European Journal of Operational Research 304 (2023) 1256–1268

Contents lists available at ScienceDirect

European Journal of Operational Research

journal homepage: www.elsevier.com/locate/ejor

Innovative Applications of O.R.

Management and takeover decisions

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A R T I C L E I N F O

Article history:
Received 16 February 2022
Accepted 4 May 2022
Available online 8 May 2022

Keywords:
Finance
Management
Bayesian methods
Mergers and acquisitions
Nonlinear models

A B S T R A C T

Firms with good management optimize and synthesize human resources, leadership, and technical and conceptual skills to enhance firm value. In this paper, we examine the role of management in merger and acquisition (M&A) decisions. M&A decisions are among the most important corporate decisions, on which firms spend a lot of resources and managerial qualities. We estimate management as a latent variable using a structural equation production model and Bayesian techniques. The key advantage of the Bayesian approach is the use of informative priors from survey-based management estimation methods, which are however available for a limited number of firms. Subsequently, we examine the effect of management on takeover events. We first show that management, on average, increases the probability of M&A deals. However, we also uncover a nonlinear U-shaped effect, which is consistent with the theoretical premise that poor management leads to many value-decreasing M&A deals, whereas good management leads to many value-increasing M&A deals.

1. Introduction

Mergers and acquisitions (M&As) are among the most important decisions of enterprises. A successful M&A leads to improved productivity and performance, whereas an unsuccessful one leads to chronic operational problems and inferior performance (e.g., Arocena, Saal, Urakami & Zschille, 2020; Chen, Xu & Zou, 2017). Firms spend approximately USD 4 trillion every year in their effort to maximize the firm value via M&As, but 70% of these events do not meet the goals originally set. A recent line of literature (Delis, Iosifidi, Kazakis, Ongena & Tsionas, 2022; references therein) emphasizes the importance of management on the performance of M&As. However, the first key step on M&A value creation is whether and how firms decide on M&As.

Identifying the role of management as a determinant of M&As is a significant, but still unexplored research question. Firms with good management are those that optimize three key characteristics: Human resource management and leadership, technical abilities including human and intellectual capital, and conceptual skills to develop ideas from abstract thoughts (Delis & Tsionas, 2018; Katz, 1974). Thus, we consider management as a general firm-wide concept that effectively encompasses the future position and strategy of the firm; this naturally includes M&A decisions.

We propose that there exist both positive and negative forces in the potential relation between this general notion of good management and the probability of M&A events, implying that the average effect of management on M&As is ambiguous. On the positive side, firms with good management can better distinguish the value-enhancing M&As from the value-decreasing M&As, due to their superior technical abilities and conceptual skills. These firms also have the right human resources, leadership, and technical skills, to organize the new firm post-M&A and smoothly transition to a value-enhancing environment. Thus, firms with good management have incentives to promote expansion via M&As, and are thus more likely to participate in M&As by scrutinizing the market and finding good deals.

On the other hand, some managers may have the mentality of empire building. Such managers acquire firms that do not add synergistic gains to the combined firm, possibly because they prefer growth over value, which might relate to their personal objectives (as opposed to the shareholders' objectives). In turn, such agency problems lead firms with low quality management to also pursue several M&A deals. As management improves, but does not become superior, this potentially negative relation between management and M&A deals weakens, because managers of average quality neither pursue their objectives (thus leading to bad outcomes), nor are they able to identify value-enhancing M&A deals. Taken together, the positive and negative forces might imply a nonlinear U-shaped relation between management and M&A deals.

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https://doi.org/10.1016/j.ejor.2022.05.005
0377-2217/

We examine this hypothesis by first estimating management, using a structural equation model and Bayesian techniques (Delis & Tsionas, 2018; Delis, Iosifidi & Tsionas, 2020). We assume that management is a latent input of production that enters a firm's production function (the first equation of our model) alongside the observed capital and labor (Bloom, Sadun & Van Reenen, 2017; Lucas, 1978). The second equation of the model assumes that management is well-approximated by a sigmoid activation function that follows an artificial neural network process. This approach, which is unique to our paper, allows for a deep-learning process that works very well for gradient-based optimization problems with log-likelihood functions, such as those in our case. Within this approach, the role of priors becomes more important compared to the variables used to approximate management (as is the case in Delis & Tsionas, 2018, who use relatively uninformative priors).

We estimate our two-equation latent variable model using Bayesian analysis, which provides superior inferences in models with latent variables, especially when good priors are available. We obtain information on our priors from the World Management Survey, which estimates management using a state-of-the-art survey of a finite number of firms and reports data on the same variables we have used, to estimate our model. Delis and Tsionas (2018), Delis et al. (2020), and Delis et al. (2022) show that this approach produces estimates of management that fare particularly well in several validation exercises. For inference on our Bayesian estimates, we use Markov Chain Monte Carlo (MCMC), which we implement using the particle Gibbs sampler.

Our analysis covers a panel of about 40,000 firm-year observations over the period 1980–2016, including 15,261 M&A deals. Using such a wide panel would not be an option without estimating management (i.e., relying on survey data). Our management score takes values between zero and one (with a mean value of 0.48) and approximately follows a normal distribution. The annual average of the score is fairly constant, which is intuitive because relative managerial skill does not significantly change over time. The cross-industry variation of our index is also small.

Mergers, according to Jovanovic and Rousseau (2002), act as a conduit for capital to flow to better projects and management. Firms with better management are more likely to acquire firms with poor management. Furthermore, when a company is acquired, the improved management will permeate the entire organization (i.e., the acquirer and target firms). When this happens, the newly formed group of companies will be more efficient in producing the final product. This means that the target's capital, which was previously used inefficiently, will now be used more efficiently, resulting in synergistic gains.

Subsequently, we examine how management affects the probability of M&A deals using logit models. We find that management has, on average, a positive and statistically significant effect on the probability of M&A deals. Economically, however, the effect is smaller than anticipated: a one standard deviation increase in our management score increases the probability of M&As by approximately 0.55%.

We mainly attribute the economically small effect to the potential nonlinearity in the relation between management and M&A deals. Indeed, consistent with our theoretical contemplations on empire-building behavior and agency problems, we find a high probability of M&A deals for low values of management. This relation is negative up to a value of management equal to 0.43, which is between the first and the second quartile of our management score. Above this minimum, the relation turns positive, consistent with our theoretical prediction of more M&A deals for firms with better management.

We delve deeper into this finding and examine if indeed M&A success is the driving force behind the identified nonlinear effect. We assume that better management implies fewer value-destroying M&As (those with negative cumulative abnormal returns) and more value-enhancing M&As (those with positive cumulative abnormal returns). Consistent with this premise, we find a negative (positive) relation of management with the probability of takeover events that destroy (create) value, especially for management scores above the minimum value of 0.43.

Our analysis and results bring together two strands of literature. The first is the operations research literature on management and its estimation. Demerjian, Lev and McVay (2012) use a two-stage data envelopment analysis (DEA) method to decompose firm efficiency into management quality and the remainder efficiency component. Andreou, Ehrlich and Louca (2013) use an equivalent stochastic frontier approach. Delis and Tsionas (2018) and Delis et al. (2020), favor and validate a Bayesian approach that is similar to the one used by us, except for the equation predicting management (for which we use a neural network process).

The second strand of literature includes studies on the intersection between operations research and corporate finance. Most related to our analysis, Bai, Jin and Serfling (2021) show that firms with more specific, formal, frequent, and explicit (i.e., "structured") management acquire firms with less structured management. Our paper extends this research in three important ways. First, we show that a management measure with a panel (firm-year) dimension that can be estimated using only widely available balance sheet data predicts M&As. Most importantly, we provide several novel results, including those on the nonlinear relation; that firms with good general management acquire more and are more likely to be frequent acquirers (again the relation being nonlinear); that firms with better management participate in more events; and that firms with better management are less likely to participate in value destroying M&As based on cumulative abnormal returns.

Our main contribution is to show that management, estimated as a latent variable from existing Bayesian techniques, predicts mergers and acquisitions. Given the scarcity of data on management, Bayesian techniques are ideal for measuring management (and other latent variables). We show that management predicts the frequency of mergers and acquisitions in a nonlinear way that can be explained by standard finance theories (inter alia, the Q-theory of mergers and the theory of empire building).

The rest of the paper is structured as follows. Section 2 provides a definition of management using the management and OR literatures; this section also discusses our Bayesian approach. Section 3 analyzes the effect of management on M&A decisions and discusses the empirical results. Section 4 concludes the paper.

