqrt{1-2\sigma_w}}.$$

At the individual level, we can compute

$$E\left(e^{w_i} \mid \varepsilon_i\right) = \frac{\lambda}{(\lambda-1)\,\chi_{2i}}\left[\Phi\left(b_{1i}\right) + \exp\left\{\frac{1}{2}\left[\left(b_{2i} + \sigma_v\right)^2 - b_{1i}^2\right]\right\}\Phi\left(b_{2i} + \sigma_v\right)\right]. \quad (8)$$

The model also provides the well-known "technical efficiency" metric,

$$\mathrm{TE} = e^{-u}.$$

Under the assumption that u follows an Exponential distribution, TE follows a Beta distribution with parameters $\alpha = 1/\sigma_u$, $\beta = 1$ and mean value, median and standard deviation,

$$E(\mathrm{TE}) = \frac{1}{1+\sigma_u}, \quad \mathrm{med}(\mathrm{TE}) = 2^{-\sigma_u}, \quad \mathrm{SD}(\mathrm{TE}) = \frac{\sigma_u E(\mathrm{TE})}{\sqrt{1+2\sigma_u}}.$$

At the observation level, setting $\chi_{1i} = \Phi\left(b_{2i}\right) + \exp\left\{a_{1i} - a_{2i}\right\}\Phi\left(b_{1i}\right)$ we have,

$$E\left(\mathrm{TE}_i \mid \varepsilon_i\right) = E\left(e^{-u_i} \mid \varepsilon_i\right) = \frac{\lambda}{(1+\lambda)\,\chi_{1i}}\left[\Phi\left(b_{2i}\right) + \exp\left\{a_{1i} - a_{2i} - b_{1i}\sigma_v + 0.5\sigma_v^2\right\}\Phi\left(b_{1i} - \sigma_v\right)\right]. \quad (9)$$

Since we maintain the position that management should be fully accountable for inefficiency, it is only natural to weight the management output-shift factor Ms with the actual technical efficiency achieved: we call this the "management (net) multiplier effect," defined as

$$\mathrm{Mm} \equiv \mathrm{Ms} \times \mathrm{TE} = e^{w}e^{-u}.$$

If it exceeds unity, it means that management succeeds in increasing output above its maximum unmanaged level. If it is lower than unity, management offsets inefficiency only partially, and output is below its maximum unmanaged level. Here we have, when the moments exist and under independence,

$$\begin{aligned} E(\mathrm{Mm}) &= E[\exp\{w-u\}] = E[\exp\{w\}]\cdot E[\exp\{-u\}] \\ &= [(1-\sigma_w)(1+\sigma_u)]^{-1}, \\ \mathrm{SD}(\mathrm{Mm}) &= \sqrt{\mathrm{Var}(\mathrm{Mm})},\ \mathrm{Var}(\mathrm{Mm}) \\ &= [(1-2\sigma_w)(1+2\sigma_u)]^{-1} - [(1-\sigma_w)(1+\sigma_u)]^{-2} \\ \mathrm{med}(\exp\{w-u\}) &= \begin{cases} \left(\frac{\sigma_w+\sigma_u}{2\sigma_u}\right)^{\sigma_u} & \sigma_u > \sigma_w \\ 1 & \sigma_u = \sigma_w \\ \left(\frac{\sigma_w+\sigma_u}{2\sigma_w}\right)^{-\sigma_w} & \sigma_u < \sigma_w\,. \end{cases} \end{aligned}$$

We note that while in a deterministic setting, $w - u < 0 \implies \exp\{w - u\} < 1$, this is not true in a stochastic setting and in terms of expected values. Namely, we may have $E(w - u) < 0$ and at the same time $E[\exp\{w - u\}] > 1$. This would be a case where Jensen's inequality holds with extreme prejudice.

At observation level, we can consider as before the expected value conditional on the composed error term. But note that

$$E[\exp\{w - u\} \mid \varepsilon] \neq E[\exp\{w\} \mid \varepsilon] \cdot E[\exp\{-u\} \mid \varepsilon],$$

because w and u stop being independent, conditional on ε. The formula here is (see Papadopoulos 2018, ch. 3),

$$E\left(e^{w_i} e^{-u_i} \mid \varepsilon_i\right) = \frac{\exp\left\{(1+\sigma_u)\left(a_{1i} + \frac{\sigma_v^2}{2\sigma_u}\right)\right\} \Phi\left(b_{1i} - \sigma_v\right)}{(\sigma_w + \sigma_u) f_\varepsilon(\varepsilon)} + \frac{\exp\left\{(1-\sigma_w)\left(a_{2i} - \frac{\sigma_v^2}{2\sigma_w}\right)\right\} \Phi\left(b_{2i} + \sigma_v\right)}{(\sigma_w + \sigma_u) f_\varepsilon(\varepsilon)}. \tag{10}$$

5 An empirical application

For our empirical study, we use a subset of the data used in Bloom et al. (2012a), specifically the 1888 observations from the year 2006.[16] The availability of WMS scores will allow us to examine whether our results align meaningfully with them or not.

