Measuring Managerial Ability in the Hotel Industry

Abstract

This note develops and implements a novel model to estimate managerial ability for different hotels over time. Our model is a dynamic Multiple Indicator Multiple Causes (MIMIC) model. We use Bayesian techniques organized around Markov Chain Monte Carlo and we perform detailed posterior sensitivity with respect to the prior. We propose estimating managerial ability using accounting data only, hence facilitating more studies and hypothesis testing in this area.

Introduction

As the hotel industry continues to suffer from the impact of the COVID-19 pandemic, managerial ability becomes crucial as managers "have to quickly transition from the traditional firm objectives (market share; revenue growth) to the sole objective of firm survival" (Kumar and Zbib, 2022, p.1). The increasing economic uncertainty certainly creates more pressure on managers to be strategic and innovative.

A rather neglected topic from the hospitality literature is how to measure managerial ability. This neglect is partly due to the challenge of obtaining unique survey data to measure managerial ability (Delis and Tsionas, 2018). In consequence, the construct has been largely ignored in the hospitality literature albeit it potential high usefulness for both researchers and practitioners. The aim of this paper is to take one important step toward a novel and and more practical measurement of managerial ability. We draw on recent attempts from the operation research literature and treat managerial ability as an integral part of the inefficiency component in frontier-based methods. Our goal is to propose a model to measure managerial ability solely based on usual accounting data on inputs and outputs, thereby making lengthy survey-based data collections redundant. Earlier attempts to measure managerial ability in the broader management literature have used innovative survey techniques to collect data on management practices from several countries around the world. For example, Bloom and Van Reenen (2003) collected data on 18 different management practices from 732 medium-sized firms in the United States, France, Germany, and the United Kingdom.

Replicating such process, especially within the context of the hotel industry, is highly challenging given the length of the survey, the scarcity of detailed data and the challenge to have access to management from each company. We draw here on recent attempts from the operation research literature and rely on frontier methods to avoid survey data all together. Data Envelopment Analysis (DEA), for example, was recently used to measure managerial ability. Demerjian et al. (2012), for instance, used DEA to estimate firm inefficiency and then regressed the efficiency scores on "firm size, market share, positive free cash flow, and firm age (all aiding management), as well as complex multi-segment and international operations (challenges to management)". After controlling for the above, they used the residual ("the unexplained portion of firm efficiency to management") as a measure of management ability. Bonsall et al. (2017) later applied the same methodology to examine the impact of managerial ability on the credit rating process.

One issue with DEA however, it that it is non-parametric and hence it is highly sensitive to the selection of inputs and outputs and the potential noise in the data. For this reason, Delis and Tsionas (2018) used the stochastic frontier technique, the parametric counterpart of DEA. The authors treated management ability as a latent input that affects the production process. They then derived the conditional posteriors of management ability and several interesting measures such as the "responsiveness of total costs to a change in management price" and "the elasticity of inefficiency with respect to management practices". Delis and Tsionas (2018) tested their estimated managerial ability scores against the well-established and detailed managerial ability data of Bloom and Van Reenen (2007). They found high correlation (92%) between the two, providing evidence of the internal validity of their approach.

Motivated by the above, this paper builds on the stochastic frontier methodology to measure managerial ability. In the model we propose, managerial ability is for the first time treated as a dynamic latent indicator in which we allow a reciprocal and dynamic process between inefficiency and managerial ability. In other words, we allow managerial ability to depend on lag values of inefficiency and other predetermined variables (such as profit indicators). Managerial ability, in turn, determines inefficiency and some predetermined variables. Our model is fundamentally different from Delis and Tsionas (2018) as there are lagged variables that have an impact on managerial ability (even latent variables like $u_{\{i,t-1\}}$) and, in turn, managerial ability affects current period variables as well as inefficiency, u_{it}. In other words, our framework is more comprehensive as managerial ability has both indicators and causes as in as in Multiple-Index Multiple-Cause (MIMIC) model. Also, such dynamic and reciprocal relationship is critically important in estimating managerial ability. As argued by Delis and Tsionas (2018, p. 66), the "dependency of the inefficiency component on management practices is intuitive from a theoretical viewpoint as management is considered to be part of the overall firm efficiency".

In our model, inefficiency is derived from an output distance function where all outputs are endogenous (an assumption that is not always recognized as important in applied research). Firm inefficiency is also a dynamic latent variable that depends on control variables and, importantly, managerial ability. Managerial ability itself is determined in the context of a dynamic MIMIC model and estimated simultaneously with inefficiency. The simultaneity in the model creates econometric complexities which are successfully resolved to estimate parameters, inefficiency, and managerial ability in a single step. We apply the new technique to a sample of US hotels from Smith Travel Research (STR). As mentioned, our approach requires only accounting data, and frees the researcher from the need to measure management ability via lengthy survey. We find that better managerial ability increases efficiency in different types of hotels as well as overall. Posterior sensitivity to different priors is also examined in detail.

2. The Model

Our latent construction for managerial ability is described in Figure 1. In line with Demerjian et al. (2012) we select variables that along with inefficiency are known to help or hinder management's ability. This include a firm's profit and other control variables z_{it}. The level of inefficiency and profit of a firm in period *t*-1 affect managerial ability in period *t*. Such relationship seems to be well established in the literature (Delis and Tsionas, 2018). In turn, we also assume that managerial ability affects profit and inefficiency at period t. The impact of managerial ability on inefficiency is well established and dates back Leibenstein's X-inefficiency and Debreu's coefficient of resource utilization. We also assume that better managerial ability result in higher profit.