2. Management and its estimation

2.1. Defining management

Management is critical to firm performance. Therefore, measuring the general performance management is important for the relevant literature (e.g., Harris & Holmstrom, 1982; Hietschold, Reinhardt & Gurtner, 2014, Delis et al., 2020; Silva, 2010; Tarí, Molina & Castejon, 2007). Following Lucas (1978), Manne (1965), and Bloom et al. (2017), we argue that management should be regarded as a distinct production factor that influences firm productivity and performance. According to Bloom et al. (2017), management can be viewed as technology in the production function, alongside other technologies, capital, and labor. Management is endogenously driven in their model and acts as a force to increase production by hiring highly skilled workers or improving the firm's organization. Our approach to measuring management is an empirical reflection of this theoretical model (similar to Demerjian et al., 2012 and Koester, Shevlin & Wangerin, 2017; who however rely on linear programming techniques). Finally, from a financial standpoint, good management can be defined as a manager's ability to generate positive synergies through takeover activities by passing on good management to a target firm (e.g., Delis et al., 2022; Jovanovic & Rousseau, 2002).

As a result of standard models of production, our measure of management is broad. We should note that this definition of management and their estimation is not unique in the literature. Several studies in management science differentiate between leadership, operations, and strategy components (distinction first made by Katz, 1974). Empirical studies distinguishing between these aspects require unique (usually survey-based) data that reflect the underlying qualities. In our setting, relating management to the probability of M&As, all three elements encompass important information. First, human resource management and leadership, not only motivate employees, but also interact with different entrepreneurial forces to improve the position of the firm in the corporate world and seek for value-enhancing M&As. Second, technical abilities, which account for the human and intellectual capital that managers at different echelons have about their respective roles can also affect the probability to identify targets. Third, managers with higher conceptual skills are more broad-minded and think about the future position of the firm among its competitors and consumers; thus these skills might also affect M&As.

This definition characterizes a good manager from his/her ability to gather, allocate, and distribute resources and products efficiently, thus being able to increase firm value and the position of the firm in the eyes of its stakeholders (Pasiouras, 2013). Examples are when managerial decisions increase firm sales and revenue from using the same but better allocated inputs, and when competent managers identify or achieve lower debt premiums (Bonsall, Holzman & Miller, 2017). Several studies show that such skills result in higher managerial compensation (e.g., Falato, Li &Milbourn, 2015).

Recent literature on management, especially by Bloom et al. (2017), builds on early models of management, such as Lucas (1978), and shows that apart from labor and capital (including physical and financial capital, R&D expenses, and land), management is an important factor of production and *the one that completes the list*. This theoretical literature shows that management explains large firm productivity differences and operate as a superior technology. Therefore, differences in management between the top and the bottom of the distribution of firms can generate large differences in performance. To this end, we treat management as a missing input of production, the one encompassing these general firm-specific traits.

Our definition of management and its representation as the missing link in the production process is also fully in line with the literature on total quality management (e.g., Prajogo & Sohal, 2006; Tarí et al., 2007) and managerial ability (Delis & Tsionas, 2018; Demerjian et al., 2012; Koester et al., 2017). These studies also reflect the broad firm-level nature of management, including leadership, training, human resource management, information and analysis, supplier and process management, and continuous improvement. Notably, these are dynamic characteristics that can drastically change with time, although they also present large cross-firm heterogeneity.

2.2. Measuring management

We focus on measures of management that explicitly reflect the literature's broad definition at the firm-level. Part of this literature uses production functions and frontier techniques (data envelopment analysis or stochastic frontiers). Demerjian et al. (2012) introduce a measure of managerial ability, by measuring the managers' efficiency compared to that of their industry peers. They assume that management is the only missing input of production — our analysis follows the same premise. To measure efficiency, they use standard data envelopment analysis (DEA), differentiating between the elements of efficiency that can be directly affected by managers and those that are outside the management's reach. A manager is assumed to be more efficient when she is better able to transform corporate resources to revenues.

Several studies have utilized the dataset provided by Demerjian et al. (2012) either as a key explanatory variable, or a control in their analysis. Among others, Bonsall et al. (2017) look at how managerial ability correlates with credit risk assessment; Chang, Hayes and Hillegeist (2016) study how the risk of financial distress affects the compensation of new CEOs; and Koester et al. (2017) study the relation between managerial ability and corporate tax avoidance.

Other research uses stochastic frontier analysis (SFA) instead of DEA. Andreou et al. (2013) use this model to estimate management and study the relation between managerial ability and firm performance. Bonin, Hasan and &Wachtel (2005) study bank performance in transition countries, while Tabak and Tecles (2010) look at the Indian banking system. Finally, Sueyoshi (1994) uses this method to measure performance in public telecommunications. A good reference comparing the SFA and DEA methods is Wu, Zhou and Birge (2011).

Other studies in operations management and economics rely on survey data to measure management. A naturally related concept in the operations management literature is total quality management (TQM), which has emerged as a key tool to help firms boost their activities and performance (Powell, 1995). The TQM literature argues that higher-quality management translates into lower costs, increases productivity, and eventually yields higher competitiveness for a firm (Deming, 1982; Hendricks & Singhal, 1997; 2001). The role of well-designed surveys is the key to the proper measurement of TQM instruments (e.g., Flynn, Schroeder & Sakakibara, 1994, Prybutok & Ramasesh, 2005, Tarí et al., 2007). Similarly, a prominent example in the economics literature is that of Bloom and Van Reenen (2007 & 2010) and their World Management Survey (WMS). Using surveys is very important to assess management and its components. Our approach provides a viable alternative for the measurement of general management, which relies on simple balance sheet data. Another issue is that the questions used to infer management may not be appropriate in all circumstances and all types of firms. This may add measurement error.

We opt for a measure of management that combines both theoretical and empirical advantages. Our management score is not TFP. This is due to the structural model we have chosen that distinguishes the error term in Eq. (1) below.[1] Delis and Tsionas (2018) and Delis et al. (2020), specifically propose a model with management as a latent input of production, estimated with Bayesian techniques. From a theoretical viewpoint and consistent with the seminal literature discussed above, management is the sole missing input of production (Andreou et al., 2013; Bloom et al., 2017; Demerjian et al., 2012; Lucas, 1978). Further, the stochastic nature of this model effectively separates management from other unobserved components of the production process; this is the key advantage of this model over DEA. From an empirical viewpoint, the key advantage of this technique is that it only requires widely available accounting data on inputs and outputs. As most firms provide such information, we can measure management for a far larger number of firms, compared to the survey methods. In addition, Delis and Tsionas (2018) validate their measure against the state-of-the-art measures of management in the World Management Survey and with Monte Carlo simulation techniques. They show that their measure performs better than the previous math-

[1] We have also calculated TFP using standard methods and included it as a control in our baseline model. We found no change in our primary findings. Results are in Appendix Table A1.

Table 1
Variable definitions for the estimation of management.

Variable	Description
Output	
Sales	Sales (log in millions of dollars)
Inputs	
PPENT	Net property, plant, and equipment (log in millions of dollars)
EMP	Number of employees (log in thousands)
CINVT	Cost of inventory (log in millions of dollars)
NOL	Net operating leases (log in millions of dollars). We construct this as in Demerjian et al. (2012) and use firms' footnotes in Compustat to calculate the discounted present value of future (five years) operating lease payments. The Compustat items for the five lease obligations are MRC1-MRC5, and we use a discount rate of 10% in accordance with previous studies.

ematical methods measuring management, and is more direct in capturing the actual management and not the other latent characteristics of the firm, such as firm culture.

The model includes the following production function:

$$\ln(q_{it}) = \beta_0 + \beta_k \ln(k_{it}) + \beta_l \ln(l_{it}) + \beta_m \ln(m_{it}) + \frac{1}{2}\beta_{kk} \ln(k_{it})^2 + \frac{1}{2}\beta_{ll} ln(l_{it})^2 + \frac{1}{2}\beta_{mm} \ln(m_{it})^2 + \beta_{kl} \ln(k_{it}) \ln(l_{it}) + \beta_{km} \ln(\mathrm{k_{it}}) \ \ln(m_{it}) + \beta_{lm} \ln(l_{it}) \ln(m_{it}) + u_{it}. \quad (1)$$

In Eq. (1), q denotes the output of firm i in year t; k, l, and m, denote capital, labor, and management (the inputs of the production function), and u is an error term. We use a translog specification because of its flexibility and linearity in parameters (Greene, 2008).