The data are from various countries and industries. In their regressions, the authors use numerous controls, but we will apply the minimum specification. One could question the wisdom of pooling together such a diverse sample, but average measures over different socioeconomic regimes, regulatory environments and industries, if plausible, are estimates of deep structural common characteristics. The regression specification is

$$\ln S = \beta_0 + \beta_1 \ln K + \beta_2 \ln L + \varepsilon, \qquad \varepsilon = v + w - u, \tag{11}$$

where the dependent variable is Sales, in logarithms. The model is estimated by maximum likelihood. Table 1 contains the estimation results from OLS estimation, the 2TSF likelihood without a Copula, and the same with the Gaussian Copula attached to account for regressor endogeneity.

The high excess kurtosis of the OLS residuals is consistent with the 2TSF Exponential model, which is characterized by positive excess kurtosis. Comparing the results of the OLS and the 2TSF model without a Copula, we obtain the familiar result that the regression coefficients do not differ much, and the same holds for the error variance: the 2TSF model performs a decomposition of essentially the same magnitude. But the results from the 2TSF model with a Copula differ: first note that the correlation

[16] The full data set is "Manufacturing: 2004-2010 combined survey data (AMP)," freely available at http://worldmanagementsurvey.org/survey-data/download-data/download-survey-data/.

Table 1 2TSF Management production frontier-estimation results

	OLS	2TSF	2TSF-Cop
Constant	4.087	4.305	5.593
	[0.140]	[0.098]	[0.219]
Lppent	0.374	0.325	0.103
	[0.022]	[0.012]	[0.028]
Lemp	0.617	0.678	0.824
	[0.031]	[0.019]	[0.038]
σ_ε	0.765	0.758	0.815
σ_v	–	0.230	0.242
		[0.037]	[0.040]
σ_w	–	0.461	0.474
		[0.021]	[0.028]
σ_u	–	0.556	0.617
		[0.023]	[0.025]
$\max\lvert\hat{\rho}(\ln K, \varepsilon)\rvert$	–	–	0.351
			[0.045]
$\max\lvert\hat{\rho}(\ln L, \varepsilon)\rvert$	–	–	0.149
			[0.044]
$\hat{\gamma}_1(\varepsilon)$	−0.320	−0.380	−0.591
$\hat{\gamma}_2(\varepsilon)$	5.076	5.347	5.033

Sample size: 1888, cross-section. Year: 2006, various countries. Dependent variable: lnS (logarithm of Sales)
Numbers are truncated at 3rd decimal digit. Standard errors in brackets (robust- HC2 for OLS). Description of variables: lnS = logarithm of Sales, Lppent = logarithm of Capital, Lemp = logarithm of Labor (number of workers)

coefficients, although not very strong, are statistically significant and estimated with high accuracy. This lends support to the conjecture that there exists endogeneity. We note that under the assumption of the Gaussian Copula, these coefficients represent the maximum linear correlation between the original regressors and the error term. Adopting this model, we observe that the slope coefficient for capital has been much reduced, while for labor it has much increased.

Note that the inefficiency scale parameter σ_u is estimated as higher than the management scale parameter σ_w and that the residuals in all cases exhibit negative skewness. But in order to assess their effects on output, we must go back to the original units of measurement.

Table 2 contains sample-level statistics on the metrics we have presented earlier, based on the estimated sigmas.

The management contribution metric Mc is on average 32% of output, which appears a reasonable value. The mean value of the management shifter Ms is close to 2 (meaning that management tends to double unmanaged output), but its median value is much lower, roughly at a 40% boost on output. For the metric Mm $= \exp\{w - u\}$ that represents the net multiplier effect of management, we see that even though at

Table 2 Statistics of metrics based on estimated sigmas

Variable	Mean	Median	S.D.
Mc	0.322	0.280	0.230
Ms	1.901	1.389	3.952
TE	0.618	0.652	0.255
Mm	1.176	0.927	2.688