To estimate the model in Figure 1 we need hence a system of equations that involve three separate equations for inefficiency u_{it}, managerial ability m_{it}, and profit $R_{i,t}$.

To model inefficiency, suppose we have a vector of log inputs $x_{it} \in \mathbb{R}_{+}^{K}$, a vector of log outputs $y_{it} \in \mathbb{R}_{+}^{M}$, for hotel i and period t ($i = 1, \dots, n,\ t = 1, \dots, T$). If we use an output distance function it is well-known that we can write it in the form: $D(x, y) = 1$ so that it is increasing and linear homogenous in outputs, and decreasing in output. Exploiting linear homogeneity, we have:

$$y_{it,1} = f(\tilde{y}_{it}, x_{it}; \beta) + v_{it,1} \pm u_{it}, \tag{1}$$

where $\tilde{y}_{it} = [y_{it,2} - y_{it,1}, \dots, y_{it,M} - y_{it,1}]'$ so that the ODF is homogeneous of degree one in outputs, v_{it} is a two-sided error term, and u_{it} is an error term supported in $\mathbb{R}_{+}$ denoting inefficiency. Moreover, $\boldsymbol{\beta} \in B$ is a vector of parameters. In (1) we can allow inefficiency to depend on certain observed variables $z_{it} \in \mathbb{R}^{d_z}$ whose coefficients are $\alpha_{z,u} \in \mathbb{R}^{d_z}$, it is autoregressive with coefficient $\alpha_1 \in (-1,1)$.

Importantly, inefficiency also depends on latent managerial ability (m_{it}). We can write the inefficiency equation:

$$\log\, u_{it} = \gamma_0 + \rho_u \log\, u_{i,t-1} + \gamma_1 m_{it} + z_{it}{}'\alpha_{z,u} + v_{it,2}, \tag{2}$$

where $v_{it,2}$ is an error term. The errors $v_{it,1}$ and $v_{it,2}$ are independent normal with zero means and variances $\sigma_{v,1}^2$ and $\sigma_{v,2}^2$. Importantly we allow inefficiency to follow a dynamic framework, which is " important given the high persistence of inefficiency within firms for reasons similar to persistence in management practices and compensation" (Delis and Tsionas, 2018, p.68, Bloom et al., 2017).

Given Figure 1, we can write the managerial ability equations as follows[1].:

$$m_{it} = [\lambda_{11}\ \lambda_{12}\ \dots\ \lambda_{1Q}]\begin{bmatrix} R_{1,i,t-1} \\ R_{2,i,t-1} \\ \vdots \\ R_{Q,i,t-1} \end{bmatrix} + \rho_m m_{i,t-1} + \lambda_{mu} \log u_{i,t-1} + \begin{bmatrix} \xi_{it,11} \\ \xi_{it,12} \\ \vdots \\ \xi_{it,1Q} \end{bmatrix} \tag{3}$$

$$\begin{bmatrix} R_{1,i,t} \\ R_{2,i,t} \\ \vdots \\ R_{Q,i,t} \end{bmatrix} = \begin{bmatrix} \lambda_{21} \\ \lambda_{22} \\ \vdots \\ \lambda_{2Q} \end{bmatrix} m_{it} + \begin{bmatrix} \xi_{it,21} \\ \xi_{it,22} \\ \vdots \\ \xi_{it,2Q} \end{bmatrix}, \tag{4}$$

where Rs are the profit indicators, $\lambda_{11}, \lambda_{12}, \dots, \lambda_{1Q}$ are loadings of lagged of profit indicators on managerial ability, $\lambda_{21}, \lambda_{22}, \dots, \lambda_{2Q}$ are the effects of managerial ability of current period's indicators, and $\xi_{it,ij}$ are random errors, normally distributed, with zero means and variances σ_{ij}^2. If we define

$$\boldsymbol{\lambda}_1 = [\lambda_{11}, \lambda_{12}, \dots, \lambda_{1Q}]', \boldsymbol{\lambda}_2 = [\lambda_{21}, \lambda_{22}, \dots, \lambda_{2Q}]', \tag{5}$$

we can write these equations (after including possible determinants, z_{it}) in compact form as:

$$m_{it} = \boldsymbol{R}_{i,t-1}{}'\boldsymbol{\lambda}_1 + \rho_m m_{i,t-1} + z'_{it}\alpha_m + \lambda_{mu} \log u_{i,t-1} + \xi_{it,1}, \tag{6}$$

$$\boldsymbol{R}_{i,t} = \boldsymbol{\lambda}_2 m_{it} + \boldsymbol{\xi}_{it,2} \equiv \boldsymbol{\lambda}_2 m_{it} + \boldsymbol{\xi}_{it,2}, \tag{7}$$