Although all other variables are observed and can be measured, management is a latent variable. We measure q, k, and l using standard Compustat entries for the period 1980–2016. We measure q with the log of sales. For k we use core capital (net property, plant, and equipment), but also the cost of inventory and net operating leases (all variables in logs). For l we use the number of employees. We provide thorough definitions in Table 1.

For management m, we assume:

$$m_{it} = \sum_{g=1}^{G} \gamma_g \phi\left(a_g + x'_{it}\beta_g\right) + v_{it,2}, \quad i = 1, \ \ldots, \ n, \quad t = 1, \ \ldots, \ T. \quad (2)$$

In Eq. (2), $\phi(z) = \frac{1}{1+e^{-z}}, \ z \in \mathbb{R}$,is a sigmoid activation function that follows an artificial neural network process with G nodes. We choose a sigmoid function due to its good properties and fit in our model. First, a sigmoid function is differentiable and monotonic. Second, a sigmoid function works very well for gradient-based optimization problems with log-likelihood functions (see also Goodfellow, Bengio, Courville & Bengio, 2016), such as the ones in our case. Essentially, this approach allows for a deep learning process that places significant weight on the informative priors discussed below for the determination of m in Eq. (2) vis-à-vis the variables in x. This is the key difference of our paper, when compared with that of Delis and Tsionas (2018).

Following Delis and Tsionas (2018), we assume that management in Eq. (2) is approximated by lagged values of all inputs and the current value of labor. Practically, we contend that when inputs are used in optimal quantities and allocated efficiently, management quality is higher. Therefore, the assumption here is that management lies in the optimal use of a pre-specified vector of inputs, to maximize an output variable. The word optimal, as in Delis et al. (2020), "refers to both the absolute and the relative input quantities." We also include the price of labor as an input following governance literature, which finds a positive correlation between ability and human capital (e.g., Custódio, Ferreira & Matos, 2013). Identification through input prices has a long tradition in the production economics literature (e.g., Nevo, 2001). In our case, we assume the labor market is fairly competitive so the price of labor can be a valid instrument (Ackerberg, Caves & Frazer, 2006; Delis & Tsionas, 2018).

Eventually, Eqs. (1) and 2 determine a structural equation model (SEM), with management as a latent variable. To estimate this model, we use Bayesian techniques, which are optimal in SEMs with latent variables (e.g., Kaplan & Depaoli, 2012; Van de Schoot et al., 2014). This is because Bayesian analysis considers uncertainty by its nature and, using informative priors, can better approximate latent variables compared to the standard frequentist SEM estimation.

Scale parameters for the Bayesian estimation follow a proper prior of the form $p(\sigma) \propto \sigma^{-(\bar{n}+1)} \cdot \exp(-\frac{\bar{q}}{2\sigma^2})$.We use the following prior for our parameters: $\alpha_g, \ \beta_g, \ \gamma_g \sim iid \ N(0,1), \frac{\bar{q}}{\sigma_2^2} \sim \chi^2_{\bar{n}}$. We also assume that $\bar{n} = 50$ and $\bar{q} = 10$. This would mean that in a fictitious sample of size 50 (denoted be $\bar{n}$), σ_2^2 would be on average 1/5. We do not randomly select these priors: we choose them based on the characteristics of the variables in the WMS database.

Our management score does not measure structured management but general management, as the model we use is a result of standard economic theory. Although we use the WMS survey, which concerns structured management, this is only to feed the Bayesian algorithm with priors so that it converges faster to the posterior distribution—in large samples like ours, priors would not make much difference (Depaoli, Winter & Visser, 2020). Albeit our management score is general, we consider that structured management will be part of it.

For inference, we use Markov Chain Monte Carlo (MCMC), and we implement it using particle Gibbs sampling, which increases efficiency (Andrieu, Doucet & Holenstein, 2010; Gelfand, Hills, Racine-Poon & Smith, 1990). Specifically, the advantage of this algorithm is its ability to draw paths of the state variables in large blocks. This simulation-based algorithm approximates continuous and marginal distributions with discrete distributions (Creal, 2012). Then, the particle Gibbs sampler uses a discrete approximation to draw a single path for the latent or state variables. When the number of particles reaches infinity, the particle Gibbs sampler is practically drawing from the full conditional distribution.

The study by Creal and Tsay (2015) is a good source for this procedure. Assume that the posterior is $p(\theta, \ \lambda_{1:T}|\boldsymbol{y}_{1:T})$, with $\lambda_{1:T}$ denoting any latent variable whose prior is $p(\lambda_t|\lambda_{t-1}, \ \theta)$. We use the particle Gibbs sampler to draw the structural parameters $\theta|\lambda_{1:T}, \boldsymbol{y}_{1:T}$ from the posterior conditional distributions. Assume that in an iteration process we get the value $\lambda^{(1)}_{1:T}$. We then apply a particle filtering procedure that consists of two phases. We describe the algorithm in each phase below.

First phase: forward filtering (see also Andrieu et al., 2010).

- Draw a proposal $\lambda^{(m)}_{it}$ from an importance density $q(\lambda_{it}|\lambda^{(m)}_{i,t-1}, \ \theta), \ m = 2, \ \ldots, \ M.$

- Compute the importance weights:

$$w_{it}^{(m)} = \frac{p\left(y_{it};\ \lambda_{it}^{(m)},\ \theta\right)p\left(\lambda_{it}^{(m)}|\lambda_{i,t-1}^{(m)}\theta\right)}{q\left(\lambda_{it}|\lambda_{i,t-1}^{(m)},\theta\right)},\ m=1,\ldots,M.$$

- Normalize the weights in the following manner: $\tilde{w}_{it}^{(m)} = \frac{w_{it}^{(m)}}{\sum_{m'=1}^{M} w_{it}^{(m')}}$, $m=1,\ \ldots,\ M.$
- Do a particle resampling of $\{\lambda_{it}^{(m)},\ m=1,\ldots,\ M\}$ with probabilities $(\tilde{w}_{it}^{(m)},\ m=1,\ \ldots,\ M)$.

The original PG sampler stores values for $t=1,\ \ldots,\ T$ and a trajectory is sampled based on the probabilities of the last iteration. There is, however, an improvement on the aforesaid algorithm of the particle Gibbs sampler proposed by Whiteley (2010). He suggests drawing the path of the latent variables from the particle approximation, following the backward filtering procedure of Godsill, Doucet and West (2004). This can be described as follows:

Second phase: backward filtering (Chopin & Singh, 2015; Godsill et al., 2004).

- At $t=T$ draw a particle $\lambda_{iT}^{*} = \lambda_{iT}^{(m)}$.
- Compute the backward weights: $\tilde{w}_{t|T}^{(m)} = \frac{w_{t|T}^{(m)}}{\sum_{m'=1}^{M} w_{t|T}^{(m')}}$, $m = 1,\ \ldots,M.$
- Draw a particle $\lambda_{it}^{*} = \lambda_{it}^{(m)}$ with probability $\tilde{w}_{t|T}^{(m)}$.

Notice that following the process described above, $\lambda_{i,\ 1:T}^{*} = \{\lambda_{i1}^{*},\ \ldots,\ \lambda_{iT}^{*}\}$ is a draw from the full conditional distribution. The second step is a fast and efficient procedure, but still requires to select the importance density $q(\lambda_{it}|\lambda_{i,t-1},\theta)$. Herein, we use the following importance density: $\lambda_{it} = \alpha_{it} + \sum_{p=1}^{P} b_{it}\lambda_{i,t-1}^{p} + h_{it}\xi_{it}$, with ξ_{it} following a Student-t distribution with five degrees of freedom. For $\lambda_{i,t-1}$ we use polynomials of order P.We choose polynomials because they are easier when dealing with approximations of probability density functions (see among others Badinelli, 1996; Eubank & Speckman, 1990). In the burn-in phase, we choose the parameters α_{it}, b_{it}, and h_{it}. Here we assume $P=1$ and $P=2$. We do this because we prefer to have the weights $(w_{it}^{(m)},\ \tilde{w}_{t|T}^{(m)})$ close to a uniform distribution. Importantly, Chopin and Singh (2015) show that the sampler is uniformly ergodic and that backward sampling is more efficient asymptotically. Importantly, even in cases where the state vector is large, we can still recover the full conditional distribution.