Table 3 Sample statistics of individual measures

Variable	Mean	Median	S.D.	Min	Max
$E(\mathrm{Mc}_i \mid \varepsilon_i)$	0.321	0.245	0.156	0.212	0.994
$E(\mathrm{Ms}_i \mid \varepsilon_i)$	1.987	1.440	4.790	1.367	186.8
$E(\mathrm{TE}_i \mid \varepsilon_i)$	0.619	0.705	0.198	0.001	0.788
$E(\mathrm{Mm}_i \mid \varepsilon_i)$	1.239	0.948	3.541	0.001	136.0

Table 4 Deciles of marginals and individual metrics

decile	Mc		Ms		TE		Mm	
	Marginal	JLMS	Marginal	JLMS	Marginal	JLMS	Marginal	JLMS
0.1	0.05	0.21	1.05	1.37	0.24	0.29	0.34	0.37
0.2	0.10	0.21	1.11	1.37	0.37	0.45	0.53	0.57
0.3	0.16	0.22	1.18	1.37	0.48	0.57	0.68	0.73
0.4	0.22	0.23	1.27	1.40	0.57	0.65	0.81	0.84
0.5	0.28	0.25	1.39	1.44	0.65	0.70	0.93	0.95
0.6	0.35	0.28	1.54	1.52	0.73	0.74	1.04	1.06
0.7	0.43	0.33	1.77	1.67	0.80	0.77	1.19	1.20
0.8	0.53	0.42	2.14	1.94	0.87	0.78	1.44	1.42
0.9	0.66	0.57	2.98	2.63	0.94	0.79	2.01	1.93

the logarithmic level $E(w - u) < 0$, Mm has an estimated expected value higher than unity, implying that on average management succeeds in offsetting internal and externally imposed inefficiency, lifting output above the maximum unmanaged level. But its median, a centrality metric robust to outliers, is below unity.

Table 3 contains the corresponding individual measures and their sample statistics.

The max values for the conditional expectations of Ms and Mm are clearly outliers, and explain why the sample means and the standard deviations of these metrics exceed the corresponding statistics in the previous table. Otherwise, the table more or less paints the same picture.

We gain more insight if we examine the relative cumulative frequencies in deciles that we present in Table 4, where we have included also the deciles of the marginal distributions for comparison.

Compared to the deciles of the marginal distribution function, the empirical distributions of the JLMS metrics are more condensed, especially in the lower part. The exception are the deciles of $E(\mathrm{Mm} \mid \varepsilon)$ that track closely those of the marginal dis-

Table 5 Association between management and conventional inputs

Variables	Kendall's tau	Spearman's rho
$E(w \mid \varepsilon)$, Capital	0.253	0.369
$E(w \mid \varepsilon)$, Labor	0.130	0.194

tribution of Mm. This is remarkable because we don't expect the two distributions to coincide.

We see that for 70% of firms the JLMS metric for the management contribution ranges in the narrow interval [0.21, 0.33]. As regards the management net multiplier effect, for roughly half of the firms it is below unity, and then for the next 40% of firms rises gradually up to almost doubling the maximum unmanaged output.

We close this part of the empirical study by examining one of the theoretical implications of the production model, namely, that management is a complement to the conventional input factors. The closest we get to the management variable itself is $E(w \mid \varepsilon)$ where $w = h(m)$ is assumed to be a nonlinear function of management. For this reason, we present in Table 5 nonparametric measures of association, Kendall's tau and Spearman's rho, which are invariant to nonlinear transformations, while the more familiar Pearson's correlation coefficient is not.
In all cases, these association measures are positive and statistically significant, supporting the assumption that management is a complement to the input factors along the expansion path.

5.1 Congruence with WMS scores

In this subsection, we examine how much do the results from the 2TSF model align with the information in the WMS management scores. We do that in two ways.

5.1.1 Comparing management metrics

On the same sample we run an OLS regression,

$$\ln S = \beta_0 \; + \; \beta_1 \ln K \; + \; \beta_2 \ln L \; + \beta_m m^*_{\text{WMS}} \; + \; v. \tag{12}$$

This follows the specification in Bloom et al. (2017), where, in levels, the WMS score appeared exponentiated, as we did for w. The star in the WMS score indicates a modification: for the data sample that we used, the WMS scores were given not in the newer (0, 1) range, but in the initial $1-5$ Likert scale, with 1 being the minimum. To adjust it to the exponentiated way it enters our model and respect the neutrality of its zero-level, we subtracted 1 from the series, so $m^*_{\text{WMS}} = m_{\text{WMS}} - 1$.