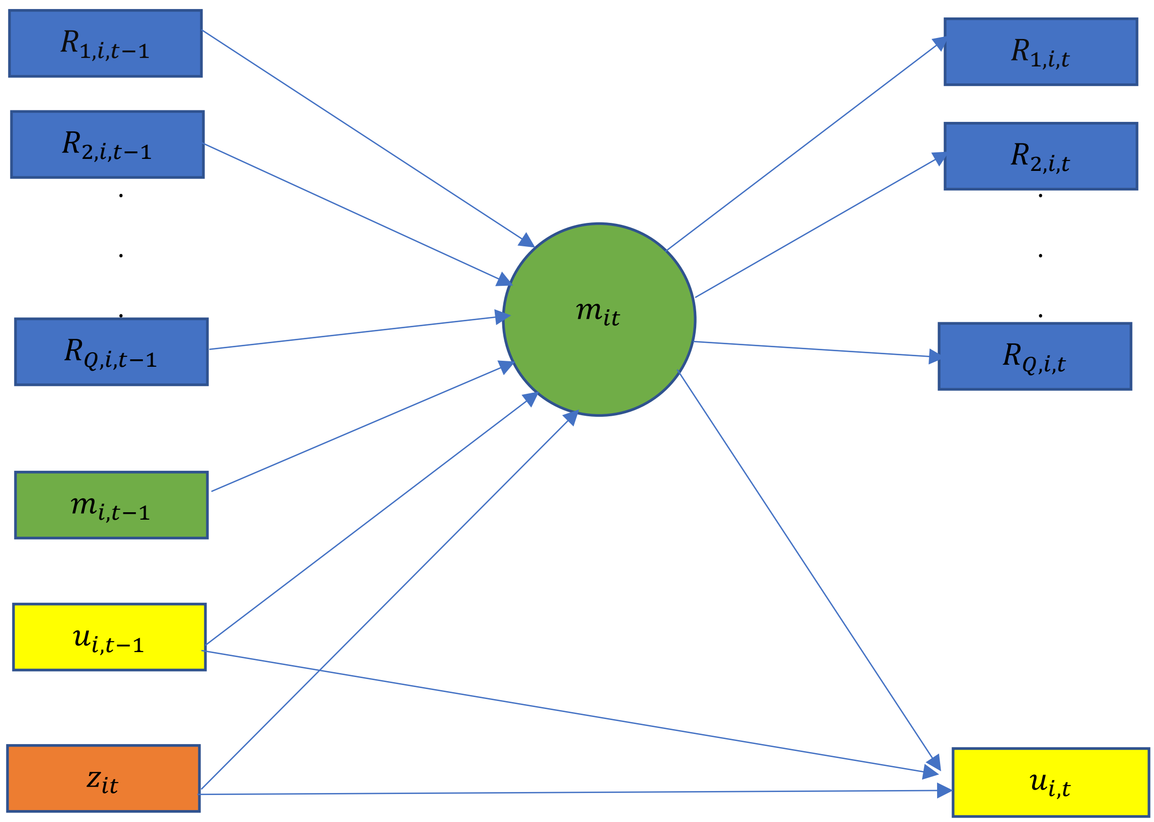
No ,mistake as intercept is not identified

where $\boldsymbol{R}_{i,t} = [R_{i,t,1}, R_{i,t,2}, \dots, R_{i,t,Q}{}']$, and $\alpha_{R,q}, \alpha_m \in \mathbb{R}^{d_z}, \boldsymbol{\alpha}_R \in \mathbb{R}^{d_z \times Q}$. Therefore, we assume latent management is also autoregressive in (6) and may depend on other observed variables $z_{it} \in \mathbb{R}^{d_z}$. Here, $\xi_{it,1}$ and $\xi_{it,2}$ represent a scalar and a vector of error terms, respectively, normally distributed with zero means and variances 1 and $\sigma_{\xi,(2),1}^2, \dots, \sigma_{\xi,(2),Q}^2$.

[1] It is intuitive to assume that that managerial ability depends on the lag values of inefficiency, and other performance indicators, as these create more drive for management to perform better and improve their ability (Delis and Tsionas, 2018).

The construction is a dynamic latent variable model with two dynamic unobservable variables (inefficiency and management). We provide in Appendix 1 more details on the Bayesian estimation of the model. More specifically, we show how one can obtain the posterior estimates of managerial ability given (1), (2), (3) (4), (6) and (7) that are estimated jointly as a system.

Figure 1. Basic latent construction for managerial ability



3. Data and Empirical Results

To estimate the model, we use data on 403 hotels from the Smith Travel Research (STR) database. The data is balanced and cover the period 2013-2017. In line with the literature (Assaf and Tsionas, 2018, Assaf et al. 2020, Assaf et al., 2021), for outputs, we use the following variables: total room revenue, total other operated revenue and occupancy rate. For inputs, we use total room expenses, total other operated department expenses, total administrative and general (A&G) expenses, total marketing expenses, total utility expenses, and total property and maintenance (POM) expenses. In both the management and inefficiency equations, we control for vector of observed variables z_{it}. These include hotel size, measured by the number of rooms, type of service (full vs. limited service), and dummy variables for luxury, upper-scale, midscale, and economy. These variables have been often included as control variables in similar settings (Assaf and Tsionas, 2018; Assaf et al., 2020). Finally, for the profit indicators we use earnings before income tax, earnings before income tax per available room, and earnings before income tax per total revenue[2].

The functional form $\boldsymbol{f(\tilde{y}_{it}, x_{it}; \beta)}$ in (1) is a translog which includes a time trend to capture the effects of technical change. Posterior moments for several parameters are reported in Table 1. They are computed from MCMC using 150,000 iterations omitting the first 50,000 in the burn-in phase to mitigate possible start up effects. These parameters represent the variables we included in (2), (6) and (7). In general, we see that all parameters are significant, providing evidence that these equations are correctly specified.

In Figure 1, we report sample distributions of posterior mean estimates of input and output elasticities of the ODF. It is clear that all elasticities satisfy the theoretical monotonicity conditions of the ODF (i.e. non-decreasing, positively linearly homogeneous and increasing in outputs, and decreasing in inputs). Further details on model validation is provided in Appendix 2, where we show that the model with managerial ability performs better than a model that excludes managerial ability. In Appendix 2 we also show that the model performs well across various priors for Bayesian estimation.