According to Geweke (1992), the main problem of the Gibbs sampler is that the sequences produced are neither independent nor identically distributed. The author introduces a method to deal with this problem, which is computationally efficient and provides the convergence criteria (converge diagnostics). In practical terms, one has to compare the last half of the chain that has converged, with a smaller interval of the chain in the beginning, utilizing the spectral density estimation. In our study, the Gibbs sampler runs for 150,000 iterations, with the first 50,000 being burnt-in to avoid any start-up effects. Convergence is achieved and verified via Geweke's (1992) criterion and autocorrelation in MCMC never exceeds 0.4 in our setting.

We report estimation results in both numerical and graphical forms. We first report the distributional characteristics of the measure in Table 2. The variable takes values from 0 to 1. The bottom 5% has a value of 0.31, while the top 5% a value of 0.66. The cases where the management score takes values above 0.75 are rare. With regard to the properties of the density function, we see that the skewness is small and kurtosis is around three, which implies that the distribution of the management score resembles a normal distribution. Fig. 1 shows the density.

Table 2
Distributional characteristics of the management score.

	Percentiles	Smallest		
1%	0.23	0		
5%	0.31	0.02		
10%	0.35	0.06	Mean	0.48
25%	0.41	0.06	Std. Dev.	0.11
50%	0.48	Largest	Variance	0.01
75%	0.56	0.93	Skewness	0.03
90%	0.62	0.94	Kurtosis	3.01
95%	0.66	0.95		
99%	0.74	1		

3. Management predicting M&A decisions

3.1. M&A sample and empirical model

To construct the M&A sample, we follow the standard filters described in Fuller, Netter and Stegemoller (2002) and used in many other studies that predict M&A decisions. Specifically, (i) the acquiring company has to be a U.S. publicly listed corporation, and the target can be either a public, private, or subsidiary U.S. company; (ii) the acquisition must be complete; (iii) the acquirer must own less than 50% of the target company before the acquisition, although it wholly owns it afterward; (iv) the transaction is at least 1% of the acquiring company's market capitalization 11 days before the announcement and it is more than \$1 million; and finally, (v) we drop all deals that occur on the same day for the same acquirer.

Following the above filtering process, we find 15,261 takeover events for the period 1980–2016. The number of observations is larger because we use a firm-year panel (there are years without events). We end up with a panel of about 40,000 firm-year observations. Table 3 defines the variables used in our M&A analysis and provides their sources. We report the relevant summary statistics in Table 4.

Before moving on to the empirical section, we show correlations between the management score and several variables. In comparison to Demerjian et al. (2012), who estimate managerial ability using standard DEA methods, we find lower correlations with some variables. We used the most recent data from Kogan et al. (2017) to calculate patents per worker. Anderson, Duru and Reeb (2009) and Anderson, Reeb and Zhao (2012) provide the data on family ownership and dual class structure. The correlations are positive for firm outcomes such as employment, employment growth, and return on assets. The family ownership correlations show both positive and negative signs. We see that firms with a higher management score are more likely to have family members owning more than 5% of the company's stock. Firms with better management, on the other hand, are less likely to have dual shares. Table 5 displays the results.

To examine the effect of management on the probability of takeover events, we use the following logit model:

$$P(Y=1|\boldsymbol{X}) = \frac{\exp\left(\beta^{T}\boldsymbol{X}\right)}{1+\exp\left(\beta^{T}\boldsymbol{X}\right)}. \tag{3}$$

In Eq. (3), Y is the dependent variable that takes the value one if there is a takeover event and zero otherwise. $\boldsymbol{X}$ denotes the explanatory variables, including management. We use two more dependent variables, i.e., the probability of being a frequent acquirer and the number of acquisitions in a year (full definitions in Table 3). For the last case, we use a negative binomial model to account for the fact that we have large clusters with zero values when no takeover events occur; that is, we have overdispersion (Cameron & Trivedi, 2013; Statacorp, 2017). In brief, assume that for a count variable y_j the Poisson distribution takes the form

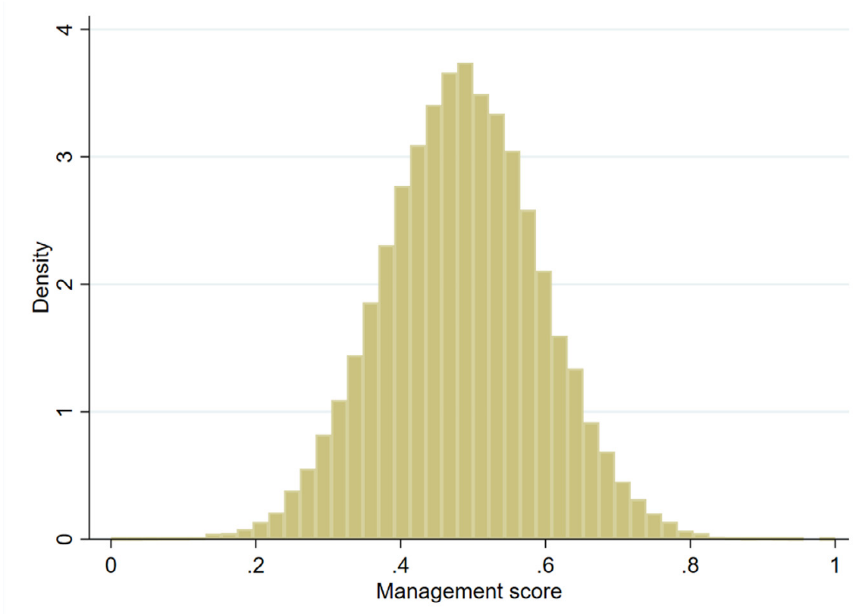

Fig. 1. Graphical illustration of management scores density function.

Table 3
Variable definitions and sources for the M&A sample
The table defines the variables used in the M&A empirical analysis. The source for the M&A variables is Thomson One Banker. The source for the firm characteristics is Compustat. For ease of replicability, we include the Compustat codes in parentheses.

Variable	Description
M&A event	An indicator variable that takes value one if a firm has announced at least one M&A event in a specific year.
Frequent acquirer	An indicator variable that takes value one if a firm has acquired at least five firms within a period of three years.
Number of annual events	The total number of M&A events in a specific year.
Log assets	Firm assets (Compustat item AT) in logs.
Leverage	Firm leverage. This is calculated as (DLC + DLTT)/AT.
PPE	Property, plant, and equipment (scaled). This variable is calculated as PPENT/AT.
Taxes	Amount of taxes paid by a firm. This variable is calculated as TXT/PI.
ROA	Earnings before interest and taxes divided by total assets. This variable is calculated as EBIT/AT.
Intangibles	Firm intangibles (scaled). This variable is calculated as INTAN/AT.
Cash	Cash and short-term investments. This variable is calculated as CHE/AT.
Tobin's q	This variable denotes the Tobin's q for a firm. It is calculated as (AT + CSHO*PRCC_F - CEQ)/AT.
Stock return	This variable denotes the stock return of a firm. It is calculated as: (PRCC_F(t)/AJEX(t) + DVPSX_F(t)/AJEX(t))/(PRCC_F(t-1)/AJEX(t-1)).
Net profit margin	This variable measures a firm's net profit margin and is calculated as NI/SALE.
MB	This variable denotes the market-to-book ratio. It is calculated as CSHO*PRCC_F/CEQ.
Demerjian et al. score	This variable uses the managerial ability score provided by Peter Demerjian. The link with the data is the following: https://peterdemerjian.weebly.com/managerialability.html

Table 4
Summary statistics.