The obtained estimate was $\hat{\beta}_m = 0.280$. The corresponding core management metrics per firm are

$$\text{Mc}_{\text{WMS,i}} = 1 - \exp\{-\hat{\beta}_{\text{m}} \text{m}^*_{\text{WMS,i}}\}, \quad \text{Ms}_{\text{WMS,i}} = \exp\{\hat{\beta}_{\text{m}} \text{m}^*_{\text{WMS,i}}\}.$$

Table 6 Conditional relative frequencies, in percentages (%), $P\left[E\left(\mathrm{Mc}\mid\varepsilon\right)\ \mid \mathrm{WMS}\right]$

WMS score	$E(\mathrm{Mc}\|\varepsilon) = 1 - E(e^{-w}\|\varepsilon)$					Total (%)
	0.0–0.2	0.2–0.4	0.4–0.6	0.6–0.8	0.8–1	
1–2	–	94.4	4.2	1.4	0.0	100.0
2–3	–	82.6	10.6	5.5	1.3	100.0
3–4	–	73.6	16.4	7.9	2.2	100.0
4–5	–	65.8	16.7	12.3	5.3	100.0
Marginal rel. frequency	0.0	78.3	13.2	6.7	1.9	100.0

Table 7 Conditional relative frequencies, in percentages (%), $P\left[E\left(\mathrm{Mm}\mid\varepsilon\right)\ \mid \mathrm{WMS}\right]$

WMS score	$E(\mathrm{Mm}\|\varepsilon) = 1 - E(e^{w-u}\|\varepsilon)$							Total (%)
	0.0–0.5	0.5–1.0	1.0–1.5	1.5–2.0	2.0–2.5	2.5–3.0	> 3.0	
1–2	40.3	41.0	16.0	1.4	0.0	0.0	1.4	100.0
2–3	20.6	40.8	25.1	5.7	3.5	1.6	2.7	100.0
3–4	9.6	36.6	32.7	10.6	4.3	2.1	4.2	100.0
4–5	7.9	32.5	30.7	9.6	3.5	7.0	8.8	100.0
Marginal rel. frequency	16.2	38.3	28.3	7.9	3.6	2.0	3.7	100.0

Their empirical means were $\hat{E}[\mathrm{Mc}_{\mathrm{WMS}}] = 0.416$, compared to 0.32 that we obtained in the 2TSF model, and $\hat{E}[\mathrm{Ms}_{\mathrm{WMS}}] = 1.77$ compared to 1.90 from our model. The WMS regression estimates as higher the proportion of output that is directly attributed to management (the Mc metric), but its gross output shift (Ms) is estimated as lower. While the values are not the same, their differences are not disturbingly large. We do not examine the Mm metric because it requires an estimate of technical efficiency TE, and this is not available in an OLS regression model.

5.1.2 Empirical conditional distributions

For a more comprehensive assessment, we stratify the sample in four strata per the WMS scores and we build contingency tables for $E(\mathrm{Mc} \mid \varepsilon)$, Table 6, and for $E(\mathrm{Mm} \mid \varepsilon)$, Table 7.

Related to $E(\mathrm{Mc} \mid \varepsilon)$, we observe a movement of probability mass to the right as the WMS scores increase. In all strata, the allocation of probability mass indicates a falling monotonic distribution. Even in the highest WMS stratum, for the bulk of firms the contribution of management to output when seen as a production input stays in the lowest category.

As regards $E(\mathrm{Mm} \mid \varepsilon)$, here too probability moves to the right as the WMS scores increase. The effect of higher WMS scores is more profound than in the previous case, because the escape of the firms from the lowest column is more massive, and in fact they "jump over" the 2nd column and move to a net multiplier effect that leads output

Table 8 Management metrics for SMEs and Large Corporations. Average values

WMS	# of firms		Mc		Ms		TE		Mm	
	SME	Large	SME	Large	SME	Large	SME	Large	SME	Large
[1–2]	114	30	0.25	0.26	1.47	1.57	0.48	0.48	0.68	0.76
[2–3]	463	289	0.29	0.33	1.86	1.87	0.57	0.62	1.08	1.15
[3–4]	400	478	0.32	0.35	2.40	1.93	0.64	0.68	1.57	1.27
[4–5]	23	91	0.35	0.39	2.00	2.30	0.64	0.69	1.28	1.55

above its maximum unmanaged level (3rd column and higher). This is in line with the perception that the organization-wide effects of management are more important.

We also observe that moving from the $[3-4]$ stratum to the $[4-5]$ has relatively little effect, except in creating outliers. This implies that striving for "best" management practices (with the associated costs) is a high-risk enterprise, with high payoffs of low probability.

These results cross-validate the WMS approach and the 2TSF model of management in production, since they indicate that, from two totally different avenues and using two totally different methodologies, they measure the same thing: a positive influence on output beyond conventional inputs, whose variability across firms aligns with the variability of management practices.

