Inputs Management in Hospitality Operations

Key Aspects for Improving Productivity

by

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Abstract

Inputs management is a central issue in hospitality because of the characteristics of service production (e.g., perishability and face-to-face interaction) and the fact that hospitality companies adapt inputs to the demand beforehand. Inputs management improves our understanding of elements of hospitality performance, such as productivity and profitability. More specifically, hospitality managers periodically schedule variable inputs such as labor. Therefore, an important question is to what extent hospitality companies adjust labor demand in response to service demand fluctuations at both the firm and department levels, i.e., relative to the most desirable or just-in-time scenario? This thesis is based on the theory of labor demand and partial adjustment, which considers a dynamic approach of identifying the desirable level, to answer this question. The findings suggest the need to improve the overall speed of labor adjustment to changes in demand at the company level, but more specifically, in bars and restaurants (i.e., food and beverages) of hospitality businesses to improve their profitability.

In contrast to labor, fixed inputs such as room capacity and management system are determined at a certain point, and an attempt to optimize these inputs requires a long time horizon. Thus, how and to what extent does excess capacity influence cost and inefficiency? Excess capacity is measured in terms of daily unoccupied rooms. This thesis uses cost theory, specifically an inputs distance function (IDF), to make theoretical predictions and answer the research question. The findings suggest that improving capacity utilization (reducing excess capacity) decreases costs and technical inefficiency. The findings also indicate that the larger the excess capacity, the greater will be the extra cost saving from the improved capacity utilization. However, efficiency improvement only occurs when capacity utilization is less than 50%.

Moreover, this thesis considers how and to what extent management practices influence cost and inefficiency in hospitality, because management can be responsible for productivity differences by influencing both the production technology and the production context. This thesis develops a theoretical framework that combines the economics of management and an IDF to test the hypothesis that improved management practices yield less-costly production technology

and higher technical efficiency. The findings suggest that improved management practice results in less-costly production technology up to only a certain level but improves efficiency continuously. That is, the best management practice yields a higher cost than the minimum possible, but with maximum efficiency.

Finally, the thesis makes a theoretical contribution and discusses the managerial and policy implications of our findings to improve inputs management in hospitality operations.

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1 Introduction

Monitoring and evaluating how the hospitality sector employs productive inputs in its day-to-day operations is crucial for understanding how well and to what extent companies can improve their efficiency and productivity. Hospitality companies combine variable inputs, such as labor, materials, and energy, and fixed inputs such as management, buildings, machinery, and equipment. Although the main product is the same (i.e., provision of accommodation and food), the companies provide heterogeneous services in terms of quality, design, climate, content, location, and other attributes, and inputs management should account for these differences.

The demand for hospitality services is determined externally by factors associated with general economic conditions, weather conditions, and seasonality, among others. The perishability of services and face-to-face interactions between the providers and customers characterize hospitality services (Baker & Riley, 1994). It is this combination of stochastic demand and the characteristics of hospitality operations that creates the particular challenge of matching resources to demand. For example, economic and political changes and other overreaching factors can greatly influence demand in each hospitality market; however, on a day-to-day basis, the demand facing a particular hospitality company can deviate from expectations because of unforeseen (i.e., stochastic) circumstances. The mismatch between actual and expected demand results in either shortages or excess use of inputs, both of which have implications for service quality and operational costs.

Changes in the hospitality industry have made it even more important to increase focus on efficient and productive inputs management. One aspect is the pressure of price transparency and competition on the profit margins of hospitality companies that results from online booking platforms (Tveteraas & Falk, 2016). Furthermore, the emergence of Airbnb has affected the market share and price of hotels, especially those that serve nonbusiness guests (Zervas, Proserpio, & Byers, 2017). Therefore, a central challenge for hospitality managers is how to optimize the inputs given the competitive environment and that demand tends to vary substantially over time.

This thesis assumes that companies aim to minimize the volume of inputs employed for a given output level determined by demand. The radial inputs distance function (IDF) is used as the primary modeling framework because it accommodates this main assumption. Specifically, the IDF model identifies the desirable (optimal) use of inputs and inefficiency based on the volume of other inputs employed and the volume of outputs. Moreover, the framework can also incorporate dynamic labor demand and partial adjustment, which are relevant in the context of hospitality operations.

A goal of this thesis is to evaluate to what extent hospitality companies successfully managed their inputs in delivering hospitality services. In this thesis, the research issues are divided depending on a key input characteristic, i.e., whether inputs are variable or fixed. In the short run, companies can change the amount of variable inputs in response to demand fluctuations, but not the fixed inputs. Nevertheless, the use of fixed inputs is a crucial concern for productivity because they influence total cost and price.

Regarding the variable inputs, this thesis focuses on labor optimization because hospitality is a labor-intensive service industry. Labor determines the profitability of the business by influencing service quality, cost (productivity), and hospitality performance in general. For instance, the earlier literature finds that labor is the most significant cost component in daily hospitality operations (Tsai, Song, & Wong, 2009), and is the source of quality differentiation, image, and competitive advantage (Huselid, 1995).

Figure 1 summarizes the conceptual framework and research issues examined in this thesis. Demand is assumed to be equivalent to output based on the hospitality services characteristics, perishability, and face-to-face interaction of providers and customers. The orientation of the elements in the figure reflects that demand is at the center of input management decisions. First, staff levels depend on the current output level of labor-intensive services because of the perishability and simultaneity of service delivery (Baker & Riley, 1994). Second, demand is externally determined, and hospitality operators need to forecast and adapt their inputs to meet the demand (Duncan, 1990; Ernst, Jiang, Krishnamoorthy, & Sier, 2004); i.e., hospitality operators make staffing decisions depending on the expected demand. However, the demand forecast can deviate from the actual demand because of demand uncertainty in service industries (Koçağa, Armony, & Ward, 2015). Poor demand forecasts lead to suboptimal staffing levels, resulting in under- or overstaffing (Ernst et al., 2004).

In this thesis, a suboptimal staffing level refers to overstaffing because the primary goal is to minimize inputs. Overstaffing makes the companies less competitive because of the unnecessary additional cost (Anyim, Mba, & Ekwoaba, 2012; Choi, Hwang, & Park, 2009). In the presence of overstaffing, the capital–labor ratio will be lower, i.e., the constant capital stock divided by more labor hours. However, the literature provides mixed evidence on the effect of overstaffing on output. Some earlier studies argue that it does not affect total revenue (Anyim et al., 2012), while others argue it helps the companies offer better service quality, but affects productivity (Goodale, Verma, & Pullman, 2003; Thompson, 1998). Others argue that overstaffing affects the volume of output (Mani, Kesavan, & Swaminathan, 2015; Tan & Netessine, 2014).

The estimation of optimal staff levels should account for heterogeneity, endogeneity, common shocks, and the reverse causal relationship between labor and output flexibilities. Labor flexibility refers to the ability to adjust labor to demand fluctuations reflected in the speed of adjustment. Besides, labor should be adjusted to the correct level, and the adjustment should also be *just-in-time* to maximize profit (Lai & Baum, 2005). The time element is important because any delay in meeting demand has implications for service quality (e.g., customers' waiting time) and the level of waste from inputs and outputs. The amount of this waste is minimized when companies optimize the staff level instantly to demand fluctuations. The degree of input optimization also determines the company image as well as the probability of success or failure (Lewis & McCann, 2004; Rocha, Oliveira, & Carravilla, 2012).

The left and right wings of the figure illustrate two different instances of how fixed inputs utilization (i.e., a fixed capacity and a fixed management system) are associated with the volume of output and inputs and, hence, total cost, which is composed of the production cost and technical inefficiency. In turn, the production cost is determined by the cost of labor and outputs. Accordingly, capacity utilization is one aspect of inputs management that influences costs and prices. Capacity utilization is measured in terms of excess (unsold) rooms, i.e., the opposite of the occupancy rate. The companies incur some costs (e.g., depreciation, cleaning, and tidying up, among others) to maintain the excess capacity, which indirectly increases the total cost through technical inefficiency. Excess capacity is expected to increase the total cost through overstaffing.

Moreover, improving capacity utilization results in better outcomes of service productivity, as it is associated with higher technical efficiency, service quality, and customer satisfaction (Grönroos & Ojasalo, 2004). Excess capacity imposes the additional cost of more staff. This is because from the first room rented to hotel guests, there is a baseline amount of staff hours required (e.g., reception duties, preparing breakfast). To exploit economies of scale, one needs to increase room capacity utilization because this will spread the cost of these baseline staff hours across a greater number of sold rooms. This will normally result in a lower number of staff hours (and labor cost) per sold room.

Because of perishability, excess capacity implies foregone revenue from accommodation services and spillovers to restaurants, cafés, and other services. Cross-subsidization compensates for part of these lost revenues in the hospitality market. Price varies negatively with the level of excess capacity because higher excess capacity means lower demand.

Conversely, lower excess capacity means higher demand for accommodation services and hence higher capacity utilization. The high price during peak season compensates for the low demand season, and in the case of hotel chains, those located in high-demand areas subsidize their lower-demand counterparts. Moreover, the higher price as a result of the premium yields a lower demand for accommodation services and a deadweight loss, i.e., foregone revenue, which was not compensated for by the cross-subsidization. Together with the cost of maintaining the capacity, the deadweight loss constitutes inefficiency. Therefore, excess capacity makes hospitality services more expensive (shifts the IDF outwards) and increases inefficiency.

Management practices refer to the managerial routines built into the organizational system, and these improved practices are achieved at a cost as developing these practices consumes time and expertise (Syverson, 2011). In this thesis, the management practices were measured based on how the staff-scheduling system software is used daily. All the hospitality companies included in the analysis use the same staff-scheduling system software. The software lets managers plan staffing based on forecasted demand and the resulting resource optimization is based on the characteristics of the hospitality company. The software will suggest optimal staffing levels and update these dynamically as forecasts are revised and other relevant information is updated in the system. This means that managers should actively use the software because the previous week's planned staff schedule may not be optimal given the revised forecasts in the current week. Active use means that managers must monitor the staff-scheduling system, ensure that the system is updated continually with the most recent data, and adjust staffing schedules dynamically following changes in forecasts and optimal resource employment. This is a balancing act where managers must trade-off between having high staff flexibility with the potential costs of making frequent staff-scheduling changes.

However, good routines in the use of the software for planning, and built-in routines can reduce the effects of unforeseen staff-scheduling changes. Software providers are aware of the importance of good routines in how hospitality managers use their software to improve productivity performance, which is why software providers monitor how managers use staff-scheduling software in the different hospitality companies that employ such software. The use of staff-scheduling software was measured using 10 items that are aggregated into an index that runs from worst (1) to best (10).

The main benefit of improved management practices (i.e., better routines in software use and staff schedules) is an improvement in efficiency, i.e., reduction of associated waste. Improved management practices also minimize costs through better optimization of staff, which creates a conducive working environment and leads to job satisfaction, better service quality, customer satisfaction, better image, and loyalty (Assaf & Magnini, 2012; Hu, Kandampully, & Juwaheer, 2009; Yee, Yeung, & Cheng, 2008). Customer loyalty and its multiplier effects through word-of-mouth, social media, and online customer reviews help to generate more demand for the services (Mani et al., 2015).

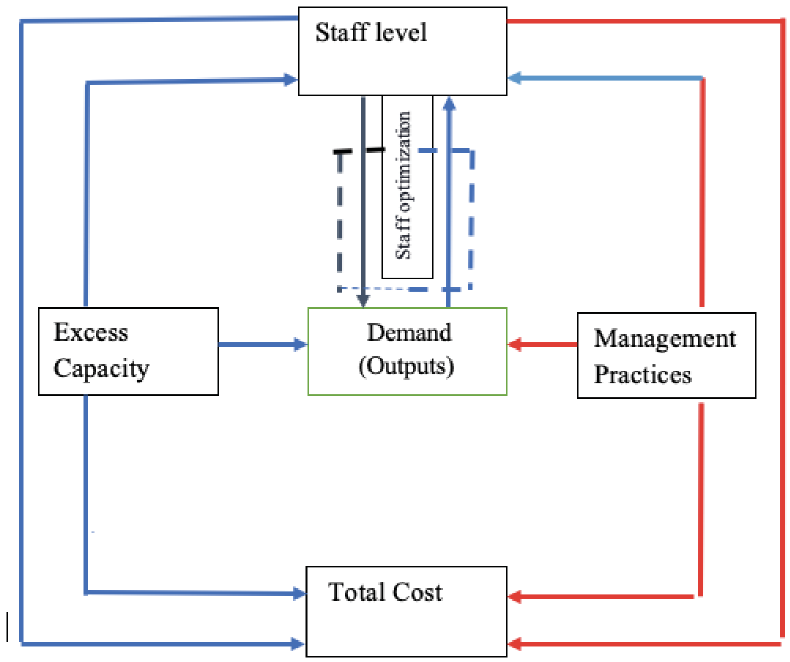

Figure 1 – Conceptual Framework

In the Introduction section, I discussed the research issues considering the characteristics of hospitality operations and summarized these in the conceptual framework. The following sections are organized as follows. Section 1.1 provides the research questions and the specific goals of the thesis. Section 2 develops a theoretical framework for our analysis and highlights the gaps in the literature. Section 3 discusses the data sources, variable construction, and the empirical approaches used in the research. Sections 4 and 5 discuss the study context and the summary of each study. Finally, section 6 provides concluding comments, together with the theoretical, managerial, and policy implications. Moreover, this section provides the limitations of the thesis and avenues for future research.