	Obs.	Mean	St. dev.	Min.	p25	Median	p75	Max.
Sales	47,188	5.750	2.122	−6.908	4.349	5.724	7.159	13.089
PPENT	47,188	3.996	2.446	−6.215	2.295	3.926	5.680	12.146
EMP	47,188	1.669	1.454	0.001	0.412	1.277	2.587	8.434
CINVT	47,188	3.516	2.556	0.000	1.132	3.639	5.440	11.775
NOL	47,188	3.247	1.919	−0.219	1.755	3.112	4.552	10.177
Management	47,188	0.484	0.109	0.000	0.411	0.485	0.558	1.000
Demerjian et al. score	41,962	0.309	0.152	0.004	0.225	0.271	0.349	1.000
M&A event	47,188	0.171	0.376	0.000	0.000	0.000	0.000	1.000
Frequent acquirer	8722	0.196	0.397	0.000	0.000	0.000	0.000	1.000
Number of annual events	69,637	0.225	0.646	0.000	0.000	0.000	0.000	9.000
Log assets	47,188	5.641	2.128	−2.235	4.161	5.576	7.075	11.882
Leverage	47,188	0.233	0.243	0.000	0.040	0.194	0.345	3.500
PPE	47,188	0.256	0.213	0.000	0.091	0.194	0.360	0.945
Taxes	47,188	0.253	0.317	−1.352	0.107	0.340	0.395	1.310
ROA	47,188	0.025	0.277	−7.371	0.002	0.065	0.124	0.421
Intangibles	47,188	0.140	0.176	0.000	0.000	0.066	0.217	0.735
Cash	47,188	0.169	0.198	0.000	0.026	0.087	0.244	0.970
Tobin's q	39,535	1.958	1.791	0.475	1.132	1.484	2.157	66.674
Stock return	39,535	1.205	0.662	0.098	0.827	1.094	1.408	4.810
Net profit margin	39,535	−0.176	2.528	−52.697	0.003	0.039	0.080	1.000
MB	39,535	2.831	4.913	−30.351	1.238	1.997	3.331	43.642

Table 5
Correlations
This table shows correlations of the management score with several variables. *Employment* denotes the number of employees. *Sales/employment* is the ratio of Compustat items SALE and EMP. *Revenue/employment* is the ratio of Compustat items REVT and EMP. *R&D/employment* is the ratio of Compustat items XRD and EMP. *Sales growth* equals $(SALE_t - SALE_{t-1})/SALE_{t-1}$. *ROA* is the ratio EBIT/AT (from Compustat). *ROE* is the ratio NI/AT (from Compustat). *ROS* is the ratio NI/REVT (from Compustat). *Foreign income/Total income* equals PIFO/NI (from Compustat). *TFP* is the residual obtained from the estimation of a production function. *Patents per worker* is the ratio of the Kogan, Papanikolaou, Seru and Stoffman (2017) patent data and Compustat item EMP. *Fam_firm5* is an indicator taking value 1 if a family owns at least 5% of the shares of a firm. *Firm_dual_class* is an indicator taking value 1 if the firm has a dual class structure.

Employment	0.002
Sales/employment	0.0006
Revenue/employment	0.0008
R&D/employment	0.0018
Sales growth	0.0032
ROA (return on assets)	0.0024
ROE (return on equity)	0.0026
ROS (return on sales)	0.0047
Foreign income/Total income (pretax)	−0.0006
TFP	−0.0007
Patents per worker	−0.0047
Fam_firm5	0.0119
Firm_dual_class	−0.0002

$Y_j \sim \text{Poisson}(\mu_j^*)$, where $\mu_j^* = \exp(\boldsymbol{x_j\beta} + offset_j + \nu_j)$. In a Poisson regression, *offset* is the variable that denotes the exposure period. We denote other covariates with $\boldsymbol{x}$. The omitted variable, ν_j, is such that $e^{\nu_j} \sim \text{Gamma}(\frac{1}{a}, a)$. In this case, α is the overdispersion parameter. Here, we assume that $\alpha = \ln(a)$ and that $\ln(\alpha_j) = \boldsymbol{z_j\gamma}$, with $\mathbf{z}$ being the vector of covariates.

3.2. Empirical results

Table 6 reports marginal effects at means and t-statistics from the estimation of Eq. (3). The first two regressions show results for the probability of the M&A to occur, and *Management* carries a positive and statistically significant marginal effect. Albeit statistically significant, economically the effect is not particularly large: a one standard deviation increase in *Management* (equal to 0.11), increases the probability for an M&A to occur by 0.55% (according to specification 2). We must note, however, that in the literature predicting M&As, the explanatory variables have particularly low predictability, as is also evident in the low R-squared (e.g., Golubov, Yawson & Zhang, 2015; references therein). Moreover, the economically relatively weak effect might be due to the nonlinear U-shaped effect of management on M&A deals. Albeit the coefficient between management and M&As might seem small, the value creation or destruction during M&A events can be particularly high. As such, even a relatively small coefficient implies many millions of dollars of value creation or value destruction. The reason is that a few good deals might help a firm grow much faster in the future meaning that one should not only look at short-term gains but also consider long-term gains, such as long-term investment, goodwill, etc.

In specifications 3 and 4 we use the probability of being a frequent acquirer as the dependent variable. The premise is that firms with better management will take up more value-enhancing M&A opportunities and become frequent acquirers. Intuitively, we find results that are economically more significant: a one standard deviation increase in *Management*, increases the probability that a firm is a frequent acquirer by approximately 1% (according to specification 4). Moreover, in columns 5 and 6, we use the Number of annual events as the dependent variable, and we estimate a negative binomial regression (as noted in Section 3.1). The results in column 6 show that a one standard deviation increase in *Management*, increases the number of annual events by approximately 0.05 events, which corresponds to a 22% increase for the firm with an average *Number of annual events* (equal to 0.225).

Given that our management score represents a relatively new endeavor to measure managerial quality, we also examine how our findings fare against DEA methods. To this end, we use the Demerjian et al. (2012) measure of management quality, directly taken from Peter Demerjian's website. This method disentangles management quality from total efficiency by regressing the efficiency scores derived from a standard DEA model on several covariates that reflect firm characteristics which managers cannot affect. The DEA model is the following:

$$\max_{\nu} \theta = (Sales) \cdot (\nu_1 COGS + \nu_2 SG\&A + \nu_3 PPE + \nu_4 OpsLease + \nu_5 R\&D + \nu_6 Goodwill + \nu_7 OtherIntan)^{-1}, \quad (4)$$

where θ denotes firm efficiency; *COGS* is the cost of inventory; *SG&A* advertising expenditure; *PPE* property, plant, and equipment; *OpsLease* net operating leases; *R&D* net research and development; *Goodwill* purchased goodwill; and *OtherIntan* other intangible assets. The authors estimate DEA efficiency by Fama-French industries, aiming for firms to have similar business models. Next, they use Tobit regression:

$$\begin{aligned} Firm\ Efficiency_i = {} & \alpha + \beta_1 \ln(Total\ assets)_i + \beta_2 Market\ Share_i \\ & + \beta_3 \mathbb{I}(Free\ Cash\ Flow_i > 0) + \beta_4 ln(Age)_i \\ & + \beta_5 Business\ Segment\ Concentration_i \\ & + \beta_6 Foreign\ Currency\ Indicator_i + Year_i + \epsilon_i. \end{aligned} \quad (5)$$

The residual from Eq. (5) constitutes their managerial ability score.

We report marginal effects and t-statistics in Table 7. The results confirm those of Table 6, showing a positive and statistically significant effect of managerial ability on the probability of M&As.[2]

In our analysis so far, we have assumed that the relation between management and M&As is linear. Although linear models allow for an easy interpretation of the findings, they may be less precise, and more advanced functional forms may be needed to achieve a better fit for the data (e.g., Chu & Zhang, 2003; Qin, Huang, Zeng, Chakma & Huang, 2007).

Theoretical and empirical evidence in corporate finance shows that very bad managers deplete firm value while good managers increase it. As a result, very low management scores capture poor-quality managers who are more likely to make decisions that harm shareholders, such as empire building through M&As (see e.g., Chatterjee, Hasan, John & Yan, 2021; Gantchev, Sevilir & Shivdasani, 2020; Jensen, 1986; Moeller, Schlingemann & Stulz, 2005). As the management score rises, we encounter managers who are neither bad nor stellar, and thus the impact of their actions on the firm is minimal; they do not participate in as many M&As, even if the deals are good. As we progress, we reach the level of stellar managers who initiate and execute successful M&A deals (Jovanovic & Rousseau's, 2002). Therefore, a nonlinear model is appropriate in this case because the relationship between management and M&As is governed by the aforesaid opposing forces.[3]

[2] Albeit the standard DEA measures yield qualitatively similar results, Delis and Tsionas (2018) and Delis et al. (2020) suggest that their correlation with the state-of-the-art measures of management provided in the WMS surveys for a limited number of firms is low. The reasons may be that the list of firm characteristics that managers cannot influence is non-exhaustive and many of these are unobserved (thus erroneously captured by the management score). Delis and Tsionas show that the Bayesian method used in this paper, compares significantly better to the WMS scores, while it is also validated by the formal Monte Carlo methods.

[3] We also perform a likelihood ratio test, comparing the linear model with the nonlinear model. For the null hypothesis that the linear model is appropriate, we obtain a chi of 8.23 and a p-value of 0.0041, indicating that between the two models, the nonlinear one is better at explaining the relationship at hand.