Next, we stratify our sample in yet one more dimension, in "Large" corporations and "Small-medium enterprises" (SMEs), using the European Union main criterion for the partition (Recommendation 2003/361/EC), which is the number of employees: an SME must have no more than 250 employees. Table 8 contains subsample averages of the JLMS measures.

The various metrics increase as the WMS score increases, which is additional evidence for the congruence of the two-tier stochastic frontier management production model with the WMS management scores. An exception is the highest WMS stratum for SMEs, where we observe a fall in the Ms and Mm metrics. But we have to note that the average values in this category come from very few firms (23). As regards the comparison between large firms and SMEs, from the allocation of firms in WMS categories we see that large firms tend to have better management systems. Yet, this brings only a rather small improvement in the management metrics and in technical efficiency, while in the [3–4] WMS stratum the SMEs appear to perform better than the large firms as regards the gross and net management multiplier effect. But overall the similarities prevail. It appears that management systems adapt to the size of a business, keeping their effect per "unit of scale" roughly constant.

As a final check, we build contingency tables per country and WMS strata, and we present the related sample averages of $E(\mathrm{Mc} \mid \varepsilon)$ and $E(\mathrm{Mm} \mid \varepsilon)$.

We observe again that the management metrics from our model tend to increase in general as the WMS scores increase: no Simpson's paradox arises from this decomposition per country. But Table 9 also indicates that the management output contribution Mc does not necessarily follow the net multiplier effect of management Mm: for example, Great Britain and Greece are essentially identical as regards the Mc metric,

Table 9 Management metrics per country and WMS scores. Average values

Country	# of firms	Mc				Mm			
		WMS score				WMS score			
		[1–2]	[2–3]	[3–4]	[4–5]	[1–2]	[2–3]	[3–4]	[4–5]
China	13	0.21	0.21	0.21	n/a	0.08	0.32	0.45	n/a
France	232	0.27	0.32	0.39	0.48	0.87	1.19	1.72	2.11
Germany	107	0.21	0.33	0.35	0.45	0.52	1.26	1.28	1.73
Great Britain	487	0.26	0.29	0.33	0.32	0.85	1.39	1.76	1.38
Greece	159	0.25	0.29	0.34	0.34	0.65	1.04	1.18	1.11
Italy	147	0.30	0.33	0.34	0.53	1.06	1.22	1.18	2.10
Japan	82	0.22	0.41	0.38	0.50	0.69	1.49	1.35	1.98
Northern Ireland	14	0.29	0.30	0.37	n/a	1.06	1.02	1.28	n/a
Poland	176	0.21	0.24	0.24	0.24	0.27	0.47	0.58	0.71
Portugal	142	0.21	0.25	0.33	0.26	0.44	0.74	1.07	0.77
Sweden	218	0.24	0.36	0.38	0.44	0.89	1.27	1.40	1.81
United States	111	n/a	0.30	0.32	0.34	n/a	1.04	1.16	1.21

but Great Britain has consistently higher Mm scores. These metrics represent distinct but not antagonistic ways to approach and measure the effects of management on production, depending on what is the goal of the study.

6 Extensions and directions of further research

We have developed a two-tier stochastic frontier model of production in order to estimate the effect that management has on output, either as another input factor, or, more appropriately, as the efficiency champion of the firm. The model treats management as a latent variable and so it does not need data on management beforehand, which usually are either unavailable or costly to obtain. Moreover, the model can be used already with cross-sectional data, and also, it provides a natural, "omitted variables" explanation for the "wrong skew" problem in stochastic frontier analysis. In an empirical study, we have validated the model against the World Management Survey scores, and we have elaborated deeper on the efficiency metrics obtained by exploiting their statistical properties. The empirical model that we used was deliberately very simple, because we wanted to show that even at such an unsophisticated level it is empirically relevant. Nevertheless, the model can and should be extended in various ways.

First, by treating management as unobservable one begs the question "how is this unobservable distinguished from other possible unobservable forces operating on output?" Put another way, how can we be certain that we conceptually (and not technically) identify the management effect here?[17] While we believe that we have provided adequate structural arguments as to why management is the most important unobservable

[17] This criticism is also valid for the individual effects panel data model, when one wants to baptize the individual effect as a measure of management.

factor affecting output positively, still, controlling for other factors would enhance the reliability of the model, and such controls should appear in empirical specifications. An associated extension of the model would be to apply it on a panel data set, estimating separately the unobservable management variable and an individual effect.[18]

Second, we have not modeled the effect that management may have on the conventional inputs and *their* affect on output—and the empirical studies surveyed indicate that the structure of the production function changes as the measure of management changes. In principle, this could be done by loosening the Cobb-Douglas production function form and introducing interaction terms, either comprehensively through a translog production function, or selectively, depending on the situation under study. But in our case, we do not have a data series on management in order to build the interaction-regressor series. A possible way to overcome this is by iterative estimation: initially estimate the model without interaction terms, obtain a JLMS predictor series for management, and then re-estimate including interaction terms. Stop when the estimates in successive iterations have stabilized.