In Figure 2, we report sample distributions of posterior mean estimates of efficiency (Figure 2a), managerial ability (Figure 2b), and the relationship between managerial ability and inefficiency (Figure 2c). The managerial ability scores are normalized to have zero mean and unit variance. The evidence shows that the distribution of managerial ability is bimodal, and the same is true for the joint distribution of managerial ability and inefficiency. As a matter of fact, the joint posteriors show that there is an inverted U-relationship between inefficiency and managerial ability (middle right panel) suggesting that lower-quality managerial ability increases inefficiency but higher quality managerial ability decreases inefficiency. We also report in Figure 3 the marginal effects of managerial ability on efficiency with 95% highest posterior density intervals for the various types of hotels in our sample: luxury, upscale, midscale and economy hotels, respectively. The overall marginal effect shows a positive relationship between managerial ability and efficiency. The marginal effect is stronger for higher levels of managerial ability across all hotel types, though the relationship seems to stabilize after a certain level of management ability, where more investment in improving managerial ability does not generate higher level of efficiency. Finally, Figure 4 reports the boxplots for managerial ability for various hotel types. It is clear that luxury hotels score the highest on managerial ability, followed by upscale, midscale and economy hotels.

4. Concluding Remarks

The role of managerial ability has always been a key research focus for hospitality and tourism management research. Yet, measuring managerial ability has constituted a substantial challenge as it

[2] We checked the correlation for these three profit indicators and we did not find a collinearity problem.

usually requires primary data obtained through lengthy surveys. In response, this study develops a novel dynamic MIMIC model for estimating managerial ability in the hotel industry, where we allow for (dynamic) feedback between managerial ability, profit indicators, and inefficiency. The key novelty of the model is that it depends solely on accounting level data, eliminating the need for lengthy survey and access to relevant respondents to measure managerial ability. We validated the performance of the model and compared its performance across various priors.

By doing so, our research contributes to managerial practice in various ways. It allows easier assessment of managerial ability across hotels at it lowers the requirements for data collection. By drawing on existing data (as we do by utilizing the data from STR), we are capable of measuring managerial ability for more than 400 hotels. Individual hotels may use this approach to benchmark how they rank in terms of their own managerial ability in comparison to their competitors. Further, we show empirically the relationship between managerial ability and efficiency, finding a positive relationship. This result is documenting that managerial ability indeed is an important variable to assess at correlates with higher efficiency. Specifically, even when efficiency measures cannot be obtained, measuring managerial ability may help to approximate it. In addition, managerial ability is particularly crucial in times of economic uncertainty, such as during the COVID-19 pandemic. Our approach is not only an easier and faster way to assess managerial ability, but also a cheaper one. This makes it usable also for the many smaller hotels that suffer during a pandemic.

Importantly, we provide measures of managerial ability for various hotel types. As we display in Figure 3, the relationship between managerial ability and efficiency is positive, yet, it varies across hotel types. For example, the relationship for midscale hotels is weakened (and almost non existent) for higher levels of ability (i.e., >.65), thereby highlighting that high levels of ability may not result in higher levels of efficiency. In contrast, economy hotels may not see improvements of efficiency as long as the managerial ability increases on a very low level but can then (once managerial ability rises further) expect a more linear relationship. For hotel managers, this information is valuable because it allow them to assess the role of their own managerial ability in driving efficiency, based on the type of their own hotel, consequently providing a more nuanced picture.

A big picture implication for hospitality research is that our findings are particularly important for future studies seeking to advance knowlege on managerial ability. The model proposed herein can be used to measure managerial ability without a need for detailed data, thereby facilitating more studies in the future. In turn, such studies that obtain data on managerial ability through our approach can use it in other research tasks such as examining the role of managerial ability in shaping or moderating hotel performance, hotel corporate social responsibility, or customer relationship management.

Table 1. Posterior moments for selected parameters and functions of interest

parameter	Posterior mean	Posterior s.d.
$\boldsymbol{\lambda_{11}}$	0.323	0.015
$\boldsymbol{\lambda_{12}}$	0.271	0.022
$\boldsymbol{\lambda_{13}}$	0.455	0.036
$\boldsymbol{\lambda_{21}}$	0.515	0.027
$\boldsymbol{\lambda_{22}}$	0.606	0.019
$\boldsymbol{\lambda_{23}}$	0.132	0.040
$\boldsymbol{\rho_u}$	0.892	0.033
$\boldsymbol{\rho_m}$	0.958	0.012
$\boldsymbol{\gamma_1}$	-0.225	0.014