Table 6
Management and M&As
The dependent variable in columns (1) and (2) is an indicator taking value one if an M&A event is observed and zero otherwise. In columns (3) and (4) the dependent variable is an indicator taking value one when an acquiring firms has made at least five acquisitions within a three-year period. Finally, in columns (5) and (6) the dependent variable is the number of M&A events for each firm in each year. Coefficients show marginal effects for the case of (panel) logit models. Standard errors for the panel logit use the observed information matrix when calculated, while they are clustered at the acquirer's level for the case of the logit and negative binomial models. We show t-statistics in parentheses. The logit model includes year and Fama-French 12 fixed effects. Table 1 shows the definitions of variables used to measure management scores. Table 3 shows the definitions of the control variables. Stars, ***, **, and *, indicate significance levels at the 1%, 5%, and 10%, respectively.

Dependent variable Estimation method	M&A event Panel logit		Frequent acquirer Logit		Number of annual events Negative binomial	
	(1)	(2)	(3)	(4)	(5)	(6)
Management	0.051**	0.050**	0.092**	0.101**	0.276**	0.422***
	(2.54)	(2.27)	(2.10)	(2.26)	(2.11)	(2.85)
Log assets	0.035***	0.026***	0.004	0.004	0.104***	0.125***
	(14.06)	(9.36)	(0.82)	(0.79)	(8.35)	(9.50)
Leverage	−0.217***	−0.260***	0.057*	0.090**	−0.382***	−0.472***
	(−8.40)	(−7.53)	(1.69)	(2.13)	(−4.04)	(−3.53)
PPE	−0.001	0.016	0.147***	0.133***	0.604***	0.688***
	(−0.03)	(0.38)	(2.97)	(2.65)	(3.52)	(4.44)
Taxes	0.010	0.004	−0.006	0.003	0.058	0.028
	(1.17)	(0.42)	(−0.25)	(0.12)	(0.66)	(0.28)
ROA	0.173***	0.188***	0.058*	0.011	0.766***	0.745***
	(8.24)	(6.59)	(1.93)	(0.16)	(4.82)	(5.32)
Intangibles	−0.016	0.043	0.383***	0.393***	1.683***	1.977***
	(−0.54)	(1.26)	(7.99)	(7.68)	(11.73)	(12.73)
Cash	0.226***	0.249***	0.031	0.011	1.051***	0.877***
	(9.64)	(8.04)	(0.64)	(0.19)	(8.77)	(6.06)
Tobin's q		0.006***		0.003		0.031***
		(2.83)		(0.95)		(2.94)
Stock return		0.020***		0.033***		0.221***
		(5.04)		(4.48)		(8.63)
Net profit margin		0.005**		0.018		0.039***
		(2.33)		(1.15)		(3.89)
MB		0.001		−0.000		−0.005
		(0.77)		(−0.14)		(−1.23)
Observations	47,188	39,535	8722	7093	69,637	59,781
Pseudo R^2	0.025	0.025	0.181	0.192	0.06	0.041
Log-likelihood	−14,605.4	−12,333.8	−3529.8	−2861.6	−36,909.4	−31,266.8

Table 7
Management measured with DEA methods and M&A events
This table replicates table 6's models shown in columns (1) and (2), but instead of using the management score calculated with Bayesian methods, we use the DEA-based Demerjian et al. (2012) scores. The estimation method is panel logit and we report marginal effects. The dependent variable is an indicator taking value one if an M&A event is observed. Standard errors use the observed information matrix when calculated. We show t-statistics in parentheses. Table 1 shows the definitions of variables used to measure management scores. Table 3 shows the definitions of the control variables. Stars, ***, **, and *, indicate significance levels at the 1%, 5%, and 10%, respectively.

	(1)	(2)
Demerjian et al. score	0.145***	0.109***
	(5.89)	(3.57)
Controls	Same as column 1, Table 6	Same as column 2,Table 6
Observations	41,962	35,207
Pseudo R^2	0.027	0.025
Log-likelihood	−13,029.5	−11,029.6
χ^2	734.92***	574.20***

We report results testing this hypothesis in Table 8, where we additionally include the squared term of management. Consistent with our hypothesis, we observe that the coefficient on the level term is negative and the coefficient on the squared term is positive; both are statistically significant. Setting $\frac{\partial M\&A\ event}{\partial Management\ \ practices} = 0$ yields a minimum equal to 0.43, at which point the effect of management on the M&A event turns positive (based on the results of specification 2). We illustrate this U-shaped relation in Fig. 2. Fig. 2a precisely reflects the nonlinear U-shaped effect: the left-hand side shows a negative relation between management and an M&A event for lower scores of management (approximately up to 0.43) and the right-hand side shows a positive relationship (from 0.43 onward).[4]

[4] We have also tried with a specification where we included CEO incentives as additional control variables. Our main results, found in Appendix Table A3, remain intact.

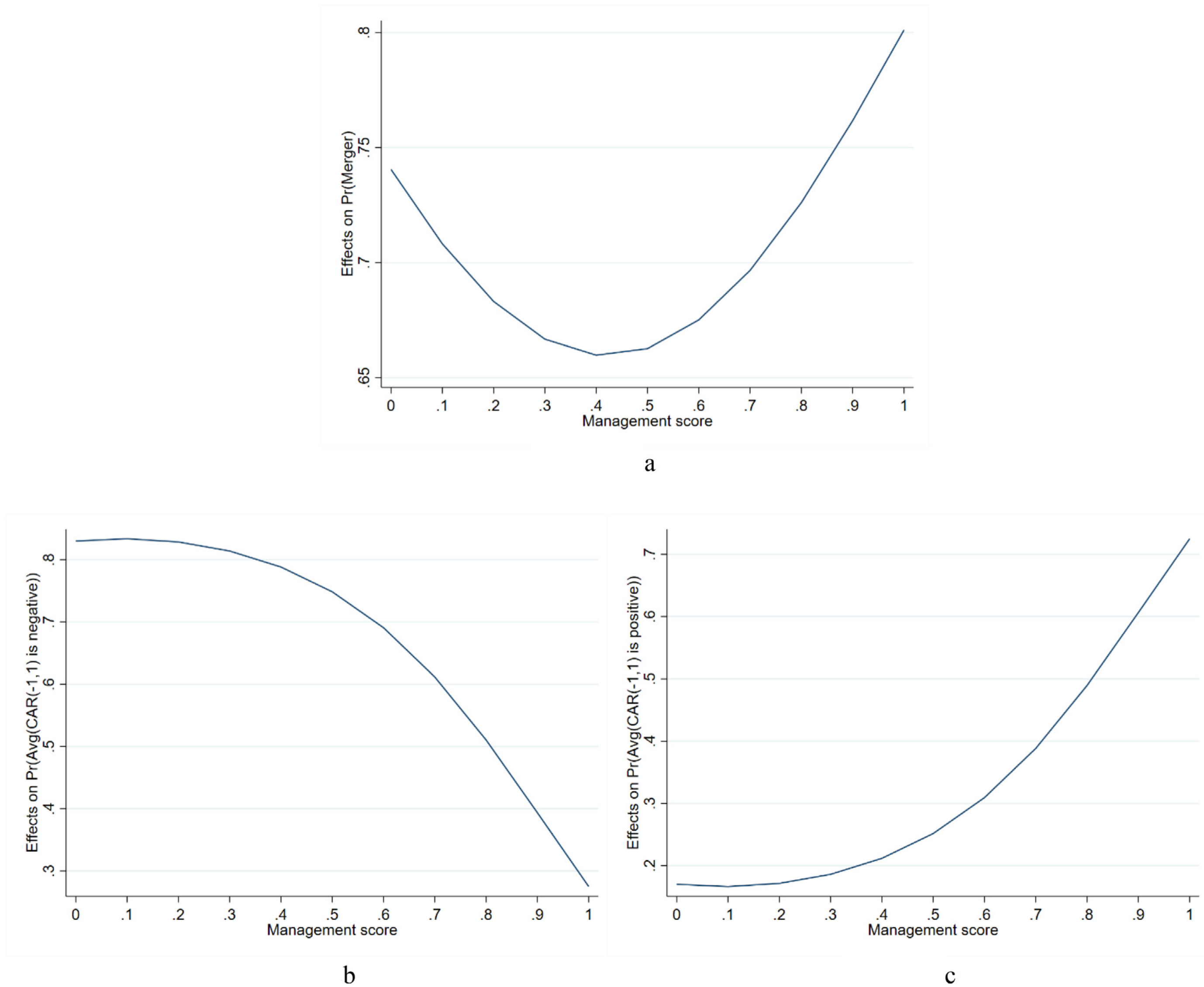

Fig. 2. Graphical illustration of management's non-linearities on takeover events
The top panel (Fig. 2a) shows graphically the effect of management non-linear effects on the probability of a merger event. The bottom panel from the left (Fig. 2b), shows the effect of management non-linear effects on the probability of a merger that destroys firm value (negative CAR), and the bottom panel from the right (Fig. 2c), shows the effect of management non-linear effect on the probability of a merger that creates firm value (positive CAR).