Third, while the model accounted for the dependence between management and the conventional inputs, its statistical specification treated the management variable w as being statistically independent from the inefficiency component u. If we want to directly account for the targeted effort of management to reduce inefficiency, we must accept that the two should exhibit dependence. Moreover, dependence may be present between management and the external environment that also operates through the inefficiency term: Genakos (2018) took three World Bank indices of the country-level business environment, "ease of doing business," "trading across borders" and "labor market regulation" and graphed them against the country averages WMS management scores: as these indices worsened, there was a clear downward trend of the WMS scores, indicating that such external determinants of inefficiency affect directly management practices. We offer the following intuition for this phenomenon: as regulation increases, the effective freedom and power of management to intervene in production decreases, while at the same time more resources are spent for compliance. Then the cost–benefit ratio to implement and maintain a structured system of management practices gets worse from two routes, and the end result is a lower "management presence" overall. In a sense, regulation is "management imposed externally" and so it substitutes for the firm's management to a degree. Such intra-error statistical dependence can be accounted for using 2TSF models with dependence recently developed by Papadopoulos et al. (2020).

Fourth, by disentangling management from inefficiency, the 2TSF model makes a step in decomposing the efficiency analysis analogue of the "Solow residual" in growth theory. This decomposition can go deeper and get finer, by making the w and u variables a function of a vector of observables "z" as discussed in Kumbhakar and Parmeter (2010), if, of course, they are available as data. In turn one can then exploit the "Scaling property" and treat $w(z_w)$ and $u(z_u)$ as regressors (see Parmeter 2018). This will eliminate the need to make distributional assumptions on w and u, and it will also transform the intra-error dependence and the dependence between production

[18] The two-tier stochastic frontier model was developed for panel data sets in Polachek and Yoon (1996). An alternative methodology is described in Papadopoulos (2020c).

inputs and the unobservable management into correlation between regressors. Such correlation needs no special treatment and permits us to use the much simpler nonlinear least squares estimator.

These extensions highlight the versatility of the model that we have proposed, and make it a promising tool for empirical analysis.

Compliance with ethical standards

Conflict of interest All authors declare that they have no conflicts of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

Appendices

A The distribution of management

Introduced by Stacy (1962), the Generalized Gamma distribution has density

$$f_m(m) = \frac{p}{\alpha^d 0(d/p)} m^{d-1} \exp\{-m^p/\alpha^p\}, \quad \alpha, p, d > 0.$$

Assume a subfamily of this distribution with $p = d = \gamma < 1,\ \alpha > 0$. Then the density becomes

$$f_m(m) = \frac{\gamma}{\alpha^\gamma} m^{\gamma-1} \exp\{-m^\gamma/\alpha^\gamma\}, \quad \alpha > 0, 0 < \gamma < 1.$$

Consider the random variable $w = m^\gamma$. We have

$$w = m^\gamma \implies m = w^{1/\gamma} \implies \frac{\partial m}{\partial w} = \frac{1}{\gamma} w^{(1/\gamma)-1}.$$

Applying a change of variables, the density of w is

$$f_w(w) = \left|\frac{\partial m}{\partial w}\right| \cdot f_m(w^{1/\gamma}) = \frac{1}{\gamma} w^{(1/\gamma)-1} \cdot \frac{\gamma}{\alpha^\gamma} \left[w^{1/\gamma}\right]^{\gamma-1} \exp\{-[w^{1/\gamma}]^\gamma/\alpha^\gamma\}$$
$$\implies f_w(w) = \frac{1}{\alpha^\gamma} \exp\{-w/\alpha^\gamma\}.$$

But this is the density of an Exponential random variable with scale parameter $\sigma_w = \alpha^\gamma$.

B Distribution and moments of management metrics

We derive below the distribution of the various metrics we use in the main text, under the assumption that the variables w, u follow Exponential distributions and are independent.