Figure 1. Aspects of the model

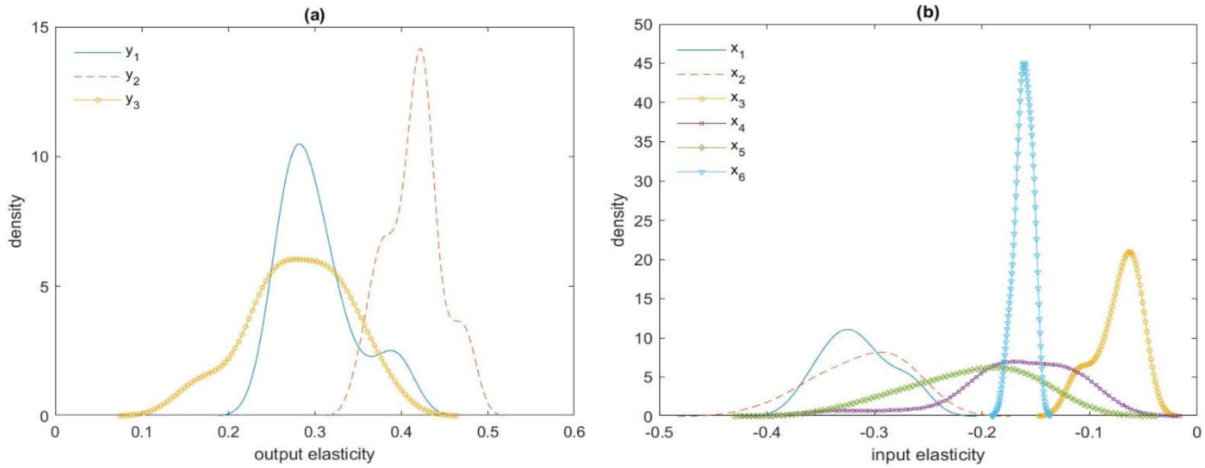


Figure 2. Efficiency and Managerial Ability

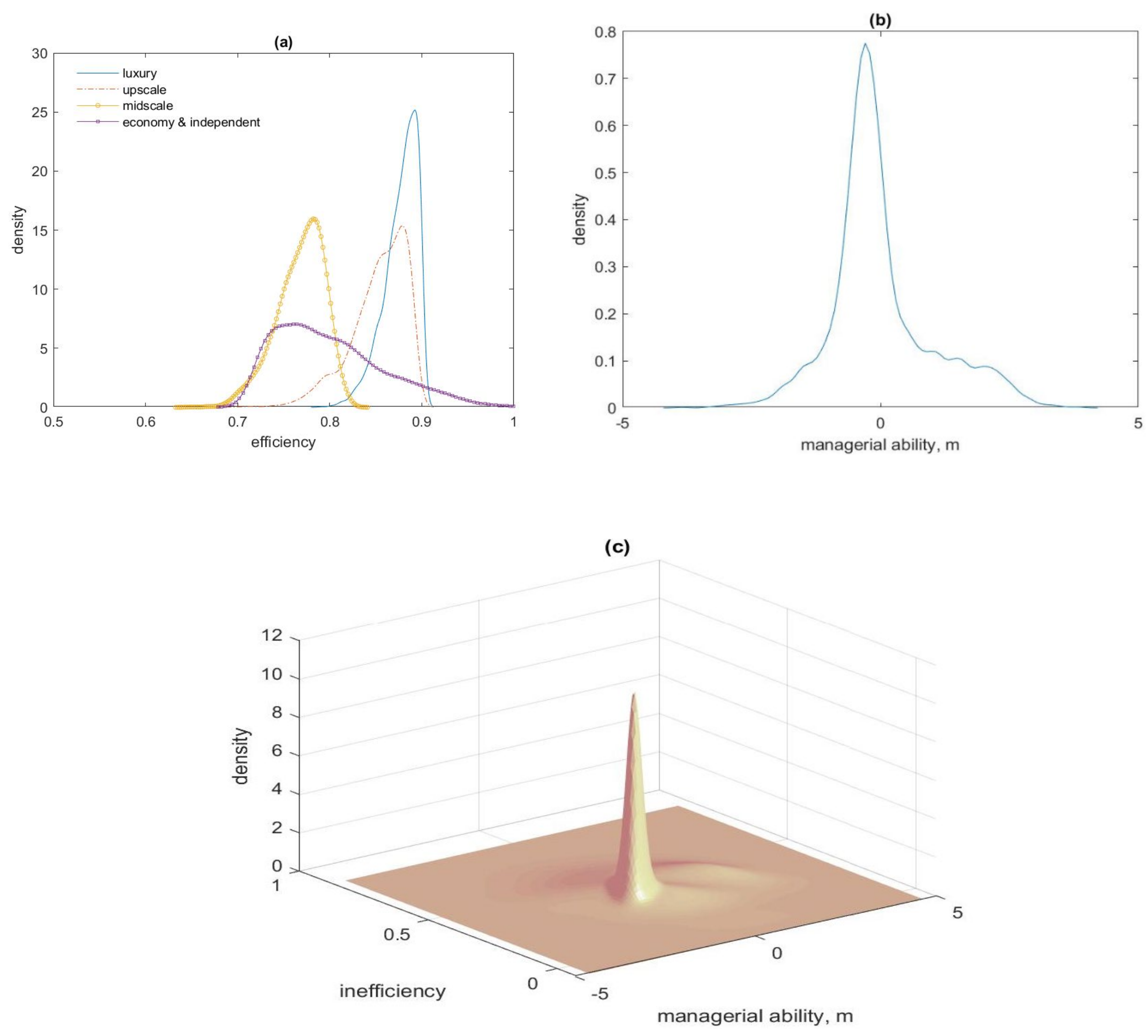