1.1 Research Aims, Goals, and Contributions

The primary aim of this thesis is to understand the determinants of productivity in inputs management among Norwegian hospitality companies. The degree to which the companies optimally manage inputs depends on the input characteristics, i.e., whether the inputs are variable or fixed, among others. Suboptimal use of both types of inputs have negative consequences for service delivery and cost performance; however, only variable inputs have implications for managerial decision-making. That is, the companies can correct errors in staff levels or the speed of staff adjustment daily; however, hospitality operators have limited scope to improve the management of fixed inputs within a short period of time. The companies need to change the available capacity or improve demand to change the level of excess capacity. Moreover, the operators need to change the inbuilt organizational routines that depend on managerial ability, which also does not seem to be plausible within a short period of time. Therefore, this thesis accordingly divides the research theme into two main research questions as follows:

- To what extent do hospitality companies get their staff levels right and at the right time?
- How do fixed inputs use influence cost performance?

The first paper deals with staff optimization as it is the primary input that determines profitability in hospitality and other service industries. The study further examines the extent to which the companies determined the correct staff levels and whether this process is *just-in-time*. The correct speed of staff adjustment is the easiest way to make hospitality services efficient and effective. The latter two studies measure the in(direct) effects of suboptimal amounts of fixed inputs on firm performance.

This thesis aims to help owners improve the operations of hospitality businesses. Paper 1 deals with optimization of staff scheduling by focusing on the time required to match staff levels with demand. We also examine the characteristics of hospitality operations such as hotel and department level characteristics, heterogeneity, endogeneity, reverse causality, and similar shocks (e.g., terrorism, economic crises, among others).

The second and third studies examine the in(direct) effects of excess capacity and management practices on the performance of hospitality companies. The direct and indirect effects are measured as the effects on the production technology and the technical efficiency, respectively. The second study contributes by providing empirical applications of the effects of excess capacity, which is lacking in the literature. The final paper contributes by measuring the effectiveness of management practices in such a way that the measures are streamlined to the specific hospitality business goals. This was a limitation of the earlier literature on the empirical economics of management.

2 Theoretical Framework

This thesis builds on the theory of cost (production), while emphasizing the application to the service sector using the concept of service probability. However, for convenience, I divided the theoretical framework into two parts: service probability model and IDF.

2.1. Service Probability Model

Duncan's (1990) stylized model of service probability states that service companies predict the demand for the next period based on the information at its disposal and make production and inputs requirement decisions ahead of time. Firms make production decisions based on predicted demand, but this might not always coincide with the actual case because of inadequate information on demand fluctuations (Ernst et al., 2004). Moreover, the degree to which the operators collect and interpret information and make a precise demand forecast depends on managerial quality, which is unobservable in real data. Based on this premise, production economics propounds that productivity differences can be attributed to differences in management practices (see Syverson, 2011).

The research on empirical economics of management emerged recently (in the past two decades) except for a few studies (e.g. Lucas Jr, 1978; Mundlak, 1961), which considered management to be a fixed effect. However, the measurement of unobserved managerial talent using management practices remains a challenge, as measures of management practices in previous studies are too general and lack evidence from the hospitality sector. Therefore, this thesis aims to fill this gap.

Gaynor & Anderson (1995) extend the theory to a two-stage decision; first, the decision on fixed inputs; second, variable inputs because the characteristics of these inputs are different. In the short run, fixed inputs also indicate maximum capacity and the demand determines how much of this capacity is utilized. Therefore, service probability indicates the level of capacity utilization. When service probability is at a maximum (one), capacity is fully utilized, and the same is true for the variable inputs. Grönroos and Ojasalo (2004) regard capacity efficiency as one aspect of service productivity because the mismatches between capacity and demand have negative consequences for performance. That is, capacity inefficiency implies higher cost without the corresponding return, while capacity shortage implies negative impacts on quality and customer satisfaction. All other things remaining constant, these anomalies were eliminated at the point of capacity efficiency (where demand equals capacity) according to the theory of cost in microeconomics. In the short run, it is not easy to change the levels of fixed or quasi-fixed inputs because the expansion or downsizing in response to demand takes a long period of time.

In the second stage, the companies need to forecast demand and adjust variable inputs, such as labor and materials, given the fixed capacity. Duncan's (1990) forecast information is relevant to understanding the levels of these inputs ahead of time. Staff levels are the main variable input in hospitality; therefore, the optimization of staff and the speed of adjustment are issues of concern in this sector. The optimization of staff is defined based on the theory of dynamic labor demand, and the current staff level is defined as a function of the past staff level, wage rate, and outputs. Dynamic partial adjustment states that the desirable (profit-maximizing) level of staff adjustment is unobservable but computed based on the current and past staff adjustment levels. Therefore, the degree of staff adjustment is the proportion of the current staff adjustment level to the difference between the current and past staff adjustment levels (Caballero, Cowan, Engel, & Micco, 2013). Staff adjustment is sticky if the proportion is closer to zero, but the adjustment becomes flexible if it is closer to one. Earlier studies in hospitality (Park, Yaduma, Lockwood, & Williams, 2016; Yaduma, Williams, Lockwood, & Park, 2015) approached the issue of staff adjustment on a part-by-part basis, i.e., the studies provided the effects of labor flexibility on output independently from the effect of demand fluctuation on labor flexibility. Furthermore, the literature does not consider endogeneity, reverse causality with output flexibility, heterogeneity, and common shocks.

2.2. Input Distance Function

The radial IDF was developed by Shephard (1953) to measure the inputs distance technology for a single output and was extended to multi-output technology by Fare and Primont (1995). The motivation for applying the theory of cost (IDF) lies in the major implications of the service probability model discussed in subsection 2.1. First, the inputs are derived from the demand and the outputs which in other words mean that the inputs levels are equivalent to outputs. The relationship reflects on the endogeneity issues as also documented in the literature (e.g. Chen, Lin, & Liao, 2014). Second, the goal of these companies is to minimize cost, where cost is measured in terms of inputs use because it is difficult to obtain input and output prices in multiservice-producing companies, which are required to align variable inputs to their exogenously determined demand and production technology. Therefore, IDF is advantageous because it permits endogeneity and does not require input prices.

Based on the theory of cost, the IDF is constructed from vectors of inputs x, outputs y, and environmental variables z, which control for differences in contexts. Moreover, we included time t to emphasize the role of experience gained over time through learning by doing, among others (Teece & Pisano, 1994). Therefore, the IDF is specified as $D = F(y, \theta x, z, t)$. Based on the property that the distance function is homogeneous of degree 1 in θx, and the area of the distance function equals one, the transformation function becomes $1/\theta x_1 = F(1, \tilde{x}, y, z, t) \equiv f(\tilde{x}, y, z, t)$ where, $\tilde{x}_2 = x_2 / x_1$, etc. are the input ratios (Kumbhakar & Lovell, 2000). Furthermore, a natural logarithmic transformation gives $\ln\theta = -u \leq 0$, implying that a company is technically efficient when $\theta = 1\,\theta < 1$. Random noise is implicitly specified together with the distance function (Kumbhakar, Wang, & Horncastle, 2015). The theory specifies the technology and the corresponding production cost as a function of the input ratios, vector of outputs, other environmental variables, and time. All other things remaining the same, the environmental variables can potentially make the production technology cheaper or more expensive, and the technical inefficiency lower or higher. Therefore, the environmental variables are included as potential determinants of the inefficiency variance.

The larger the excess capacity, the higher the production cost and vice versa because excess capacity makes the technology more expensive, ceteris paribus. Moreover, the larger the excess capacity, the higher will be the technical inefficiency because of perishability. Location, defined as small metro town, suburban, urban, or airport areas, and regional differences in Norway, were included as environmental variables. We control for these variables because they are sources of heterogeneity in hospitality services.

Management practices impact production technology in two ways. First, conducive organizational routines that result from better management practices help companies realize that technologies reduce input use. Second, better management practices cannot be realized without an additional cost (Syverson, 2011). Therefore, the impact of better management practices on production costs depends on the net effect, because the cost can offset the positive impact. Besides, better management practices make the companies respond to demand fluctuations more precisely which improves the efficiency of hospitality services provision. That is, management practices reduce technical inefficiency.

3 Data Methodology

The analyses in this thesis used secondary data from d2o, a private company that supports hospitality businesses in terms of productivity management; e.g., by supplying staff forecasting software. The software collects the historical data required to forecast demand. Although the primary purpose of the data collection was to develop support systems for productivity improvement, d2o and its clients were willing to share their data with us for this project.

The dataset consists of unbalanced daily panel data from 94 hotels and restaurants for a period from 2003 to 2014. The original dataset consists of 263,587 observations, but the number of usable observations is lower because of missing values and outliers. The hospitality companies used in this study belonged to three chain hotel groups and were geographically dispersed all throughout Norway (small metro towns, suburbs, urban areas, airports).

The dataset includes variables for outputs, staff levels, training, wage rates, and fixed effects (e.g., location, region, city, market coverage, operation). In the dataset, outputs are measured in terms of revenue from three sources: food and beverage (F&B), accommodation (room service), and other sales. It also provides detailed information on staff levels, training, and the wage rate for each activity (e.g., cafe, bar, restaurant). Based on these data, we computed the quality-weighted staff levels from various departments using a *divisia index*. The quality-weighted staff hours were essential for measuring hotel-level staff with diverse skills and levels of experience.

The financial data (revenues and wage rates) were deflated to 2015 prices using the Norwegian consumer price index collected from Statistics Norway to account for differences in price levels and inflation over the study period. Furthermore, the outputs are measured in terms of single or multiple outputs. Total revenue was used as the measure of a single output while the revenues from each department (F&B, accommodation services, and other sales) were used to measure multiple outputs.

The thesis applied various econometric approaches to these data. Paper 1 estimated the labor flexibility at the hotel and department levels based on the full sample using a newly developed econometric model: *dynamic common correlated effects approach*. The empirical model is constructed using staff level (labor hours) as the dependent variable, and lagged labor hours, output, and wage rate as the independent variables. The approach provides estimates of the adjustment coefficient and degree of labor flexibility, as well as the short-run dynamics and long-run elasticities. These estimations were mainly conducted at the hotel and department levels to examine and compare labor flexibility in each case.

Paper 2 estimated the effects of excess capacity on production technology and technical efficiency using the full sample. The model uses stochastic frontier analysis based on IDF. In this framework, one of the inputs, e.g., capital, is specified as a function of the input ratio and outputs. The time trend and the regional and location dummies are used as potential determinants of production technology. The inefficiency term was specified as a function of excess capacity, and the regional and location dummies.

Finally, paper 3 investigated the effects of management practices for 92 companies over the period 2012 to 2014 because the staffing software, which was used in the measurement of management practices were implemented in 2012. The estimation of the empirical models was conducted in a similar way to paper 2 using stochastic frontier analysis. In this case, the dependent variable is staff hours and the determinants of production technology were input ratio, outputs, management practices, chain dummies, and time trend, while technical inefficiency was specified as a function of management practices, chain dummies and firm fixed effects.

Finally, the estimations of the empirical models in both papers 2 and 3 were conducted using a maximum likelihood estimator.

4. Study Setting

Norway is a prosperous but small economy in terms of its population. For example, the population of Norway was about 5.35 million and the economy generated a gross domestic product (GDP) of about 3552 billion NOK in 2019[1]. Norway is divided into five administrative regions: Central, Eastern, Western, Northern, and Southern. See Figure 2 for a map of Norway and the location of these regions on the map.

Innovation Norway (2017) states that the contribution of the tourism sector to GDP was about 4.2% in 2016. The tourism sector provides employment and income opportunities. For instance, The Norwegian Tourism Partners (2019) states that the tourism sector generates employment for 170,000 people and income of about 164 billion NOK per year on average.

[1] The statistics is taken from the front page of Statistics Norway. https://www.ssb.no.