B.1 Management contribution to output

Applying the change-of-variables technique, we have

$$\mathrm{Mc} = 1 - e^{-w} \implies w = -\ln(1-\mathrm{Mc}) \implies \frac{\partial w}{\partial \mathrm{Mc}} = \frac{1}{1-\mathrm{Mc}}.$$

Then

$$f_{\mathrm{Mc}}(\mathrm{Mc}) = \frac{1}{1-\mathrm{Mc}}\frac{1}{\sigma_w}\exp\left\{\frac{-1}{\sigma_w}\big[-\ln(1-\mathrm{Mc})\big]\right\} = \frac{1}{\sigma_w}(1-\mathrm{Mc})^{1/\sigma_w - 1}.$$

This is the density of a Beta distribution, with parameters $\alpha = 1$, $\beta = 1/\sigma_w$, and applying the moment expressions for the specific parameters we obtain

$$\begin{aligned}
E(\mathrm{Mc}) &= \frac{\alpha}{\alpha+\beta} = \frac{1}{1+1/\sigma_w} = \frac{\sigma_w}{1+\sigma_w},\\
\mathrm{Var}(\mathrm{Mc}) &= \frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)} = \frac{1/\sigma_w}{(1+1/\sigma_w)^2(2+1/\sigma_w)}\\
&= \frac{1/\sigma_w}{(1+\sigma_w)^2(1+2\sigma_w)}\cdot\frac{1}{1/\sigma_w^3}\\
&= \frac{\sigma_w^2}{(1+\sigma_w)^2(1+2\sigma_w)} \implies \mathrm{SD}(\mathrm{Mc}) = \frac{E(\mathrm{Mc})}{\sqrt{1+2\sigma_w}}
\end{aligned}$$

Moreover, when one of the parameters of the Beta distribution is equal to unity, the distribution becomes identical to the Kumaraswamy distribution (see Jones 2009), which gives us a simple closed-form quantile function,

$$Q(p) = 1 - (1-p)^{1/\beta} = 1 - (1-p)^{\sigma_w}, \quad p \in (0,1).$$

From this, we obtain

$$\mathrm{med}(\mathrm{Mc}) = 1 - 2^{-\sigma_w}.$$

B.2 Management as an output shifter.

We have

$$\mathrm{Ms} = \exp\{w\} \implies \ln(\mathrm{Ms}) = w \implies \frac{\partial w}{\partial \mathrm{Ms}} = \frac{1}{\mathrm{Ms}}.$$

Then

$$f_{\mathrm{Ms}}(\mathrm{Ms}) = \frac{1}{\mathrm{Ms}}\frac{1}{\sigma_w}\exp\left\{\frac{-1}{\sigma_w}\ln(\mathrm{Ms})\right\} = \frac{1/\sigma_w}{\mathrm{Ms}^{(1+1/\sigma_w)}}.$$

This is the density of a Pareto distribution with minimum value 1 and shape parameter $\alpha = 1/\sigma_w$.

If they exist, the moments are given by

$$\begin{aligned}
E(\mathrm{Ms}) &= \frac{\alpha}{\alpha-1} = \frac{1/\sigma_w}{1/\sigma_w - 1} = \frac{1}{1-\sigma_w},\\
\mathrm{Var}(\mathrm{Ms}) &= \frac{\alpha}{(\alpha-1)^2(\alpha-2)} = \frac{1/\sigma_w}{(1/\sigma_w-1)^2(1/\sigma_w-2)}\\
&= \frac{1/\sigma_w}{(1-\sigma_w)^2(1-2\sigma_w)}\cdot\frac{1}{1/\sigma_w^3}\\
&= \frac{\sigma_w^2}{(1-\sigma_w)^2(1-2\sigma_w)} \implies \mathrm{SD}(\mathrm{Ms}) = \frac{\sigma_w E(\mathrm{Ms})}{\sqrt{1-2\sigma_w}}.
\end{aligned}$$

For the median of this Pareto distribution, we have the quantile function

$$Q(p) = \frac{1}{(1-p)^{1/\alpha}} = \frac{1}{(1-p)^{\sigma_w}}, \quad p \in (0,1) \implies \mathrm{med}(\mathrm{Ms}) = 2^{\sigma_w}.$$

B.3 Technical efficiency

Here we have

$$\mathrm{TE} = e^{-u} \implies u = -\ln(\mathrm{TE}) \implies \frac{\partial u}{\partial \mathrm{TE}} = -\frac{1}{\mathrm{TE}}.$$

Then

$$f_{\mathrm{TE}}(\mathrm{TE}) = \frac{1}{\mathrm{TE}}\frac{1}{\sigma_u}\exp\left\{\frac{-1}{\sigma_u}[-\ln(\mathrm{TE})]\right\} = \frac{1}{\sigma_u}(\mathrm{TE})^{1/\sigma_u - 1}.$$