Figure 3. Relationship between efficiency and managerial ability

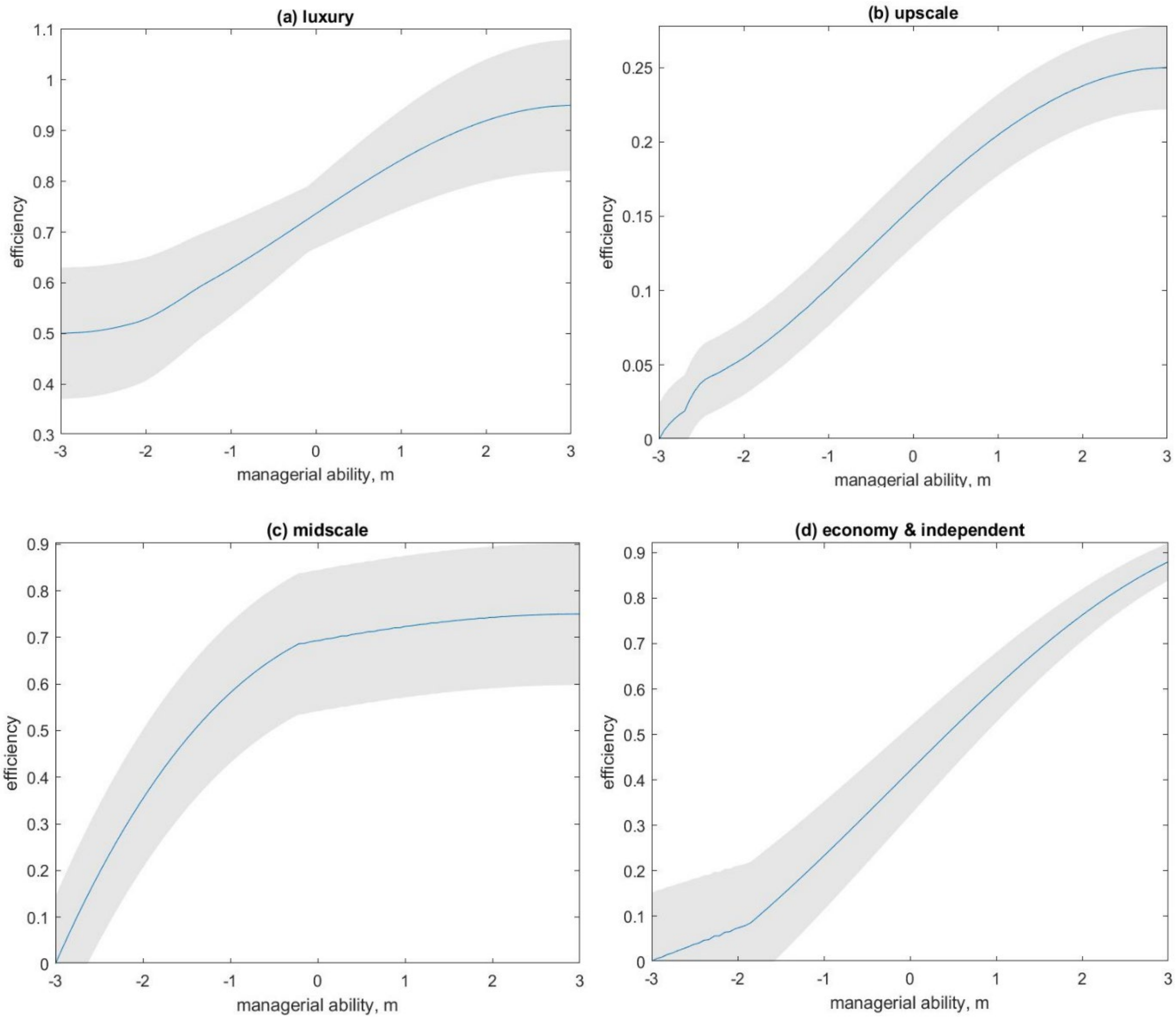
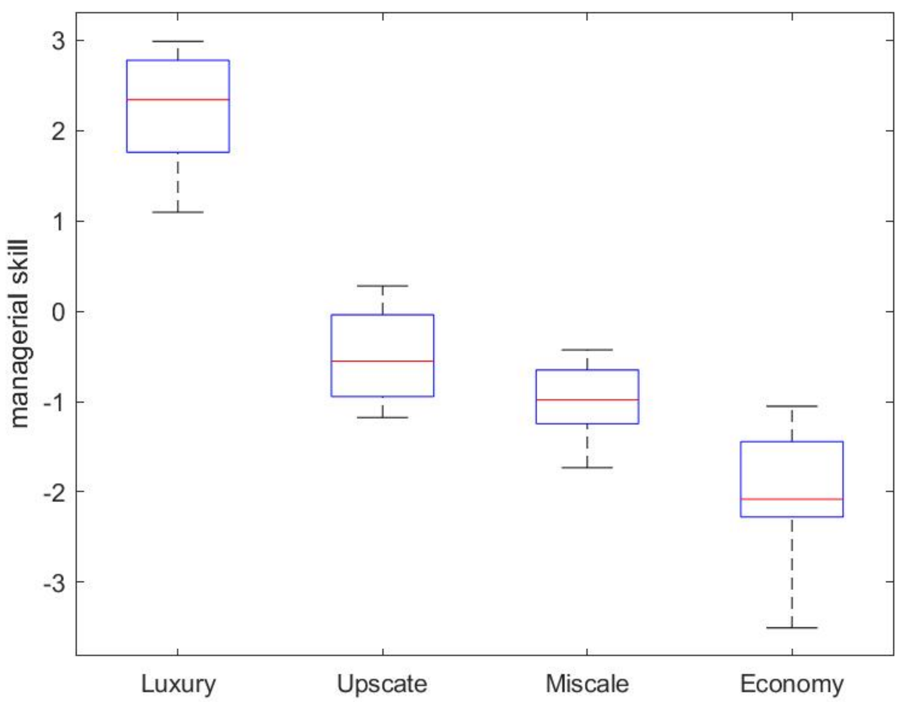