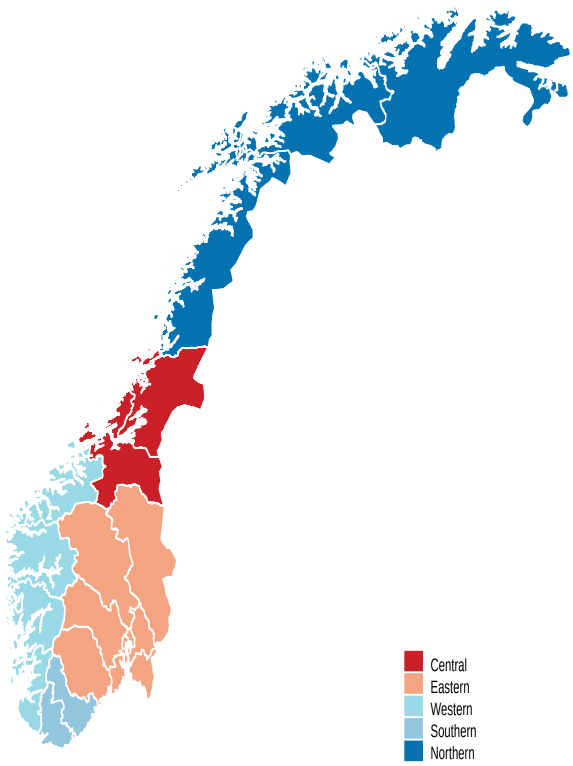

Figure 2 – Map of Norway and its regional classifications

Because the statistics mentioned above relate to tourism in general, I calculated the contributions of accommodation and food services (hospitality sector) from 2008 to 2017 (Statistikknett Reiseliv, 2019). The data show that the number of firms providing hospitality services increased from 5400 in 2008 to 9151 in 2017. Moreover, the sector generated employment for about 84,930 people and an income of about 61.43 billion NOK. The data also show an economic surplus of 1.55 billion and tax revenue of 679.5 million NOK over this period. The line graphs in Figures 3 and 4 illustrate the trends over the years in total revenue and total cost, and the major cost components: i.e., salary and materials costs.

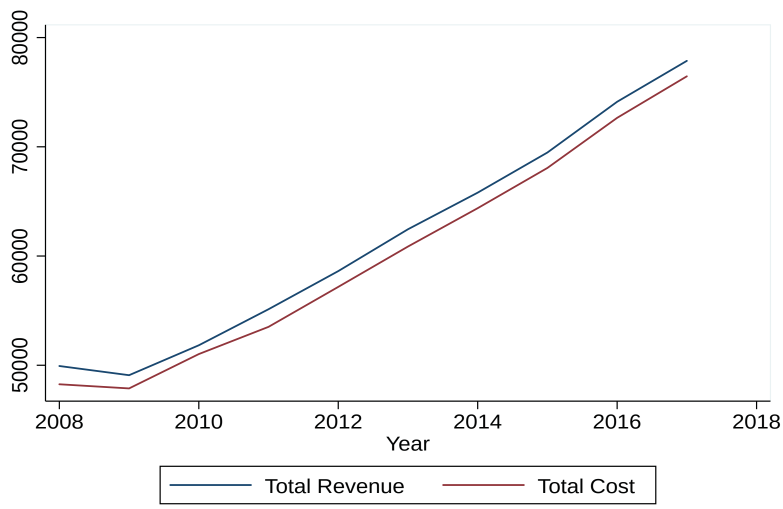

Figure 3 – The average revenue and cost of hospitality operations (2008 – 2017)

Source: Own illustration using data from tourism statistics (Statistikk.net)

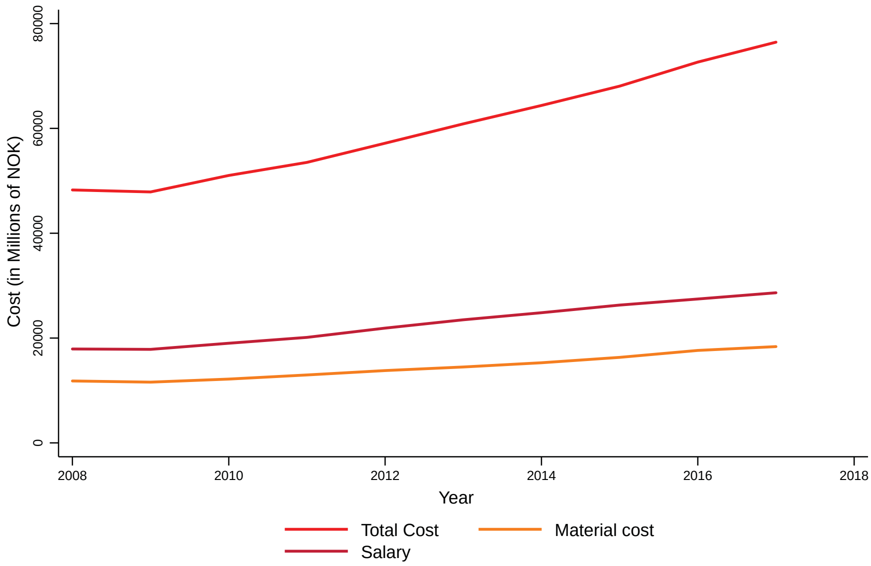

Figure 4 – Major cost components of hospitality operations (2008 – 2017)

Source: Own illustration using data from tourism statistics (Statistikk.net)

Youth, women, and immigrants dominate the hospitality sector, and this attempts to improve the productivity of this sector implies addressing these groups of the society. Besides, the main stakeholders emphasized improving the productivity and competitiveness of this sector for several reasons. First, Innovation Norway (2015) states that the contributions of tourism in Norway are less than in other countries. Similarly, the report of the Norwegian Productivity Commission (2015) states that improving productivity in the nonoil sectors is a main policy goal. Second, the Norwegian Tourism Partners (2019) underline the importance of improving productivity in the tourism sector. This is because Norwegian companies struggle to cope with the fast-changing business environment and suffer a competitive price disadvantage internationally leading to lower demand and thin tourism markets that result in high excess capacity in some areas. Moreover, the uncertainty about the activity levels in related domestic industries like the oil industry also creates unpredictability about demand. Third, The Organization for Economic Co-operation and Development (OECD, 2014) examined the high price level in Norway using a comparison with other OECD countries and found that the average wage level in 2014 in Norway was 69% higher than the OECD average. The report of the Norwegian Ministry of Trade and Industry (2012) stated that a high wage rate resulted in either exit from the market or created bias toward capital-intensive technologies for many labor-intensive companies. The cost disadvantage of the Norwegian tourism industry, in particular in relation to labor cost, means the industry must focus on increasing on productivity growth. In the long run, the only way to allow for higher wage level than competing destinations and hospitality markets is by achieving a higher productivity level. Finally, improving productivity is essential for reducing food waste from hotels and restaurants, and improving efforts towards sustainability.

5. Summary of Papers

This PhD thesis aims to shed light on productivity issues linked to the use of inputs among 94 hospitality companies in Norway. The thesis focuses on three different inputs; labor, room capacity, and management practices; because efficient hospitality operations management requires synergetic use of these inputs. Therefore, the thesis evaluates inputs management from three perspectives: (i) the extent to which the companies adjust labor use to demand fluctuations; (ii) the effects of excess capacity; and (iii) management practices regarding both production costs and technical efficiency. A summary of these three studies is presented below.

Paper 1 deals with labor flexibility: i.e., the extent to which hospitality companies respond to demand fluctuations by adjusting staff levels. Labor flexibility is judged relative to the most desirable level in the long run: e.g., a situation where no time is wasted to find and match the required staff level to demand. The paper also compares the flexibilities among these departments (room service, F&B, and overheads) because the hospitality operations in each department are conducted by labor with different skills and group characteristics. The results show that labor flexibility is about two-thirds of the profit-maximizing level on average, which implies that labor is quite flexible. A comparison among the departments shows that room service is the most flexible at about two-thirds, overheads are moderate at about half, and F&B is the least flexible at about less than one-fourth of the profit-maximizing level. Conversion into time required using the half-life formula shows that the companies take less than a day on average to adjust half of the gap between the desired and the realized levels. Room service and overheads also take less than a day to correct half of this gap, but F&B takes several days. Therefore, the findings suggest improving the labor flexibility at a company level and in F&B in particular.

Paper 2 analyzes how excess capacity influences production costs and technical efficiency. The empirical model controls for a time trend, location, and regional differences in the production technology, and location and regional differences in technical efficiency. The study shows that excess capacity affects the performance of hospitality companies both by making the production technology more expensive and increasing technical inefficiency. For example, a 1% increase in excess capacity increases production costs by 1.59% and technical inefficiency by 0.58%. The sample hospitality companies have an excess capacity of about 45% per day, which implies that production costs are about 70% higher than the minimum possible level and technical inefficiency is about 26%.

Nevertheless, the marginal effects of excess capacity are heterogeneous. The marginal effect of excess capacity on production technology varies positively with the amount of excess capacity, but the effect on technical efficiency begins at the 50% level and increases steadily after that. Technology was improving over the study period by an average of 2.11% annually, but the actual rate declined over this period. The finding also suggests that the companies need to expand their scale of operations to reduce costs and improve efficiency.

Paper 3 examines how and how much management practices influence production costs using a similar approach to paper 2. The effectiveness of management practices was measured using the use of forecasting software from worst to most effective on a scale from 1 to

10. The findings show that improved management practices make the production technology more expensive on average, but improve technical efficiency. Improving management practices by one unit increases the cost of production by about 1.17%, but improves technical efficiency by about 0.88% on average. The marginal effects of management practices are heterogeneous. The effect on the production technology has a U-shaped pattern implying that improved management practices initially improve the production technology up to some threshold level, but after this level, improved management practices make the technology more expensive. However, the effect on technical inefficiency declines monotonically as management practices improve. As a result, the most-effective management practices yield the most-efficient hospitality companies, ceteris paribus.

Study	Title	Coauthors	Methodology	Status
1	Long-run labour flexibility in hospitality: A dynamic common correlate effects approach	Sigbjorn Tveteraas (Professor)	Dynamic common correlate effects approach	Published in tourism economics
2	Excess Capacity, Production Technology and Technical Inefficiency in Hospitality.	Subal C. Kumbhakar (Distinguished Research professor)	Stochastic Frontier Analysis	Under second review in Tourism Management
3	Do Management Practices Make a Difference in Hospitality Sector?	Sigbjørn L. Tveteraas (Professor) Kristin H. Roll (Professor) Ragnar Tveterås (Professor)	Stochastic Frontier Analysis	Manuscript

Table 1 – Summary of papers

6. Concluding Remarks

This PhD thesis examines the inputs management of hospitality operations and calls upon hospitality operators, managers, investors, and policymakers to improve this management. In hospitality, the costs relating to fixed inputs are assumed to be a sunk cost, and a much greater focus is on the optimization of labor, food, energy, and other inputs that directly relate to hosting guests receive the bulk of attention. However, this thesis shows stakeholders that the management of fixed inputs also influences the day-to-day performance of hospitality operations. Therefore, both the variable and fixed inputs should be considered in managing the operations. The thesis also divides the contributions into theoretical and managerial and policy implications. Finally, the thesis discusses the limitations and areas for further research.

6.1. Theoretical contributions

The theoretical formulation of labor flexibility should account for the endogeneity of output flexibility, bidirectional relationships between these flexibilities, heterogeneity, and common shocks.

i. Labor flexibility should be measured at a subgroup level because the characteristics (skills, experience, requirements for vocational training, and so on) differ among the departments.
ii. Excess capacity should be considered among the factors that explain production technology and technical efficiency because the loss of revenues and the additional cost imposed by excess capacity makes hospitality production more expensive and wastes labor, food, materials, etc. unnecessarily. Excess capacity is the outcome of demand for accommodation service, which is determined by external factors and which the companies cannot influence. Our results support the contribution of Grönroos and Ojasalo (2004) on the inclusion of capacity efficiency in measuring the productivity and efficiency of service companies from a different perspective.

iii. Location and regional differences should be included in the hospitality production technology and technical efficiency because these variables are essential in both cases in our findings because they influence both demand and available pool of labor.

iv. Management practices in staffing decisions should be simultaneously considered among the potential factors that determine both production technology and technical efficiency.

v. The cost and benefit analysis of improved management practices should be considered in management practices research. The benefit of hospitality management practices involves better planning and responsiveness to demand changes, which in our case, refers to forecasting demand and adapting the inputs requirement. However, the impact of the organizational routines on production costs can be positive, zero, or negative depending on whether the cost of implementing the practices is less, equal to or greater than the benefits.

vi. The differences in chain affiliations should be considered in both the technology and efficiency of hospitality firms.

6.2. Managerial and Policy Implications

The findings of the three studies in this thesis suggest that there is scope to improve the use of inputs in hospitality production. Specifically, we provide the following managerial and policy recommendations.

- Improving the pace at which labor is adapted to demand fluctuations because the companies require more flexibility to reach the profit-maximizing level, and special attention should be given to improving the labor flexibility of F&B. However, the increased flexibility should consider the hospitality characteristics and the preferences of employees. In this case, the role of managers is to minimize decision errors. More importantly, government policies and external restraints governing the hospitality market should consider the constraints and contribute to the competitiveness of hospitality companies.
- Increasing the capacity utilization (demand for accommodation services) results in cheaper production technology and reduced waste of inputs. Hospitality managers of the respective companies should improve efforts to win a fair share of the available market,

but improving tourism demand during low demand seasons is challenging. Increasing the demand for accommodation services out-of-season outwards is more of a destination level issue that likely requires policy interventions because hotel guests' demand is driven by several factors at the destination level and factors related to guests' preferences and income.

- Improving technical efficiency and increasing investment in research and development helps companies improve input use and reverse the diminishing rate of technical progress.
- By improving management practices, the companies can benefit up to some level in terms of lower production costs (inputs saving technology), and lower input wastage. However, improvements in technology mature at some point before the best management practices are reached. Therefore, managers should be aware of the optimal level of management practices.
- Expanding the size of the companies enables them exploit improved cost efficiency given the demand-side constraint and management ability.