To disentangle the two opposite effects, we next examine the role of the M&A success. We expect that better management implies fewer M&As that destroy value and more M&As that create value. We use cumulative abnormal returns (CAR) with a one-day window, to categorize events into value-enhancing and value-destroying. To calculate cumulative abnormal returns, we first define abnormal returns as: $AR_{it} = R_{it} - \mathbb{E}(R_{it})$, with AR_{it} being the abnormal returns for firm i at time t, R_{it} the actual return for firm i at time t, and $\mathbb{E}(R_{it})$ the expected return for firm i at time t. The CAR is then calculated as $CAR(t_1, t_2) = \sum_{t=T_1}^{T_2} AR_{it}$. In our case $T_1 = -1$ and $T_2 = 1$, with $\tau = 0$ indicating the event date.

Fig. 2b shows a negative relation of management with the probability of takeover events that destroy value. This effect especially holds for scores of management above the optimal value of 0.43, identified in the results of Table 8 (beyond this score, the slope of the negative relation becomes considerably steeper). In contrast, Fig. 2c shows a positive relation between management and the probability of value-enhancing takeover events. Again, the positive effect gains considerable momentum (the elasticity of the regression line increases) for scores on management higher than 0.43.

4. Conclusion

Management and M&A decisions theoretically go hand-in-hand. Firms with good management target value-enhancing M&A deals, whereas firms with poor management target value-decreasing M&A deals. Both groups of firms might thus conduct more M&A deals. In this study, we examine this hypothesis using more than 15,000 M&A events over the period 1980–2016. We estimate management using a structural equation model, which includes management as a latent input of production. For the estimation method, we resort to a Bayesian approach that involves an artificial neural network process for the identification of management, and we obtain inferences from MCMC.

Our baseline results show that management has, on average, a positive effect on M&A deals. Delving deeper into this relation and consistent with our theoretical arguments, we next identify a non-linear U-shaped effect. Specifically, low levels of management are linked to a higher probability of M&A deals that are, on average, value-decreasing, while high levels of management are linked to higher probability of M&A deals that are value-increasing. Firms

Table 8
Nonlinearity in the management and M&A relation
The dependent variable is an indicator taking value one if an M&A event is observed and zero otherwise. The estimation method is panel logit. Coefficients show marginal effects. Standard errors use the observed information matrix when calculated. This table presents t-statistics in parentheses. Table 1 shows the definitions of variables used to measure management scores. Table 3 shows the definitions of the control variables. Stars, ***, **, and *, indicate significance levels at the 1%, 5%, and 10%, respectively.

	(1)	(2)
Management	−0.408**	−0.484**
	(−2.15)	(−2.28)
Management (squared)	0.485**	0.562**
	(2.47)	(2.57)
Log assets	0.043***	0.033***
	(11.12)	(7.76)
Leverage	−0.270***	−0.332***
	(−8.49)	(−8.15)
PPE	−0.002	0.020
	(−0.04)	(0.37)
Taxes	0.012	0.0048
	(1.17)	(0.42)
ROA	0.215***	0.239***
	(8.05)	(6.86)
Intangibles	−0.020	0.054
	(−0.55)	(1.25)
Cash	0.279***	0.317***
	(8.62)	(7.73)
Tobin's q		0.007***
		(2.82)
Stock return		0.026***
		(5.00)
Net profit margin		0.006**
		(2.36)
MB		0.001
		(0.73)
Observations	47,188	39,535
Log-likelihood	−14,601.244	−12,329.241

with management within the first and second quartiles have a lower probability to originate M&As.

Our results have important implications, especially for the firms' shareholders. Shareholder screening of the quality of management is equally difficult and important, and our analysis suggests that management quality can be the key difference between value-enhancing and value-decreasing M&As. Our analysis provides the first evidence on this important problem. Future work can further highlight the determinants of management, including corporate governance characteristics that point to specific agency problems, which in turn are linked to the probability and performance of M&A deals.

Appendix A. Appendix title

This appendix provides further discussion about the management score, as well as several additional empirical tests.

Management vs. TFP

The management score we use in this work measures total management quality (including top management quality and lower management quality). Based on the theoretical literature, management quality is one part of operation efficiency. Our management score is not total factor productivity. To better understand this, consider a standard model based on a Cobb-Douglas production function used to estimate TFP.

$$\log\left(y_{i,t}\right) = \mu_i + \mu_t + \alpha_s^k \log\left(k_{i,t-1}\right) + \alpha_s^n \log\left(n_{i,t}\right) + \epsilon_{i,t}.$$

In the above equation, $y_{i,t}$ is the output, $k_{i,t-1}$ is capital, $n_{i,t}$ is employment, and μ_i and μ_t denote firm and year fixed effects. To get TFP, we just need to run a simple OLS regression and then retrieve the residuals, which constitute TFP.

The model we propose in our paper is quite different. We rely on two main equations:

$$\ln\left(q_{it}\right) = \beta_0 + \beta_k \ln\left(k_{it}\right) + \beta_l \ln\left(l_{it}\right) + \beta_m \ln\left(m_{it}\right) + \frac{1}{2}\beta_{kk} \ln\left(k_{it}\right)^2 + \frac{1}{2}\beta_{ll} ln\left(l_{it}\right)^2 + \frac{1}{2}\beta_{mm} \ln\left(m_{it}\right)^2 + \beta_{kl} \ln\left(k_{it}\right) \ln\left(l_{it}\right) + \beta_{km} \ln\left(\mathrm{k_{it}}\right) \ln\left(m_{it}\right) + \beta_{lm} \ln\left(l_{it}\right) \ln\left(m_{it}\right) + u_{it} \tag{A1}$$

$$m_{i,t} = \sum_{g=1}^{G} \gamma_g \phi\left(\alpha_g + x'_{i,t}\beta_g\right) + \nu_{it,2} \tag{A2}$$

Eq. (A1) is the production function (in a translog form) and contains management (m), which is a latent variable (and is an input, not part of the residual). Eq. (A2) models management. Consistent with the underlying theory cited in our paper, management in (A2) is approximated by lagged values of all inputs and the current value of labor. The two equations together constitute a structural equation model (SEM), with management being a latent variable. To estimate SEM, we use a Bayesian approach that also recovers the latent variable (the management score). We choose the Bayesian approach because in SEMs with latent variables it performs very well. We feed the SEM with data and priors and let the system solve. By construction, the management score is not the error term shown in Eq. (A1), thus it cannot be TFP (m and u are different).

We show empirically that our measure of management and TFP are not correlated. To do this, we calculate TFP using standard techniques, such as through an OLS process in a Cobb-Douglas production function with capital and labor as inputs, and the well-established Levinsohn and Petrin (2003) method. We do this in the whole Compustat database. Because the Levinsohn-Petrin method requires specific characteristics (such as payments at the sectoral level), we lose many observations in the process, as such data do not exist, or if they do exist they are scarce. We find that our management score is not correlated with these variables—the correlation is practically zero—as expected because management is an input and TFP is a residual.

Correlations		
	TFP based on a Cobb-Douglass production function	TFP based on Levinsohn-Petrin method
Management	−0.0007 (not significant)	−0.0083 (not significant)

A further test that we do is to include the TFP as an additional control variable in our baseline model. We show the results in Table A1 below. We find that the management score enters with a positive and statistically significant coefficient. In fact, its value is close to the baseline model presented in Table 6 of the original text. This is also true when we include the squared term for management. Importantly, TFP carries a positive and statistically significant coefficient.

On the use of a translog production function and a sigmoid activation function

We use the translog production function due to its good mathematical properties (see e.g., Coelli, Rao, O'Donnell & Battese, 2005; Greene, 2008). Specifically, the translog is a flexible generalization of the Cobb-Douglas production function. Because of these properties, we can approximate more accurately the empirical form a production function.