Figure 4. Boxplots of Managerial Ability across various hotel Types



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Appendix 1: Technical Details

From equations (1), (2), (6), and (7) the posterior distribution is given as follows.

$$p(\theta, \boldsymbol{\sigma}, \{\log u_{it}, m_{it}\}|D) \propto \sigma_{v,1}^{(-nT+1)} \exp\left\{-\frac{1}{2\sigma_{v,1}^2}\sum_{i=1}^{n}\sum_{t=1}^{T}\left[y_{it,1} + f(y_{it}, x_{it}; \beta) + \right.\right.$$
$$\sigma_{v,1}^{(-nT+1)} \exp\left\{-\frac{1}{2\sigma_{v,2}^2}\sum_{i=1}^{n}\sum_{t=1}^{T}\left[\log u_{it} - \gamma_0 - \rho_u \log u_{i,t-1} - \gamma_1 m_{it} - z_{it}'\alpha_u\right]^2\right.$$
$$\exp\left\{-\frac{1}{2}\sum_{i=1}^{n}\sum_{t=1}^{T}\left[m_{it} - \boldsymbol{R}_{i,t-1}\boldsymbol{\lambda}_1 - \rho_m m_{i,t-1} - z_{it}'\alpha_m\right]^2\right\} \quad \text{(A.1)}$$
$$\exp\left\{-\frac{1}{2}\sum_{i=1}^{n}\sum_{t=1}^{T}(\boldsymbol{R}_{it} - \boldsymbol{\lambda}_2 m_{it} - z'_{it}\boldsymbol{\alpha}_R)'\Sigma^{-1}(\boldsymbol{R}_{it} - \boldsymbol{\lambda}_2 m_{it} - z'_{it}\boldsymbol{\alpha}_R)\right.$$
$$\prod_{j=1}^{Q}\sigma_{\xi,(2),j}^{-(nT+1)} \cdot \mathbb{I}_B(\beta),$$

where $\Sigma = \text{diag}[\sigma_{\xi,(2),1}^2, \dots, \sigma_{\xi,(2),Q}^2]'$. Our prior is flat for all scale parameters of the model. For the location parameters β we assume a flat prior over the domain B where monotonicity conditions hold at the geometric means of the data and ten other randomly selected points in the support of the data, D. All parameters except scale parameters which are collected in $\boldsymbol{\sigma}$, are denoted θ.[3]

Conditional on $\{\log u_{it}, m_{it}\}$ drawing the remaining parameters in θ and $\boldsymbol{\sigma}$ is straightforward using a Gibbs sampler. To draw from the conditional posterior distribution of $\log u_{it}$ we consider the system:

$$r_{it,(1)} \equiv -y_{it,1} - f(y_{it}, x_{it}; \beta) = e^{\log u_{it}} + v_{it,1}, \quad \text{(A.2)}$$

$$r_{it,(2)} \equiv \gamma_0 + \rho_u \log u_{i,t-1} + \gamma_1 m_{it} + z'_{it}\alpha_u = \log u_{it} + v_{it,2}, \quad \text{(A.3)}$$

$$r_{it,(3)} \equiv \log u_{i,t+1} - \gamma_0 - \gamma_1 m_{i,t+1} - z'_{i,t+1}\boldsymbol{\alpha}_u = \rho_u \log u_{it} + v_{i,t+1,2}. \quad \text{(A.4)}$$

Given an existing MCMC draw, say $\log u_{it}^{(0)}$ we linearize the exponential term in (A.2) to obtain

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[3] The Jacobian in terms of the endogenous variables $[-y_{it,1}, \log u_{it}, m_{it}, \boldsymbol{R}_{it}]$ is unity. In an ODF, the variables $\tilde{y}_{it}$ are considered endogenous. To correct for potential endogeneity, we replace $\tilde{y}_{it}$ with the fitted values of their regression on z_{it}.

$$r_{it,(1)} \equiv -y_{it,1} - f(y_{it}, x_{it}; \beta) - e^{\log u_{it}^{(0)}}(1 - u_{it}^{(0)}) \\ = \phi \log u_{it} + v_{it,1}, \tag{A.5}$$

where $\phi = e^{\log u_{it}^{(0)}}$. Therefore, an approximate draw can be obtained as

$$\log u_{it} \mid \cdot, D \\ \sim \mathcal{N}\left(\frac{\sigma_{v,2}^2 \phi r_{it,(1)} + \sigma_{v,1}^2 \big(r_{it,(2)} + \rho_u r_{it,(3)}\big)}{\sigma_{v,2}^2 \phi^2 + \sigma_{v,1}^2 (1+\rho_u)^2}, \frac{\sigma_{v,1}^2 \sigma_{v,2}^2}{\sigma_{v,2}^2 \phi^2 + \sigma_{v,1}^2 (1+\rho_u)^2}\right). \tag{A.6}$$

The procedure is applied another time linearizing around the new expected value of $\log u_{it}$ for more precision.