6.3. Limitations and Areas of Future Research

This thesis has some limitations, which should be considered in future research. The dataset used in this thesis was obtained from a secondary source, and it is comprised of three hotel chains although a larger number of hotel chains operate in Norway. Therefore, including hotels and restaurants from the remaining chains would improve the validity of the findings. Moreover, the data we used consist of daily observations for the total number of labor hours at both department and hotel levels. Nevertheless, the demand for F&B requires intraday data to understand labor flexibility in these departments more precisely. Furthermore, the measurement of outputs using revenue in NOK might bias the findings in the presence of market power. Therefore, the estimation of labor flexibility using hourly demand and labor-use data and controlling for market power would improve the reliability of the results.

Labor use was measured in terms of total labor hours per day, but does not identify the type of work, e.g., whether the labor hours refer to regular overtime work, part-time work, or agency work. More specific data would help researchers understand the implications of labor flexibility on cost and quality. The presence of low labor flexibility in F&B might affect employee welfare, e.g., because of long working hours, burnout, and so on. However, high labor flexibility in room service might be at the expense of service quality or cost if the companies use inexperienced temporary staff or source the workers from a third-party. These potential trade-offs make the research on labor flexibility and corporate social responsibility in the hospitality industry highly interesting for future research. Moreover, instead of labor, the flexibility of other variable inputs (e.g., materials) is another aspect to be explored in the future.

Given the strong seasonality and thinner market, there was a considerable amount of excess capacity among the sample firms. The findings suggest that by increasing demand (say by attracting more tourists), a company can make a considerable cost saving. Nevertheless, how to increase tourism demand in Norway and make hospitality companies improve the utilization of their capacity requires more research, e.g., we need more knowledge about drivers of the demand for domestic and international travel to Norway, especially during low-demand seasons. Moreover, the goal of hospitality companies is not to avoid excess capacity at all, but rather minimize the cost of maintaining the extra capacity. Besides, hospitality companies have a system where high revenue (price) during a peak season subsidizes the low season. Considering this price subsidy, identifying the optimal capacity helps the companies make an informed decision. Moreover, incorporating the state of nature (e.g., seasonality) in the estimation of optimal excess capacity is also another avenue for extending the research in the future.

Finally, as the thesis deals with inputs management in hospitality operations, the scope of the impact of management practices is limited only to input use. However, the impact of management practices extends beyond cost-efficiency. For instance, improved management practices can yield better working conditions, better employee and guest satisfaction, and other positive outcomes, which the companies benefit from. Therefore, the research in this area should be extended to measuring the impact on output or profit maximization, and from an intertemporal dimension.

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Paper 1

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Paper 2

Excess Capacity, Production Technology and Technical inefficiency in Hospitality[2]

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Excess Capacity, Production Technology and Technical Inefficiency in Hospitality Sector

Abstract

This article examines the effects of excess capacity on the production cost and technical inefficiency of hotels and restaurants in Norway. The dataset includes a daily unbalanced panel of 94 hotels and restaurants from 2003 to 2014. To accommodate inefficiency, we use an input distance function (IDF). Inefficiency in the IDF means that if inputs are overused by k% then production cost is also increased by k%. We also allow inefficiency to differ across locations and regions by using them as determinants. The results indicate that excess capacity considerably affects the cost and increases inefficiency. The marginal effect on cost increases with excess capacity, but the effect on inefficiency sets in when it exceeds 50 percent. Furthermore, we find less overuse of inputs by firms in small metro towns and the Northern region causing them to be more efficient [except for the Southern and Western regions] than their counterparts.

Keywords: Excess capacity, hospitality, technical inefficiency, stochastic frontier analysis, input distance function.

1. Introduction

Hospitality firms are plagued with excess capacity despite exerting immense effort in marketing their services to boost capacity utilization, i.e., the occupancy rate, using their own website and other platforms such as Booking.com, Expedia and TripAdvisor. In Norway, for instance, over the period from 2007 to 2016, the capacity utilization of accommodation services was on average 49.34%, with a range of 23% to 89%[3]. This could also be the case in other countries. For instance, firms might have some excess capacity to cope with demand fluctuations when uncertainty is high (Pulina, Detotto, & Paba, 2010; Shang, Wang, & Hung, 2010). Higher capacity utilization is expected during the peak season or when the demand for hospitality services increases because of certain special events, but there is excess/unused capacity during the off-peak seasons. If firm sizes are limited to the extent that they can only satisfy the off-peak demand optimally, it will clearly be non-optimal for all seasons. This is because a hospitality firm operating at the optimum scale during the off-peak seasons will have a capacity shortage during

3 The figures are calculated based on the statistics from www.statistikknett.no.

the peak season and therefore many customers will be refused services because of frequent full booking. Thus, the fixed nature of the available capacity constitutes one of the major reasons for excess capacity. Furthermore, firms keep some excess capacity to influence the outputs of competitors and prohibit potential rivals from entering the market (Nishimori & Ogawa, 2004). In short, excess capacity is beyond firms' control and cannot be avoided because demand cannot be predicted with certainty and capacity cannot be changed in the short run. Presence of excess capacity means firms are operating below their installed capacity in terms of, say, number of guest rooms, building size, etc. Thus, excess capacity is reflected, for example, in the room utilization rate (being less than 100%). This leads to lower revenue and/or higher cost. That is, revenue is less than what it could be under full utilization of say guest rooms. Similarly, since low demand for rooms, restaurants, etc., are not anticipated beforehand, cost (labor, food, materials, etc.) is higher than what it could be had all the resources been fully used. Thus, excess capacity is costly, and it might be of interest to estimate the percentage increase in cost because of excess capacity for each firm at every point in time. Another reason why cost of a firm would be higher is the presence of technical inefficiency, i.e., excessive use of inputs. Cost of technical inefficiency is defined as the percentage by which cost is increased because of excessive use of inputs. That is, a firm is technically inefficient if it uses more inputs than the minimum required to produce a given level of output (see Kumbhakar and Lovell (2000) for details). Thus, a firm's cost can be higher than its minimum cost because of excess capacity as well as technical inefficiency. These issues are not examined in the hospitality industry. The hospitality literature (Chen, Chiu, & Hsu, 2016; Chen & Lin, 2013) investigated the relationship between demand uncertainty and capacity of hospitality businesses but not the effects. Therefore, the main goal of this study is to estimate the extent to which excess capacity can affect production cost and technical inefficiency for individual firms. Since the estimates of increased cost is firm-specific, our results will show which firms are inefficient and by how much of their increased cost is due to technical inefficiency and how much is due to excess capacity. We also introduce factors that can explain inefficiency and cost therefrom. These issues are not addressed in the hospitality literature.

The economics literature has explored the issue of excess capacity since 1935 (Kaldor, 1935), including in services sectors, such as banking, airlines, hospitals, electricity, telephone and postal services, are abundant. Rodríguez-Álvarez and Knox Lovell (2004) applied an input distance function (IDF) and share equations to investigate the effect of excess capacity on the allocative behavior of hospitals. Recently, Tovar and Wall (2015) estimated the technical inefficiency of Spanish ports, while accounting for excess capacity. However, the issue of efficiency and capacity utilization has not been explored empirically for hospitality. In a theoretical paper, Grönroos and Ojasalo (2004) regarded efficiency in capacity utilization as one of the three pillars for measuring firm performance. The majority of firm efficiency and productivity studies in the hospitality literature to date are predominantly devoted to measuring technical efficiency. These studies implicitly assumed that firms become fully efficient when all the available capacity is fully booked, all other factors remaining constant. Methodologically, few hospitality studies have applied the distance function (Assaf & Tsionas, 2018; Barros, Peypoch, & Solonandrasana, 2009; Peypoch & Solonandrasana, 2008) details of which is discussed later. Some studies (Assaf & Magnini, 2012; Yu & Lee, 2009) include customer satisfaction in the measure of efficiency and productivity in the hospitality sector, but the measure remains incomplete without the inclusion of excess capacity.

Given this backdrop, the current study examines the effect of excess capacity and inefficiency on cost using daily unbalanced panel data of hospitality firms observed over the period from 2003 to 2014 in Norway. Production technology and technical inefficiency are estimated using an IDF that is dual to the cost function. That is, all the information about the technology can be obtained from either the cost or the IDF. Given that we are dealing with a service industry for which outputs are exogenous (demand determined), the use of a cost (IDF) is appropriate. One could use a cost function, but its estimation requires information on input prices, which is not available. Because the technology is represented by the IDF, which is dual to the cost function, the effect of a variable on the technology is the same as its effect on cost. Given that we have data on excess capacity, we use it as an argument in the IDF as well as a determinant of inefficiency among other variables. The average effects of excess capacity on cost (via the IDF) and the technical inefficiency are, on average, found to be about 1.59% and 0.58%, respectively.

However, these effects vary with the degree of excess capacity. We also find technical progress (cost diminution) of 2.11% per annum, but it declined over the study period. Location and regional differences were proved to be important in explaining the differences in the production technology and technical inefficiency. Firms in small metro towns were found to be most technically efficient, while those near airports were the least efficient. Firms in the Northern region had better production technology (had lower cost, ceteris paribus) but they were better than only the Central and Eastern regions in terms of technical efficiency. After controlling for these factors, hospitality firms are found to be highly efficient (96.26 percent) with very little room for improvement. We discuss the managerial and policy implications to improve the efficiency of firms in the hospitality industry.

This study contributes to the literature in several ways. First, the study fills a gap in the literature by providing an empirical analysis from a different perspective and in a different setting compared with earlier studies (e.g., Tovar & Wall, 2015, who examined the productive efficiency of port efficiency in the presence of uncertainty). Although the hotel and restaurant sectors share some characteristics with hospitals and ports, the demand and performance characteristics are specific to each sector and even differ within the same sector, i.e., this makes the research setting different from the earlier ones. In addition, our approach is different from Tovar and Wall (2015). Second, unlike previous studies in this area the present study uses a unique dataset with a large number of daily observations. Third, the study is relevant because it estimates the degree of inefficiency for each hospitality firm (which are anecdotally known for strong seasonality, high service price, but low service quality) and shows whether certain types of firms perform better than others and whether there is scope to improve their efficiency. Also this is the first efficiency study incorporating excess capacity of Norwegian hotels and restaurants. Finally, in addition to estimating inefficiency and cost therefrom for each firm at every point of time, our model also shows by how much cost is increased due to excess capacity. Both of these are relevant to the management who might be aware of the size of their excess but the cost of it.

The remaining sections of this article are organized as follows. Section 2 describes the theoretical model used to examine the effect of excess capacity on cost (via the IDF); technical change and technical efficiency.

Section 3 discusses the implementation of the IDF, followed by Section 4, which describes the data sources and construction of the variables. Section 5 discusses the results, while the final section provides the key findings, conclusions, and the managerial and policy implications on tourism management.

2. Theoretical Framework

2.1. Excess Capacity in Hospitality Services

Excess capacity can be defined in terms of the scale of operation of a production unit. If the scale of operation is at the minimum point of the average cost function, the operation is said to be at the optimum. In other words, if the returns to scale for a unit is unity, it is said to be operating at an efficient scale and there is no excess capacity. According to this definition, excess capacity exists when a unit operates with decreasing returns to scale (which is determined by the technology), thereby meaning that there will be cost saving in expanding output/services. In many cases, the scale of operation is determined by demand which is not under the control of a production unit. Thus, an unforeseen reduction in demand can cause excess capacity because a firm cannot adjust its inputs (mostly quasi-fixed inputs) instantaneously to accommodate lower demand for outputs.

In some cases, it is possible to construct an index of excess capacity without estimating returns to scale from the estimated technology. For example, in hospitality/hotel operations, full capacity is determined by the number of rooms available in a day. If the number of rooms booked is less than the number of available rooms, then the capacity is not fully used. The advantage of this approach is that we can examine the effect of excess capacity on cost econometrically. We examine the effect of excess capacity on cost, as well as on efficiency by estimating an IDF.

2.2. Input Distance Function

Excess capacity can affect cost directly through the production technology, as well as indirectly through inefficiency. The goal of our empirical model is to estimate both of these effects. However, instead of estimating the cost function, which requires data on input prices, we estimate the IDF, which is dual to the cost function when the firm's objective is to minimize cost. In this setup, inputs are endogenous, and outputs are exogenous. This suits our application because firms in our model are hotels and restaurants for whom outputs (services provided) are demand determined and therefore exogenous to the firms. Inefficiency in this setup is input oriented, i.e., inefficient firms overuse their inputs, which in turn increases the cost. Thus, if inputs are overused by k%, the cost will be k% higher. Therefore, we can obtain cost information by estimating the IDF.