Table A1
Baseline results including TFP
The dependent variable is an indicator taking value one if an M&A event is observed and zero otherwise. Coefficients show marginal effects. Standard errors use the observed information matrix when calculated. We show t-statistics in parentheses. Table 1 shows the definitions of variables used to measure management scores. Table 3 shows the definitions of the control variables. Stars, ***, **, and *, indicate significance levels at the 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
Management	0.056**	0.051**	−0.537***	−0.522**
	(2.26)	(2.31)	(−2.61)	(−2.39)
Management squared			0.619***	0.603***
			(2.95)	(2.68)
TFP	0.020**	0.017**	0.024**	0.023**
	(2.46)	(2.25)	(2.46)	(2.24)
Log assets	0.024***	0.023***	0.029***	0.029***
	(6.98)	(7.12)	(6.30)	(6.30)
Leverage	−0.268***	−0.250***	−0.317***	−0.326***
	(−8.57)	(−7.18)	(−9.85)	(−7.93)
PPE	−0.013	0.010	−0.016	0.013
	(−0.27)	(0.23)	(−0.28)	(0.24)
Taxes	0.007	0.004	0.008	0.005
	(0.69)	(0.40)	(0.70)	(0.40)
ROA	0.241***	0.209***	0.285***	0.270***
	(8.29)	(6.54)	(9.09)	(7.00)
Intangibles	0.030	0.054	0.036	0.070
	(0.80)	(1.57)	(0.80)	(1.56)
Cash	0.265***	0.242***	0.313***	0.314***
	(9.01)	(7.70)	(8.45)	(7.45)
Tobin's q		0.004**		0.006**
		(2.11)		(2.10)
Stock return		0.021***		0.027***
		(5.04)		(5.02)
Net profit margin		0.002		0.003
		(1.03)		(1.04)
MB		0.001		0.001
		(1.39)		(1.35)
Observations	42,186	38,273	42,186	38,273
Log-likelihood	−13,235.456	−11,949.745	−13,230.339	−11,944.693

We have used a sigmoid activation function that follows an artificial neural network. As we explain in the paper, our management score takes values between zero and one, and the sigmoid function works very well in gradient-based optimization problems, such as the one we have (see also Goodfellow et al., 2016). Also, the output of a sigmoid function can be interpreted as probability, which is a key component in Bayesian econometrics. Further, models with multi-layered neural networks can be considered hierarchies of generalized linear models, for which activation functions are link functions. Finally, the sigmoid function has a minimal structure and captures our ignorance about a model.

Regarding validation

The system of Eqs. (A1) and (A2) essentially constitutes a structural equation model (SEM) with a latent variable. We estimate this model using Bayesian techniques—specifically, a Bayesian normal linear regression. The key theoretical reason for this is that the Bayesian analysis incorporates uncertainty in measurements because of the infusion of prior knowledge (if priors are informative) or lack thereof (if priors are uninformative) into the prior distributions. In our case, we have good priors on explanatory variables, owing to Bloom and Van Reenen (2007) and their WMS data. The score obtained from the Bayesian model (see Section 2.2 in Delis & Tsionas [2018] for details) is highly correlated with the WMS score (see also Section 3.1 in Delis & Tsionas [2018]). This is the first step in validating this measure.

The key exercise for the external validity of the measure (thus, the second validation exercise) from an econometrician's viewpoint is always the simulation-based analysis.

For the Monte Carlo simulations, we start with a frontier model of production inefficiency that takes the following form:

$$Y = F(K, L) = K^{\alpha} L^{\beta} \exp(v - u),$$

where Y is firm output and $K,\ L$ are capital and labor, whose relative prices are $w_K,\ w_L$, respectively. Further, v is the error term and u is the inefficiency component. We prefer a frontier stochastic efficiency model to show that our findings hold within an environment unfavorable to our approach (that does not include an inefficiency component) and more favorable to the literature estimating management from a frontier approach.

Based on the same literature, we assume $u = 1 - M$, where M is management with price w_M. Without loss of generality, we normalize the price of output to unity and generate relative prices of inputs as uniform numbers in the interval (0, 1). We generate technical inefficiency as $u \sim N_{+}(0, \sigma_u^2)$. Then we generate M from $u = 1 - M$ and the price of management $w_M = 10M\exp(\varepsilon_{\mathrm{M}})$, where $\varepsilon_{\mathrm{M}} \sim N(0, 0, 1^2)$.

We take first order conditions and do the necessary substitutions in the production function to get firm output and inputs, as well as the price of management. We allow some measurement error for realism. Then we perform the simulation with 1000 replications and estimate all necessary components. After that we check the correlations between the simulated and estimated management scores. Rank correlations, shown in Table A2 below, range from 0.85 to 0.92, thus being quite high.

Concerning managerial preferences

An important issue in this analysis is that our results might be driven by personal managerial preferences or ambition. To exam-

Table A2
Rank correlations between simulated and estimated management
The table reports rank correlations between simulated management from the Monte Carlo method and estimated management from the translog production function and the simulated samples. We report results from different sample sizes, where n is the number of cross-sections (firms). The number of periods T is fixed to $T = 10$.

	All prices observed	Missing w_L	Missing w_L and w_K
$n = 1500$	0.85	0.80	0.75
$n = 2000$	0.89	0.83	0.79
$n = 2500$	0.92	0.88	0.85

Table A3
Management and M&As including CEO incentives
The dependent variable in both columns is an indicator taking value one if an M&A event is observed and zero otherwise. Coefficients show marginal effects. *Delta* and *vega* capture managerial incentives and are calculated based on Core and Guay (2002) by Coles et al. (2006). Standard errors for the panel logit use the observed information matrix when calculated. We show t-statistics in parentheses. Table 1 shows the definitions of variables used to measure management scores, and Table 3 shows the definitions of the control variables. Stars, ***, **, and *, indicate significance levels at the 1%, 5%, and 10%, respectively.

Dependent variable Estimation method	M&A event Panel logit (1)	M&A event Panel logit (2)
Management	0.097*	−0.394*
	(1.76)	(−1.89)
Management squared		0.484**
		(2.32)
Delta	−2.12e-07	−1.59e-07
	(−0.25)	(−0.23)
Vega	2.72E-05	2.24E-05
	(0.71)	(0.72)
Controls	Yes	Yes
Observations	11,899	11,899
Prob > chi2	0.000	0.000
Log-likelihood	−4140.8	−4139.08

ine whether managers' incentives matter, we use specifications including *delta* and *vega*. These are computed by Coles, Daniel and Naveen (2006) and are based on the method proposed by Core and Guay (2002). Albeit the sample has decreased significantly, we observe that they inclusion of these variables did not alter the main findings of our work. The results are in Table A3.

R&D and investment as additional control variables

In this paper, we argue that management is a factor of production and one that completes the list. This adage is not new; it has been mentioned by Mundlak (1961) and Lucas (1978), and recently revived in the theoretical literature by Bloom et al. (2017). Some critics might argue that variables, such as ICT and R&D should be included in our analysis. Given the nature of our measure of management, we argue that other more granular inputs are part of capital, labor, and management. ICT and R&D are part of capital and labor, and skill is of course part of management.

We proceed, nonetheless, to include additional controls in our baseline model, specifically R&D and investment. We are unable to use the same controls used by Bloom et al. (2019) because we do not have access to the datasets used by these authors. We show the results in Table A4 below. The two additional control variables are not statistically significant in any specification. Importantly, the coefficients on management are almost unchanged.

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Table A4
Baseline results including R&D and investment
The dependent variable is an indicator taking value one if an M&A event is observed and zero otherwise. *R&D* is the logarithm of Compustat items XRD to EMP. *Investment* is the logarithm of Compustat items CAPX to EMP. Coefficients show marginal effects. Standard errors use the observed information matrix when calculated. We show t-statistics in parentheses. Table 1 shows the definitions of variables used to measure management scores. Table 3 shows the definitions of the control variables. Stars, ***, **, and *, indicate significance levels at the 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Management	0.052**	0.049**	0.050**	−0.481**	−0.488**	−0.495**
	(2.40)	(2.27)	(2.27)	(−2.26)	(−2.28)	(−2.30)
Management squared				0.561**	0.565**	0.573***
				(2.56)	(2.56)	(2.59)
R&D	−0.010		−0.011	−0.013		−0.014
	(−1.39)		(−1.54)	(−1.43)		(−1.58)
Investment		0.006	0.007		0.007	0.008
		(1.12)	(1.27)		(1.11)	(1.26)
Controls	Y	Y	Y	Y	Y	Y
Observations	39,165	38,709	38,709	39,165	38,709	38,709
LR χ^2	621.93	609.45	611.96	631.06	618.65	621.23
Log-likelihood	−12,230.619	−12,097.699	−12,096.444	−12,226.055	−12,093.097	−12,091.809

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