To draw from the conditional posterior distribution of m_{it} we consider the system:

$$W_{it,(1)} \equiv \log u_{it} - \gamma_0 - \rho_u \log u_{i,t-1} - z'_{it} \alpha_u = \gamma_1 m_{it} + v_{it,(2)}, \tag{A.7}$$

$$W_{it,(2)} \equiv \boldsymbol{R}_{i,t-1}{}' \boldsymbol{\lambda}_1 + \rho_m m_{i,t-1} + z'_{it} \alpha_u = m_{it} + \xi_{it,(1)}, \tag{A.8}$$

$$W_{it,(3)} \equiv m_{i,t+1} - \boldsymbol{R}'_{it} \boldsymbol{\lambda}_1 - z_{i,t+1}{}' \alpha_m = \rho_m m_{it} + \xi_{i,t+1,(1)}, \tag{A.9}$$

$$\boldsymbol{W}_{it,(4)} \equiv \boldsymbol{R}_{it} - z'_{it} \boldsymbol{\alpha}_R = \boldsymbol{\lambda}_2 m_{it} + \boldsymbol{\xi}_{it,(2)}. \tag{A.10}$$

Therefore, the conditional posterior distribution of m_{it} is given as

$$m_{it} \mid \cdot, D \sim \mathcal{N}(\widetilde{m}_{it},\ s_m^2), \tag{A.11}$$

where $\widetilde{m}_{it} = \frac{\gamma_1 W_{it,(1)}/\sigma_{v,1}^2 + W_{it,(2)} + \rho_m W_{it,(3)} + \boldsymbol{\lambda}'_2 \Sigma^{-1} \boldsymbol{W}_{it,(4)}}{\gamma_1^2/\sigma_{v,1}^2 + 1 + \rho_m^2 + \boldsymbol{\lambda}'_2 \Sigma^{-1} \boldsymbol{a}_2}$,

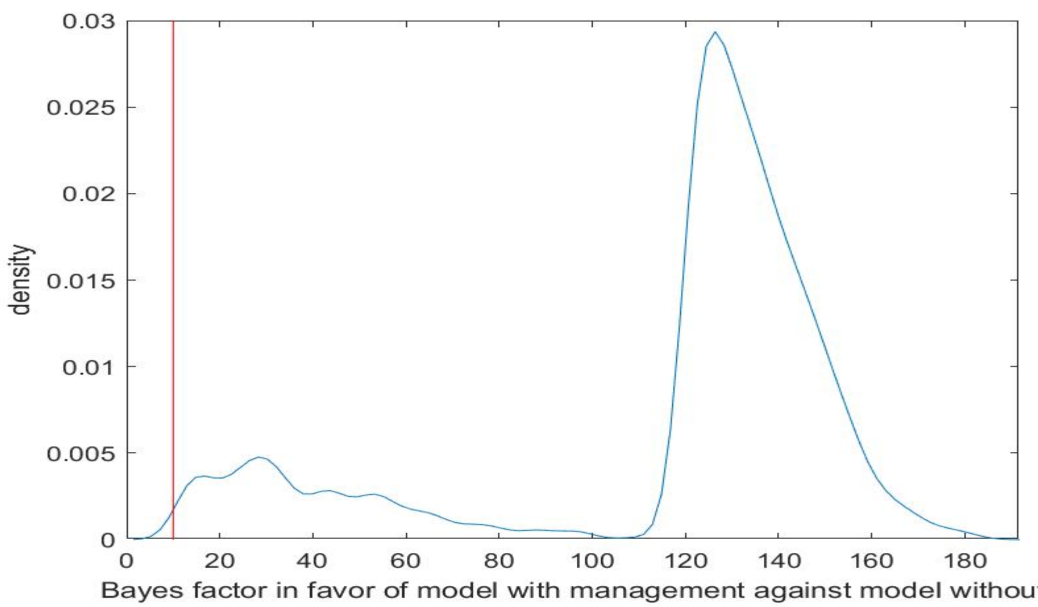
and $s_m^2 = \frac{1}{\gamma_1^2/\sigma_{v,1}^2 + 1 + \rho_m^2 + \boldsymbol{\lambda}'_2 \Sigma^{-1} \boldsymbol{\lambda}_2}$.

Appendix 2: Model Validation and Prior Sensitivity Analysis

To validate the model, we compare it with a model where $\gamma_1 = 0$ and we drop (3) and (4), or (6) and (7). In Figure **4** we show the distribution of Bayes factors in favor of the new model when we omit a block of observations for B hotels where B is uniformly distributed between 1 and 15. Therefore, the Bayes factors are, really, predictive or cross-validated Bayes factors that compare the predictive ability of the two models, in the light of the data.

We repeat these 1,000 times and the results are shown in Figure A.1. We also draw a vertical line at 10, as 10 is used widely (Kass and Raftery, 1995, p. 791) a value beyond which we have significant evidence in favor of the new model. For the most part, predictive Bayes factors are greater than 10 or even 100 (which, according to Kass and Raftery, 1995, corresponds to decisive evidence) although in certain sub-samples the predictive Bayes factor indicates that the new model does not perform as well as the model without managerial ability. However, these are very few sub-samples.

Figure A.1. Distribution of predictive Bayes factors for $y_{it,1}$



For prior sensitivity analysis, we change the prior parameters of the model $\bar{b}, \bar{s}^2$ using $\bar{b} \sim N(0,10^2)$ and $log\sigma^2 \sim N(0,10^2)$ so that the prior is proper but flat in the region where the monotonicity conditions hold, as we mentioned earlier. Posterior sensitivity analysis is performed using the Sampling-Resampling-Algorithm (SIR; Rubin, 1987, Smith and Gelfand, 1992) drawing 1,000 different priors, updating the posteriors and re-computing posterior moments of parameters and functions of interest like managerial ability. We found that the changes are small so the model is robust to changes in prior assumptions.