Instead of starting from the IDF the way it is defined in Shephard (1953) (see also Fare & Primont (1995), Kumbhakar & Lovell (2000), we rationalize it by specifying a transformation function that is more general in the sense that one can use it to model the technology without inefficiency. With input-oriented inefficiency, we specify it as $F(y,\theta x,k,t)A=1$ where y and x are vectors of J outputs and M inputs, and $\theta \le 1$ is radial input inefficiency. The vector of environmental variables is z; t is a time trend variable and A is specified as $A = exp(v)$ where v is the noise term. For identification, we assume that $F(y,\theta x,k,t)$ is homogeneous of degree 1 in θx, and rewrite the transformation function as $1/\theta x_1 = F(1,\tilde{x},y,k,t) \equiv f(\tilde{x},y,k,t)$ where $\tilde{x} = x_2/x_1, \ldots, x_J/x_1$. Taking logs of both sides, we obtain $-\ln x_1 = \ln f(\tilde{x}_2, y_j, k, t) - u + v$, where $\ln\theta = -u \le 0$ and $\tilde{x}_2 = x_2/x_1$, etc., are the input ratios. This is how a standard IDF is specified (Kumbhakar & Lovell, 2000). Here, we derived it from a transformation function (see Kumbhakar, 2013 for more details).

Assuming a translog form for $\ln f(\tilde{x}, y, k, t)$, we write the IDF as $-\ln x_1 = TL(\ln \tilde{x}_2; \ln y, k, t) - u + v$ where TL (.) is the translog function. In our application, we have two inputs (x_1 is capital and x_2 is labor) and three outputs (revenues from food and beverages y_1, accommodation services y_2 and other sales y_3). Finally, k is excess capacity in percentage terms (defined as one minus the occupancy rate, $\tilde{d}$) and t is a time trend (see Kumbhakar, Wang, & Horncastle, 2015) for more on the IDF). For multiple outputs and with excess capacity, the full TL IDF is

$$\begin{aligned}
-\ln x_1 = {} & \beta_0 + \sum_{j=1}^{3} \beta_{y_j} \ln y_j + \beta_{\tilde{x}_2} \ln \tilde{x}_2 + \beta_k k + \beta_t t + \frac{1}{2} \sum_{j=1}^{3} \sum_{j'=1}^{3} \beta_{y_{jj'}} \ln y_j . \ln y_{j'} \\
& + \frac{1}{2} \beta_{\tilde{x}_{22}} \left(\ln \tilde{x}_2 \right)^2 + \frac{1}{2} \beta_{kk} \left(k \right)^2 + \frac{1}{2} \beta_{tt} \left(t \right)^2 + \sum_{j=1}^{3} \beta_{y_j \tilde{x}_2} \ln y_j . \ln \tilde{x}_2 + \sum_{j=1}^{3} \beta_{y_j k} \ln y_j . k \\
& + \sum_{j=1}^{3} \beta_{y_j t} \ln y_j t + \beta_{\tilde{x}_2 k} \ln \tilde{x}_2 . k + \beta_{x_2 t} \ln \tilde{x}_2 . t + \beta_{kt} k . t + \sum_{n=1}^{3} \beta_{l_n} l_n + \sum_{m=1}^{4} \beta_{r_m} r_m + v - u(k, l_n, r_m)
\end{aligned} \tag{1}$$

The symmetry restrictions imply that $\beta_{y_j \tilde{x}_2} = \beta_{\tilde{x}_2 y_j}$, $\beta_{y_j \tilde{x}_2} = \beta_{\tilde{x}_2 y_j}$, $\beta_{y_j t} = \beta_{t y_j}$, $\beta_{\tilde{x}_2 k} = \beta_{k \tilde{x}_2}$, $\beta_{\tilde{x}_2 t} = \beta_{t \tilde{x}_2}$, $\beta_{kt} = \beta_{tk}$. Note that our model is for a panel of hotels/restaurants, but we have not added subscripts for i and t for simplicity. We added location dummies, l_n (where n = 2, 3, 4) and region dummies, r_m (where m = 2, 3, 4, 5) in the above IDF to control for regional and locational effects. Inefficiency is assumed to be distributed as half-normal whose variance is a function of k, l_n and r_m. In other words, excess capacity, location and regional dummies are viewed as determinants of inefficiency. The noise term is assumed to be normally distributed (iid over time and across hotels/restaurants), although it can be made to be heteroscedastic. Because k, l_n and r_m appear in both the IDF and in the expression for inefficiency, we can estimate their impacts on cost (represented by the IDF) and inefficiency. Note that because the IDF is dual to the cost function, the derivative $\partial \ln x_1 / \partial \ln y_j$ can be interpreted as the cost elasticity of outputs (Fare & Primont, 1995). Similarly, the impact of excess capacity on cost can be measured from $\partial \ln x_1 / \partial k$ when k is measured in percentage terms and technical change (cost diminution over time, ceteris paribus) from $-\partial \ln x_1 / \partial t$. These are direct effects. The indirect effect of k on cost is obtained from $\partial \ln x_1 / \partial k = \partial u / \partial k$. The indirect effects of regions and location can be obtained by taking the difference in the estimated u (instead of the derivative) from that in the reference region/location, ceteris paribus.

Our main focuses in this study are the following: (i) the cost elasticity of outputs, (ii) cost elasticity of excess capacity, (iii) technical change and (iv) marginal effect of k on inefficiency. Because technical efficiency is defined as $TE = exp(-u)$, the percentage change in TE over time can be computed from $100(\partial \ln TE / \partial t) = -100 \partial u / \partial t$. After estimating the model parameters, u can be estimated using the conditional mean of $u \mid (v-u)$ and the marginal effect of k on u can be obtained from $\partial E(u \mid (v-u)) / \partial k$. See Kumbhakar, et al. (2015) for the exact formula for computing these marginal effects.

Based on the IDF in (1), the formulas for (i)–(iii) above are:

$$-\frac{\partial \ln x_{1it}}{\partial \ln y_j} = \beta_{y_j} + \sum_{j'=1}^{3} \beta_{y_{jj'}} \ln y_{j'} + \beta_{y_j \tilde{x}_2} \ln \tilde{x}_2 + \beta_{y_j k} k + \beta_{y_j t} t \qquad (i)$$

$$-\frac{\partial \ln x_1}{\partial k} = \beta_k + \beta_{kk} k + \sum_{j=1}^{3} \beta_{y_j k} \ln y_j + \beta_{\tilde{x}_2 k} \ln \tilde{x}_2 + \beta_{kt} t \qquad (ii)$$

$$-\frac{\partial \ln x_1}{\partial t} = \beta_t + \beta_{tt} t + \sum_{j=1}^{3} \beta_{y_j t} \ln y_j + \beta_{\tilde{x}_2 t} \ln \tilde{x}_2 + \beta_{kt} k \qquad (iii)$$

The cost elasticity of outputs ($\partial \ln x_1 / \partial \ln y_j$) shows the percentage increase in cost for a one percent increase in the j^{th} output. The advantage of the translog IDF is that estimates of these cost elasticities in (2) are observation specific and they also vary over time. Because outputs are measured in terms of revenue, the cost elasticities show the percentage increase in cost for a one percent increase in revenue from each output. Therefore, if it is less than unity for a particular output, it means that there is a cost advantage in expanding that output. The sum of the cost elasticities ($E_{cy} = \sum_j \partial \ln x_1 / \partial \ln y_j$) is related to scale economies, which is defined as $SCE = 1 - E_{cy}$. A positive value of SCE means there is a cost advantage in expanding all outputs proportionally. Because it varies over time, one can examine how scale economies evolve over time. The cost elasticity of excess capacity shows the percentage by which cost will decrease when excess capacity is reduced by one percent. The formula in (2) gives an estimate of it, which is observation specific. A measure of technical change (shift in technology) is given by (3).

Because it is a measure of cost diminution, ceteris paribus, a positive value indicates technical progress. Again, this measure is observation specific. In addition, we are also interested in the effect of excess capacity on cost efficiency and change in technical efficiency over time. These measures are specific to the hotel/restaurant and vary over time.

2.3. Estimation

The model in (1) is estimated using the maximum likelihood method. We assume that u is distributed as half-normal with mean zero and variance $\sigma_u^2(q_{it}) = exp(\mu' q_{it})$ where q includes excess capacity, locational/regional dummies (k, l_n and r_m) and μ are the corresponding parameters. Because $E(u_{it}) = \sqrt{(2/\pi)}\sigma_u(q_{it})$, we view the q_{it} variables as determinants of inefficiency. We assume $v_{it} \sim i.i.d.\, N(0, \sigma_v^2)$ so that the distribution of $v - u$ is skew normal, which gives the probability density function of $(v-u)$ and hence the likelihood function. See Kumbhakar & Lovell (2000) for details. We used Stata to estimate the model parameters as well as the estimates of u and the effects of k and t on u (i.e., $\partial E(u_{it}) / \partial k_{it}$ and $\partial E(u_{it}) / \partial t$). Wang (2002) gives the formula of these marginal effects.

3. Data Source and Variable Construction

We obtained the data from *d20*, a staffing software provider for hotels and restaurants in the Nordic countries. The dataset includes a daily unbalanced panel of 94 hotels and restaurants in Norway from 2003 to 2014. After excluding outliers and observations with zero revenues, the total number of observations is 171,750. *Table 1* provides definitions of the variables and summary statistics.

The table shows that outputs are measured in terms of deflated revenues following Syverson (2011) and assuming that prices and hence revenues reflect quality differences. The limitation of this approach is that the difference in market power, if any, can lead to some measurement error but the revenue measure is still more appropriate than using physical units of services outputs (e.g., number of meals and rooms rented) because of service differentials and environmental amenities that can influence customers' perception about service quality. The revenues were classified into three major sources: sales of food and beverages, hotel/accommodation services and other goods/services. These multiple outputs reflect the fact that the hotel and restaurant industry provide several integrated services such as a hotel, bar and restaurant on the same premise. We also consider a model with one output, where total revenue y is the sum of the revenues from the three sources.

Table 1: Descriptive Statistics

Variable	**Label**	**Mean**	**Std. Dev.**	**Min**	**Max**
y_1	Food and beverages (in NOK)	2514.66	31679.80	0.37	442973.20
y_2	Room services (in NOK)	77373.01	61049.90	4.79	609808.80
y_3	Other sales (in NOK)	42903.50	56055.05	1.46	607040.10
y	Total revenue (in NOK)	145417.20	129136.40	398	807774.10
x_2	Labor hours	173.36	151.92	0.21	962.83
d	Number of rooms booked/night	85.39	60.50	1.00	435.00
x_1	Number of available rooms	156.68	85.64	23.00	435.00
$\tilde{d}$	Occupancy rate (in %)	56.06	0.29	0.00	1.00
K	Excess capacity, $1-\tilde{d}$ (in %)	43.94	0.29	0.00	1.00
t	Time trend	8.49	2.71	1.00	12.00
n = 171,750					

Capital is measured as the number of available rooms because it reflects the number of fixed assets such as buildings, machinery and structures, which support the services provided by the rooms. Several hospitality studies (e.g., Assaf & Agbola, 2011; Barros, 2005) used this variable as a proxy for capital. Meeting space could have been the other proxy of capital but there are no meeting spaces in many places and restricting the sample to only those with a meeting space is likely to create a selectivity problem and will reduce the number of observations substantially. Total labor hours are calculated as the sum of quality-adjusted labor hours in each department using the *Divisia index*. The quality of labor (education, experience, etc.) in each department (e.g., administration and general, bar and restaurant, front-office) is measured by the average wage rate.

Excess capacity is defined using the occupancy rate. When room demand equals the maximum number of available rooms, the occupancy rate is 100 percent and excess capacity is zero. Conversely, when the occupancy rate is zero, all available capacity is excess. Sometimes, the demand for hotel services is higher than the available capacity but we do not consider this because actual service provision is limited to what the maximum capacity can support. The impact of excess capacity is evaluated for the three groups of outputs together because it can indirectly influence the demand for the other services. For instance, guests who occupy hotel rooms are more likely to use other services too. Furthermore, excess capacity affects all the services provided by the hotel/restaurant. The time trend covers the years 2003 to 2014.

Table 1 provides variable definitions and summary statistics. The observed firms are located in small metro towns, suburban areas, urban areas and airports, and are dispersed over all five regions of Norway. Therefore, the location/region dummies were defined as categorical variables where small metro towns and the Northern region were the reference groups [see *Tables 2* and *3* below].

Table 2: Distribution of Key Variables by Location

Location	n	y	x_1	x_2	z
Small metro town	27	98204.80	117.35	145.66	48.82
Suburban	24	163389.20	170.69	166.82	46.45
Urban	38	142587.40	159.27	183.27	40.08
Airport	5	197869.80	220.37	168.71	39.63

Note: *n* refers to the total number of firms in each location/region.

Table 3: Distribution of Key Variables by Region

Region	n	y	x_1	x_2	z
Northern	25	107074	119.89	146.97	47.03
Central	7	245305.10	256.06	256.18	46.24
Western	17	156084.90	160.55	174.63	38.69
Southern	13	115010.90	126.17	138.78	50.07
Eastern	42	136337.10	158.87	166.38	44.13

Note: *n* refers to the total number of firms in each location/region

4. Results

4.1. Single Output Model

This section summarizes the model results using a single output[4] to provide a general picture before proceeding to the multiple-output case. The results show that all the coefficient estimates of the IDF are significantly different from zero at less than one percent level. The cost elasticity of output $\partial \ln x_1 / \partial \ln y$ (at the mean) equals 0.49%, suggesting that a one percent increase in output would increase cost by about half a percent, on average. Thus, hospitality firms can benefit from expanding their scale of operation because the percentage change in cost is less than the percentage change in output. The above result indicates that the hospitality firms need to double their size to reach their optimum scale, which might not be possible. As we will see later, this result is driven by the use of a single output.