This is the density of a Beta distribution, with parameters $\alpha = 1/\sigma_u$, $\beta = 1$, and applying the moment expression for the specific parameters we obtain

$$\begin{aligned}
E(\mathrm{TE}) &= \frac{\alpha}{\alpha+\beta} = \frac{1/\sigma_u}{1+1/\sigma_u} = \frac{1}{1+\sigma_u},\\
\mathrm{Var}(\mathrm{TE}) &= \frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)} = \frac{1/\sigma_u}{(1+1/\sigma_u)^2(2+1/\sigma_u)}\\
&= \frac{1/\sigma_u}{(1+\sigma_u)^2(1+2\sigma_u)}\cdot\frac{1}{1/\sigma_u^3}\\
&= \frac{\sigma_u^2}{(1+\sigma_u)^2(1+2\sigma_u)} \implies \mathrm{SD}(\mathrm{TE}) = \frac{\sigma_u E(\mathrm{TE})}{\sqrt{1+2\sigma_u}}.
\end{aligned}$$

The quantile function here is

$$Q(p) = p^{1/\alpha} = p^{\sigma_u}, \quad p \in (0, 1).$$

From this we obtain

$$\operatorname{med}(\mathrm{TE}) = 2^{-\sigma_u}.$$

B.4 The management net multiplier

We are examining the random variable $\exp\{z\}$, $z = w - u$, with w, u independent. When they exist, we can obtain the mean and standard deviation of $\mathrm{Mm} = \exp\{w - u\}$ using the moment generating function of the Exponential distribution,

$$\begin{aligned} E[e^{w-u}] &= E[\exp\{w\}] \cdot E[\exp\{-u\}] = \frac{1/\sigma_w}{(1/\sigma_w - 1)} \frac{1/\sigma_u}{(1/\sigma_u + 1)} \\ &= [(1 - \sigma_w)(1 + \sigma_u)]^{-1}. \end{aligned}$$

For the variance, we need

$$\begin{aligned} E[\exp\{z\}^2] &= E[\exp\{2w\} \exp\{-2u\}] = \frac{1/\sigma_w}{(1/\sigma_w - 2)} \frac{1/\sigma_u}{(1/\sigma_u + 2)} \\ &= [(1 - 2\sigma_w)(1 + 2\sigma_u)]^{-1}. \end{aligned}$$

So

$$\operatorname{Var}(\mathrm{Mm}) = [(1 - 2\sigma_w)(1 + 2\sigma_u)]^{-1} - [(1 - \sigma_w)(1 + \sigma_u)]^{-2}.$$

Regarding the median of this distribution, it is a well-known result that the difference of two independent Exponential random variables $z = w - u$ has density

$$f_z(z) = \frac{1}{\sigma_w + \sigma_u} \begin{cases} \exp\{z/\sigma_u\} & z \le 0 \\ \\ \exp\{-z/\sigma_w\} & z > 0\,. \end{cases}$$

This leads to the distribution function

$$F_Z(z) = \begin{cases} \frac{\sigma_u}{\sigma_w + \sigma_u} \exp\{z/\sigma_u\} & z \le 0 \\ \\ 1 - \frac{\sigma_w}{\sigma_w + \sigma_u} \exp\{-z/\sigma_w\} & z > 0\,. \end{cases}$$

For the Mm variable, we have

$$\Pr\left(e^z \le \mathrm{Mm}\right) = \Pr\left(z \le \ln \mathrm{Mm}\right) = F_Z\left(\ln \mathrm{Mm}\right),$$

and so

$$F_{\mathrm{Mm}}(\mathrm{Mm}) = \begin{cases} \frac{\sigma_u}{\sigma_w+\sigma_u}\mathrm{Mm}^{1/\sigma_u} & \mathrm{Mm} \leq 1 \\ 1 - \frac{\sigma_w}{\sigma_w+\sigma_u}\mathrm{Mm}^{-1/\sigma_w} & \mathrm{Mm} > 1\,. \end{cases}$$

The corresponding quantile function is

$$Q_{\mathrm{Mm}}(p) = \begin{cases} \left(\frac{\sigma_w+\sigma_u}{\sigma_u} \cdot p\right)^{\sigma_u} & 0 < p \leq \frac{\sigma_u}{\sigma_w+\sigma_u} \\ \left(\frac{\sigma_w+\sigma_u}{\sigma_w} \cdot (1-p)\right)^{-\sigma_w} & \frac{\sigma_u}{\sigma_w+\sigma_u} < p < 1\,. \end{cases}$$

From this, we can obtain the expression for the median shown in the main text.

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