The cost elasticity of excess capacity, $\frac{\partial \ln x_1}{\partial k}$ is about 0.85%, implying that a reduction in excess capacity by a percentage point would reduce

[4] We do not report the table of results for the single output model here to save space, but it can be provided upon request.

the cost of production, on average, by 0.85%. The technical change, $\frac{\partial \ln x_1}{\partial t}$ was found to be negative, indicating that, on average, the cost of these firms was declining at a rate of 1.79% per year during the study period. The results also provide a comparison of production costs across locations and regions. The cost of production among the firms in suburban, urban and airport areas were 0.21%, 0.22% and 0.20% higher than those in small metro towns, ceteris paribus. Similarly, the production cost of firms based in the Eastern, Western, Southern and Central regions were 0.38%, 0.43%, 0.45% and 0.66% higher than the cost of their counterparts in the Northern region, ceteris paribus.

The results also show that all the coefficients of the determinants of technical inefficiency (except for the central region dummy) were different from zero at less than one percent level. The effect of excess capacity on inefficiency ($\partial u / \partial k$) is about 0.01%, which means a one percent increase (decrease) in excess capacity will increase (decrease) inefficiency, on average, by 0.01%. The comparison of these firms across locations/regions shows that the firms located near airports were, on average, 0.82% more inefficient, whereas those in urban and suburban areas were, on average, 0.6% and 1.46% less inefficient than those in small metro towns. Moreover, firms in the Southern, Western and Eastern regions were 0.05%, 0.29% and 0.02% less inefficient than their counterparts in the Northern region, but the results do not provide any evidence of differences in the inefficiency of firms based in the Central and Northern regions.

Finally, the overall technical efficiency index shows that the firms, on average, are operating quite efficiently with an average efficiency score of about 86%, implying that there is scope to improve the cost of hospitality service production.

4.2. Multiple Outputs

4.2.1. Determinants of Production Technology

A summary of the results from the multiple outputs IDF is provided in *Table 4* and the full results are reported in the appendix [*Table 6*]. This table shows that the coefficients of the IDF, except for the dummy of the Southern region, are all significant at less than one percent level. *Table 4* shows that the coefficient estimate of the input ratios is negative and the cost elasticities of the three outputs, ($\partial \ln x_1 / \partial \ln y_1, \partial \ln x_1 / \partial \ln y_2$, and $\partial \ln x_1 / \partial \ln y_3$) are positive, implying that these results are consistent with the theoretical expectation from an input distance perspective.

The cost elasticity of outputs indicates that a one percent increase in outputs (y_1, y_2 and y_3) would, ceteris paribus, increase the cost by 0.10%, 0.72% and 0.04% implying the scale economies because these elasticities are less than one. The density plots in the left panel of *Figure 1* illustrates the distributions of these elasticities. Alternatively, a simultaneous increase in all three outputs by 1% will increase cost by 86% (0.10 + 0.72 + 0.04), on average. This shows that there are scale economies (14%, 1–0.86), on average, but much smaller than what is predicted by the single output model. The density plots in the right panel of *Figure 1* show that the sum of the cost elasticities largely reflects the economies of scale estimates except for a few cases in the right tail. For these cases, a contraction rather than an expansion of outputs helps the firms to reach the optimum scale because SCE is positive.

The table also shows that the marginal effect of k on cost, $\partial \ln x_1 / \partial k$ is positive, as expected. This implies that a 1% increase in excess capacity increases cost by 1.59%, on average. This is larger than the effect of k that we found in a single output case. Moreover, the density plot in the left panel of *Figure 2* illustrates a bimodal distribution of the effect, where the density peaks at about 1% and 2.1% and that the majority of the firms had these effects. Technical change $TC = -\partial \ln x_1 / \partial t$ is positive. Because of technical progress, costs, on average, decreased over time. The results show an average rate of technical progress of 2.11% per annum over the study period. This is higher than the rate of technical change we found in a single output case. The density plot of TC shows that it ranges from about 6% to zero, with a mean of 2.11% because the distribution is skewed to the right as shown in the right panel of *Figure 3*.

Location/regional variations are also important in influencing production technology. The suburban, urban and airport dummies are all positive, indicating that inefficiency is different from that in small metro towns. According to these findings, the costs of hospitality services among firms located in suburban, urban and airport areas were, on average, 0.01%, 0.03% and 0.15% higher than their counterparts located in small metro towns [*Table 5*]. The findings are similar to the single output case except that the dispersion in inputs overuse (and hence cost) among the locations becomes larger in this case. The estimates of the regional dummies (Western, Central and Eastern) are positive and statistically significant at the conventional levels. This implies that the input overuse of firms based in these regions were 0.19%, 0.07% and 0.12% larger than their counterparts based in the Northern region, ceteris paribus. Compared with the finding in the single output case, these coefficients are smaller in size and the Southern region dummy affects production technology rather than technical inefficiency.

Table 4: Summary of Results from the Multiple Outputs IDF

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
$\partial \ln x_1 / \partial \ln y_1$	0.1021***	0.0415	0.0000	0.2533
$\partial \ln x_1 / \partial \ln y_2$	0.7243***	0.0711	0.0738	0.9291
$\partial \ln x_1 / \partial \ln y_3$	0.0389***	0.0370	0.0000	0.4322
$\partial \ln x_1 / \partial t$	0.0211***	0.0087	–0.0047	0.0667
$\partial \ln x_1 / \partial z$	1.5899***	0.4627	0.4940	2.7169
$\partial u / \partial z$	0.5789***	1.5475	0.0000	22.4250

TE	0.9624***	0.0963	0.0553	1.0000

4.2.2. Determinants of Technical Inefficiency

The empirical results also show that excess capacity and location/regional dummies are important factors that influence the technical inefficiency of the hospitality firms. The summary of the empirical results in *Table 4* shows that the effect of k on inefficiency, $\partial u / \partial k$ is positive and significant at less than the 1% level. This implies that a 1% increase in excess capacity would increase technical inefficiency by 0.58%, on average. However, the kernel density in the right panel of *Figure 2* shows that the majority of the hospitality firms operate at the point where $\partial u / \partial k$ is almost zero and this is similar to the finding in the single output case. The results also show that the coefficients of the three location dummies are positive, implying that the firms located in suburban areas, urban areas and near airports were, on average, 0.35%, 0.31% and 1.66% more inefficient than their respective counterparts in small metro towns. These findings are different from the single output case because the coefficient of the airport dummy is larger, and the sign of the urban and suburban dummies turned positive.

The coefficients of the Central and Eastern regions are positive and different from the Northern region, implying that the firms based in these two regions are, on average, 0.21% and 0.24%, respectively, more inefficient than those in the Northern region. However, the results show no significant differences in inefficiency, on average, between the firms based in the Western and Northern regions, as well as between those based in the Southern and Northern regions. These results differ from the single output case from a different perspective. The Western and Southern region dummies were not statistically significant at the conventional levels, the coefficient of the Central region becomes significant, and the coefficient of the Eastern region becomes smaller than in the single output case.

The technical efficiency score is, on average, 96.24 percent, implying that these firms are highly cost efficient and there is little room for improvement [*Table 4*]. Furthermore, this efficiency score is larger than the score in the single output case. Previous empirical studies that did not account for excess capacity estimated a lower efficiency score. For instance, Salman Saleh, Assaf, and Son Nghiem (2012) found average technical efficiency of about 83 percent in Malaysia; Assaf and Tsionas

(2018) found an average efficiency score of 92.42 percent for European hotels in a study of several countries. Assaf and Barros (2013) also found an efficiency score of 82% for a few leading Norwegian hotels and restaurants in a similar international comparison. However, we did not find any comparable earlier studies that estimated and compared the technical efficiency of hotels and restaurants within Norway.

Table 5: Effects of Location and Regional Differences

Variables	IDF	Technical inefficiency
Location		
2. Suburban	0.010***	0.353***
	(0.0017)	(0.0420)
3. Urban	0.026***	0.308***
	(0.0015)	(0.0398)
4. Airport	0.150***	1.659***
	(0.0028)	(0.0857)
Region		
2. Central	0.186***	0.209***
	(0.0025)	(0.0632)
3. Western	0.072***	–0.0553
	(0.002)	(0.0516)
4. Southern	0.006	0.0560
	(0.0034)	(0.0748)

5. Eastern	0.119***	0.239***
	(0.0015)	(0.0385)

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

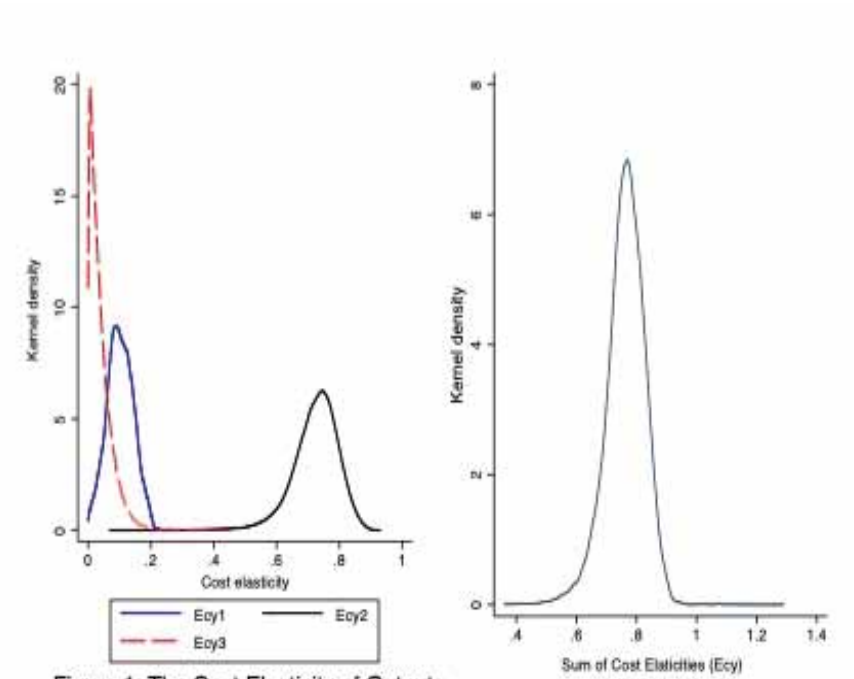


Figure 1: The Cost Elasticity of Outputs

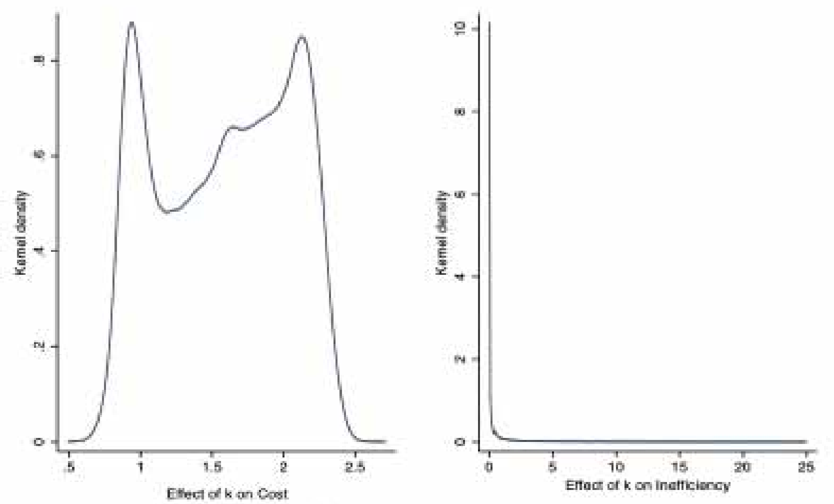


Figure 2: Effects of k on Cost and Inefficiency

5. Discussion of the Results

In this section, we check the sensitivity of the findings reported in the preceding section and discuss the managerial and policy implications in greater detail.

5.1. Effects of Excess Capacity on Production Technology and Inefficiency

The results show that a 1% increase (decrease) in excess capacity yields a 1.59% increase (decrease) in input overuse (cost of production). The descriptive statistics in *Table 1* show that excess capacity k is 44% at the mean. On average, the cost saving among the hospitality firms, which is calculated as $\frac{\partial \ln x_1}{\partial k} \times k$ is about 70% (1.59 × 44). However, the cost saving might be different for different firms because both the effect of k on cost, $\frac{\partial \ln x_1}{\partial k}$ and the quantity of excess capacity, k might be different. The left panel of *Figure 4* illustrates this using the predicted marginal effects of excess capacity and shows that the effect of excess capacity is positively related to the quantity of excess capacity—i.e., the larger the excess capacity, the larger will be the marginal effect and vice versa. For example, the average effects are 1.17% and 1.63% for the first and second quartiles, while it is 2.00% and 2.25% for the third quartile and for the top 5%. The corresponding excess capacity in these groups is 18%, 45%, 69% and 89%. Thus, the input saving for these groups is 21.06%, 73.35%, 138% and 200%, respectively.

Our results also show that, on average, a 1% increase (decrease) in excess capacity results in a 0.59% increase (decrease) in technical inefficiency. Similarly, reducing excess capacity at the mean (44%) would reduce inefficiency by about 26% (0.58×44). However, this does not uniformly hold true because both the marginal effect of k on inefficiency, $\partial u / \partial k$ and the amount of excess capacity vary. The scatterplot in the right panel of *Figure 4* shows that the relationship between the marginal effect of k on inefficiency, $\partial u / \partial k$ and excess capacity is nonlinear. The marginal effect is close to zero when excess capacity is low (less than 50%), but the effect becomes larger and larger after the 50% level. For instance, it is 0.3% for the third quartile and 3.54% at the 95% level of excess capacity.

In summary, we conclude that excess capacity affects both production technology and technical efficiency, where the marginal effects of k on both cost and technical inefficiency vary positively with the quantity of excess capacity. This suggests that reducing excess capacity is beneficial because it lowers cost both directly and indirectly via reducing inefficiency.

5.2. Cost Elasticities of Outputs and the Inputs Ratio

In a two-input world, inputs are always substituting, i.e., $\frac{\partial \ln x_1}{\partial \ln x_2} < 0$, therefore $\frac{\partial \ln x_1}{\partial \ln \tilde{x}_2} = 1 / \left(\frac{\partial \ln x_1}{\partial \ln x_2} - 1 \right)$ is always negative. Thus, along the isoquant an increase in x_2 implies a decrease in x_1 (which implies an increase in $\tilde{x}_2$). As a result, x_1 is inversely related to not only x_2 but also to $\tilde{x}_2$). This relationship assumes that there is no inefficiency. With inefficiency, it is possible for x_1 to increase, followed by an increase in $\tilde{x}_2$. In any case, from the estimates of $\frac{\partial \ln x_1}{\partial \ln \tilde{x}_2}$, it is possible to compute estimates of input substitutability, $\dfrac{\partial \ln x_1}{\partial \ln x_2}$ from the relationship

$\dfrac{\partial \ln x_1}{\partial \ln \tilde{x}_2} = 1 / \left(\dfrac{\partial \ln x_1}{\partial \ln x_2} - 1 \right)$. That is, substitutability between capital and

labor can be computed from $\dfrac{\partial \ln x_1}{\partial \ln x_2} = 1 + \left(1 \div \dfrac{\partial \ln x_1}{\partial \ln \tilde{x}_2} \right)$ which varies across firms.

One advantage of using the multiple-output technology is that we can estimate the cost elasticity of each output, i.e., $\partial \ln x_1 / \partial \ln y_1$ $\partial \ln x_1 / \partial \ln y_2$ and $\partial \ln x_1 / \partial \ln y_3$. These cost elasticities show the percentage increase in cost for a 1% increase in each output, ceteris paribus. The sum of these elasticities (E_{cy}) shows the percentage by which cost will increase for a simultaneous increase in all the outputs by 1%. Furthermore, scale economies (diseconomies) are given by $scale = 1 - E_{cy}$. If *scale* is positive (negative) there is a cost advantage (disadvantage) in expansion. *Figure 5* illustrates that the cost elasticities of y_1 and y_2 vary with the outputs [*left panel*] and the cost elasticity of y_3 varies negatively with output [*right panel*]. For instance, the first and second quartiles for the cost elasticities of y_1 are 0.07% and 0.10%, while the third and fourth quartiles are 0.13 and 0.17. Similarly, the quartiles of the cost elasticity of y_2 are 0.68%, 0.73%, 0.77% and 0.83%. Finally, the cost elasticity of y_3 varies negatively with the outputs (the cost elasticity is 0.01% and 0.03% at the first and second quartiles, while it is 0.05% and 0.11% at the third and fourth quartiles. The sum of these cost elasticities is less than one, indicating economies of scale up to 95%. Only the largest 5% of firms operate at the optimum and diseconomies of scale. Therefore, it is advantageous for the hotels/restaurants to expand their scales of operation (increase outputs).

5.2.Technical Change

Our results show technical progress (cost diminution) of 2.11% per annum, on average. Technical progress can be achieved from various sources, for instance, learning by doing—becoming better and better at doing something through repeated practice. Because we are using a translog function, technical change is not a constant. It depends on outputs, excess capacity, input ratios as well as the time trend. Because of this, technical change varies across firms and over time. For example, the density plot of technical progress in the right panel of *Figure 3* shows that it declined from 3% (first quartile) to 2% (second quartile) to 1.5% (third quartile) and further declined to 1% (fourth quartile).

The box-plot in the left panel of *Figure 3* shows a declining trend in the rate of technical progress. The demand for hospitality services might be influenced by unobserved international, regional and national trends in economic performance, in which case the firms have less to do except adapting their production as much as possible. These trends were beneficial during the earlier periods of the current study. Our findings show that the rate of technical progress was greater than 6% in 2004 and 2005. The report of Statistics Norway (Statistics Norway, 2007) corroborates this finding, stating that 2005 was more favorable compared with the previous periods. However, during the period after 2008, several incidents affected tourist flows adversely and hence the demand for hospitality services declined. For instance, the European economic/financial crisis in 2008 and its presumed lagged effects, and the terrorist attack in Oslo in 2010, as well as the oil price shock after mid-2013, resulted in a decline in the number of business travelers and consequently a decline in the demand for hotels and restaurants. The effect of these incidents is likely to be captured by the time trend, which is how we measure technical change. Perhaps a better measure would be one that controls for events that affect demand. This requires more detailed information on events that affect the demand for hospitality services, which is not available in our dataset.

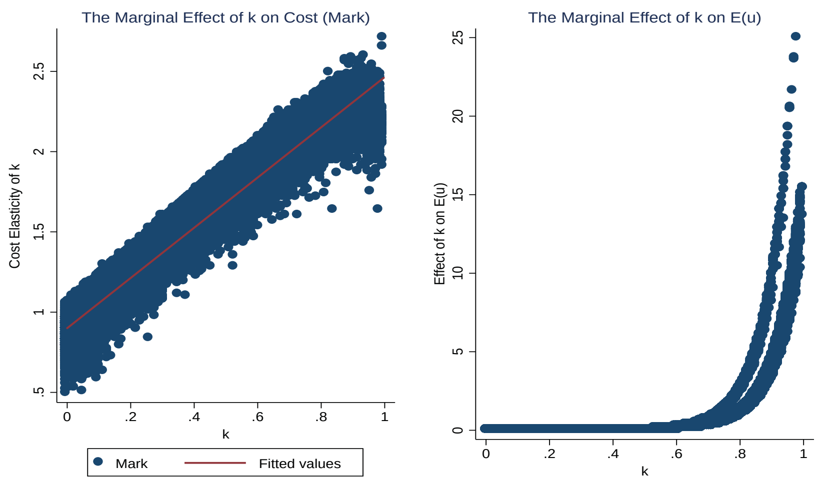
5.3.Location and Regional Differences

Our results from the IDF indicate that location and regional differences are important in explaining the differences in cost (because of overuse of inputs) and technical inefficiency. We find that firms in small metro towns overuse their inputs less and are more efficient technically than their counterparts in other locations. Firms located near airports are on the opposite side—their input overuse is greater, and they are least efficient technically. The firms located in urban and suburban areas are in between these two extremes—these firms had more inputs overuse and are less inefficient than those located in small metro towns but had more inputs overuse and are more inefficient than those located near airports.

The findings of earlier hospitality studies are consistent with the findings from a single output case but not always consistent with the findings of multiple outputs model. For instance, Assaf and Tsionas (2018) found that firms in suburban and urban areas are more efficient than those in airport and small metro towns. Chen (2007) also found similar results, with a less specific classification of location [metropolis versus non-metropolis]. The difference in these results might arise from the differences in the study setting, for example, the inclusion of excess capacity among the determinants of both inputs overuse and technical inefficiency. Given the differences, the use of multiple outputs rather than a single output constitutes one of the strengths of the current study.

Regional differences could also explain the differences in cost and technical efficiency. Input overuse for firms in the Northern region is lower than for those in the Western, Eastern and Central regions. Moreover, those in the Northern region are more efficient technically than those in the Central and Eastern regions. The demand for hospitality services is closely associated with geospatial attributes such as climatic conditions and tourist attractions. These characteristics of hospitality services justify the effects of location and regional differences.

Figure 4: The Marginal Effects of k



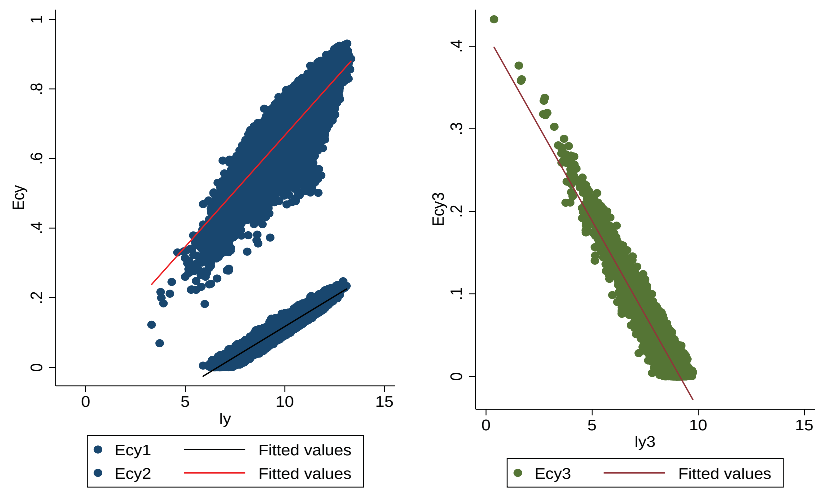


Figure 5: Marginal cost elasticities of Outputs

6. Summary, Conclusions and Implications on Tourism Management

6.1. Summary and Conclusions

In this paper, we used an IDF to represent the technology of hospitality firms and examined the impact of excess capacity on cost (input overuse) and technical inefficiency. We used a flexible parametric functional form (translog) that accommodates multiple outputs. Because we used radial input-oriented technical inefficiency, overuse of inputs modeled in the IDF is equivalent to a cost increase. That is, cost inefficiency is the same as input-oriented technical inefficiency. We estimated the effects of excess capacity on both the production technology and technical inefficiency of 94 hospitality firms using a daily unbalanced panel observed over the period from 2003 to 2014 in Norway. The multiple-output model better suits the practices in the hospitality industry and addresses the non-substitutability of the three service categories compared with the model with a single output.

Our results show that excess capacity, location and regional variations are important predictors of production technology and technical inefficiency. We find that excess capacity increases cost substantially and also increases technical inefficiency. Furthermore, greater excess capacity entails higher cost and technical inefficiency, although the relationship is nonlinear in the latter case. Overall, our findings suggest that reducing excess capacity can reduce the cost of production and enhance technical efficiency. The scale economies calculated from the cost elasticity of outputs indicate that the hotels/restaurants can benefit from expanding their scale of operation. The hotels and restaurants experienced technical progress during the study period, but the rate of growth in technical progress declined over time. We also find that the location/region can explain some of the differences in both cost and inefficiency. Firms located in small metro towns use production technologies that entail less overuse of inputs and are more efficient technically than their counterparts in suburban, urban and airports. Moreover, firms in the Northern region have fewer inputs overuse than those in the Western, Eastern and Central regions and are more efficient technically than those in the Central and Eastern regions.

6.2. Implications on Tourism Management

Several policy and managerial insights can be drawn from these findings for tourism planning and management. Policy makers can draw the lesson that reducing excess capacity can improve firms' competitiveness (i.e., reducing the cost of production and inefficiency). Excess capacity is the demand side constraint that destructs hospitality firms from achieving this goal. The literature also substantiates this because competitiveness of firms is important to cope with the intense competition from the globalizing market (Tsai, Song, & Wong, 2009) and it affects the service quality (Kandampully, 2000). All together, these call for policies that can tackle these constraints, reduce the excess capacity and improve the competitiveness of firms. Further, they can draw some lesson in evaluating firm performance after netting out the impact of excess capacity because the excess capacity might be caused by factors that are beyond the firms' control. This is especially important in implementing government regulations (e.g. taxation).

Hospitality operators can draw some insights from the findings on hospitality production. Given excess capacity, they can learn to what extent to improve inputs utilization and hence the technical efficiency;

the scale of operations to reach the optimum size and the situation of the technical progress. The operators can also on average understand the direct and indirect consequences of excess capacity on cost performance and use the insights as a guide in the day-to-day planning and decision making. Hospitality demand varies across seasons, years, locations and regions etc. The firms compensate for the cost of the excess capacity during the off-peak season using the premium during the peak demand season; the cost of excess capacity in hotels /and restaurants in low demand areas using the premium from their affiliates in high demand areas (Koenig-Lewis & Bischoff, 2005). Moreover, the operators can draw some lesson for revenue management because the price is in other words determined by the level of excess capacity. For instance, the finding on a positive marginal cost of excess capacity implies higher and higher premium as the share (level) of excess capacity increases; i.e., higher excess capacity commences more premium for cross subsidization. Finally, the operators can determine the level of capacity utilization that can minimize the effect on the production technology and/or the inefficiency, the expected cost and inefficiency at each level of excess capacity.

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Table of Footnotes

1	The figures are calculated based on the statistics from www.statistikknett.no.
2	We do not report the table of results for the single output model here to save space, but it can be provided upon request.

Appendix

A.2.1. Results of Stochastic Frontier Analysis

IDF	Coef.
β_0	0.828***
	(0.141)
β_{y_1}	–0.291***
	(0.0049)
β_{y_2}	–0.226***
	(0.0234)
β_{y_3}	0.480***
	(0.0087)
$\beta_{\tilde{x}_2}$	–0.568***
	(0.0135)
β_k	–0.421***
	(0.0681)
β_t	–0.105***
	(0.0044)
$\beta_{y_{11'}}$	0.039***

	(0.0005)
$\beta_{y_{22'}}$	0.080***
	(0.0019)
$\beta_{y_{33'}}$	–0.051***
	(0.0008)
$\beta_{\tilde{x}_{22}}$	–0.022***
	(0.0010)
β_{kk}	1.848***
	(0.0284)
β_{tt}	0.003***
	(0.0000)
$\beta_{y_1\tilde{x}_2}$	–0.006***
	(0.0009)
$\beta_{y_2\tilde{x}_2}$	0.040***
	(0.0012)
$\beta_{y_3\tilde{x}_2}$	0.012***
	(0.0010)
β_{y_1k}	0.031***

	(0.0026)
$\beta_{y_2 k}$	0.085***
	(0.0058)
$\beta_{y_3 k}$	–0.007**
	(0.0033)
$\beta_{y_1 t}$	0.001***
	(0.0003)
$\beta_{y_2 t}$	0.005***
	(0.0004)
$\beta_{y_3 t}$	–0.001***
	(0.0003)
$\beta_{x_2 k}$	0.038***
	(0.0035)
$\beta_{x_2 t}$	–0.002***
	(0.0003)
β_{kt}	0.007***
	(0.0010)
l_2	0.010***
	(0.0017)

l_3	0.026***
	(0.0015)
l_4	0.150***
	(0.0028)
r_2	0.186***
	(0.0025)
r_3	0.072***
	(0.002)
r_4	0.006
	(0.0034)
r_5	0.119***
	(0.0015)
σ_μ	
α_z	25.44***
	(0.312)
l_2	0.353***
	(0.0420)
l_3	0.308***
	(0.0398)

l_4	1.659***
	(0.0857)
r_2	0.209***
	(0.0632)
r_3	–0.0553
	(0.0516)
r_4	0.0560
	(0.0748)
r_5	0.239***
	(0.0385)
α_0	–25.07***
	(0.301)
σ_υ	
σ_0	–3.204***
	(0.0037)
Observations	171,750
*** p < 0.01, ** p < 0.05, * p < 0.1.	

Paper 3

Do Management Practices Make a Difference in Hospitality Sector? [1]

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Do management practices make a difference in the hospitality sector?

Abstract

This article investigates how different management routines to optimize productivity influence the cost of production and technical inefficiency in the hospitality sector. We tested the hypothesis that firms with improved management practices would better mitigate the negative effects of demand uncertainty on cost and efficiency. We estimated an input distance function using a translog stochastic frontier analysis based on the daily data of 92 hospitality firms in Norway. The findings show that, on average, management practices increase the cost of production but reduce inefficiency. It is likely that the increasing costs are linked to quality considerations because managers not only need to optimize productivity but also maintain a defined service quality level. The study provides managerial implications for high-contact service industries that attempt to optimize inputs by implementing better management routines.

Keywords: management practice, stochastic frontier analysis, production cost, technical efficiency, hospitality sector

1. Introduction

Emerging literature shows that management practices measured across firms and industries influence performance (Bloom and Van Reenen, 2010). In particular, when employees in an organization are active in what they do and how they do it, management practices are relatively high and vice versa. In this paper, we focus on management practices in a particular context, namely, concerning staff scheduling practices in hospitality companies. Managers of these companies often have a staff-scheduling software system at their disposal as a decision-support system; for example, in forecasting guest demand, predicting output levels ahead of time, and planning for input requirements. However, implementing software systems does not guarantee input optimizations unless backed by good management practices. Thus, this study aims at examining if management practices linked to the use of the software can predict the cost performance among hospitality companies.

Earlier studies of management practices have mainly focused on their impact on performance in the manufacturing sector using survey data (e.g. Bloom and Van Reenen, 2007, 2010). More recent extensions include studies of the education (Bloom et al., 2015a) and health sectors (Bloom et al., 2014; McConnell et al., 2013; Tsai et al., 2015). This study aims to examine the effect of management practice on both the operational costs and the technical efficiency of hospitality companies (hotel and restaurants). Given larger share of staff expenses relative to other operating expenses and the dynamic use of staff to match a stochastic demand, hospitality is an industry in which management practices can have a large impact on productivity.

We measured management practices using data that monitors managers' usage patterns of software system and the degree to which they actually follow the suggested recommendations. The software registers the client's (i.e., the hospitality manager's) access to different built-in functionalities and how well they used the system relative to the recommended use and procedures. We estimated the empirical model on inputs use (cost) using daily data from 92 hospitality companies from May 2012 to September 2014. The findings show that improved management practices increase cost but mitigate inefficiency, on average. Furthermore, these effects are heterogeneous for the different levels of management practice. The effect on cost is U-shaped, implying that the cost first declines, reaches a minimum, and then ultimately increases with an improvement in management practices. However, the effect on inefficiency declines as the management practice related to the use of the software improves. The study also provides a discussion of our findings and the managerial implications.

To our knowledge, no study has empirically investigated the effects of management practice in the tourism and hospitality literature. Another key difference from existing studies is that we use secondary data. Thus, our empirical model is free from any psychological bias associated with survey data. Moreover, we avoid any nonresponse rate issues because the software reports the data from all software users. Third, the management practices that we focus on are not general "best-practice" conduct, but are measures specifically aimed at improving labor productivity. Delis and Tsionas (2018) argue that "unique and specialized" data minimize the measurement error in proxying the unobserved management ability. Finally, the continuous data collected on the daily management routines for more than 2.5 years resolve the limitations of earlier studies in capturing the dynamics in managers' behavior. By examining these dynamics, we follow the recommendations of previous studies (Bloom et al., 2013b; Bloom and Van Reenen, 2010).

The remainder of the paper is organized as follows. Section 2 provides the background based on a review of literature on the economics of management and the gap in examining the tourism and hospitality sector. Section 3 discusses the conceptual model, identifies the key parameters of interest, and explains how the estimation is conducted using a maximum likelihood stochastic frontier analysis. Section 4 presents the empirical results, a discussion of key findings, and implications. Section 5 provides concluding remarks.

2. Background

A growing literature has been concerned with measuring and explaining the effect of management practices on productivity, beginning with the pioneering works of Mundlak (1961) and Lucas Jr (1978). Recent studies have contributed with comprehensive and well-organized management surveys to investigate these relationships. For instance, Bloom and Van Reenen conducted the *World Management Survey* to investigate the impact of management on productivity differences in the manufacturing sector (See Bloom and Van Reenen, 2007, 2010). More recently, these authors investigated the relationship between management practices and firm characteristics based on the *Management and Organizational Practices Survey* (Bloom et al., 2015b). This literature was further extended to other sectors such as schools (Bloom et al., 2015a) and health care (Bloom et al., 2014; McConnell et al., 2013; Tsai et al., 2015), using a similar method of inquiry and survey.

Furthermore, the more recent studies applied methodologies that are more appropriate for minimizing measurement errors and identifying causal effects. For example, Bloom et al. (2013b) conducted an experiment (involving randomized controlled trials) in an Indian textile manufacturing industry using a free consultancy service on “lean management” as an intervention. Triebs and Kumbhakar (2018) examined the correlation between management and firm fixed effects using stochastic frontier analysis and a semiparametric approach. Delis and Tsionas (2018) considered management as a latent variable in a production function estimated using a Bayesian approach. Although these approaches assist in mitigating some key methodological issues associated with earlier studies, the potential bias and measurement errors remain.

Studies from different disciplines have investigated how management in service companies attempts to optimize inputs while maintaining a balance between productivity and quality (Brown and Dev, 2000; Grönroos and Ojasalo, 2004; Tan and Netessine, 2014b). This literature shows that a suboptimal level of inputs used in the service production either affects the service quality or increases the cost (making the production technology more expensive and triggering a waste of resources). However, management practice per se is one of the factors that determines the extent to which these companies optimize the inputs and hence achieve the outcomes. Therefore, this study avoids certain data issues associated with earlier studies when trying to estimate the effects of management practices on labor productivity of hospitality firms.

3. Methodology and data

3.1. Conceptual model

3.1.1. Management practices

The hospitality firms included in this study employ an identical software system for optimizing labor hours. This homogeneity allows us to analyze how different software usage patterns across hospitality firms influence the benefits reaped from employing the software system. We can thus investigate how differences in management practices influence the cost (via the production technology) and technical efficiency. In previous empirical studies, management was viewed as the determinant of production technology and technical efficiency. For instance, Bloom et al. (2016) viewed management as an input (determining the production technology), whereas other studies (Bloom et al., 2017; Bloom and Van Reenen, 2007) considered it as one of the environmental variables that determine efficiency differences. Triebs and Kumbhakar (2018) considered management practices as both an input and an efficiency determinant. Thus, in our model we specify that management practices influence both the cost and the technical efficiency of the firms.

Specifically, we measure management practices using the management practices index (M_{it}). The higher is the index score, the more effectively managers use the software system as per the recommendations. Hypothetically, if all managers followed the recommended procedures on usage patterns and achieving suggested goals, there should be no cost and efficiency differences between the companies. However, this is unlikely to occur in reality for various reasons, such as differences in capital investments, demand stochastics, and management ability to engage employees in achieving this objective and implementing appropriate routines and processes in the organization.

Without proper demand forecasts, it is difficult to optimize the variable inputs consistently (Chan et al., 2005). The forecast on demand changes and the software's corresponding recommendation on changes in input levels required for the next period (day, week, or month) help managers to better anticipate the changes in demand and plan staffing schedules accordingly. Therefore, actively optimizing inputs in accordance with the software's recommendations should reduce decision errors. The suboptimal input adjustments that otherwise would have occurred because of a lack of information or demand uncertainty

(Defraeye and Van Nieuwenhuyse, 2016; Hur et al., 2004). As a result, the software system makes the companies less prone to haphazard demand changes.

The implementation of improved management routines requires more managerial effort and time. However, without this extra effort, firms will be more likely to operate with suboptimal input levels. Thus, we expect a positive effect of improved management practices on technical efficiency. However, the effect on the cost of production is ambiguous; it can be negative, zero, or positive depending on whether the cost of management inputs is greater than, equal to, or less than the cost of the inputs saved.

3.1.2. Input distance function

The empirical model for estimating the effects of management routines on productivity was formulated to fit with the input distance function (IDF) approach. The IDF approach is primarily used to address the endogeneity issue, as demand is determined by various external factors (e.g., weather conditions, seasonality, conferences, events etc.) over which the companies have no control. Therefore, the endogeneity issue implies that inputs are adapted to the expected level of outputs, which in turn depends on the demand level. An alternative method that addresses the simultaneity bias involved in the choices of inputs and outputs is the Olley–Pakes approach (Olley and Pakes, 1996). However, we selected the IDF method because we wished to estimate the production technology and the effects on inefficiency separately.

Let us assume there is an IDF with two inputs, capital (x_{1it}) and labor (x_{2it}). When one of these inputs, say, x_{1it} is a denominator on both sides of the equation and both sides are transformed into logarithmic form, the dependent variable, that is, the measure of input distance to the frontier, should have become $-\ln x_{1it}$ as the total area of the distance function equals one but we consider only $\ln x_{1it}$ in the estimation and add the negative sign in the interpretation. The resulting input ratio $\ln \tilde{x}_{2it}$ becomes one of the explanatory variables in this model. Moreover, the model includes a vector of outputs (y_{jit}), where $(j = 1,2,3)$, management practices $\left(M_{it}\right)$, the annual time trend $\left(t\right)$ and the chain dummy (*Chain*). The time trend controls for the technical changes over time, while the chain dummies control for the differences in technology (e.g., differences in quality). The firms in each chain are assumed to follow a similar approach to service production and, hence, to have a similar input usage, as the strategic leadership is provided from the chain management team. Therefore, the IDF defined in terms of a translog stochastic frontier analysis is $\ln x_{1it} = F\left(\ln x_{2it}; \ln y_{jit}, \tilde{M}_{it}, t, chain\right) + \upsilon_{it} - \mu_{it}$.

The construction of a translog function imposes homogeneity of degree one and symmetry assumptions. The homogeneity assumption was addressed by dividing the distance function by one of the inputs, as explained above. The symmetry assumption implies that the sequence in a pair of interaction terms does not affect the coefficient, for example, $\beta_{\tilde{y}_j \tilde{x}_2} = \beta_{\tilde{x}_2 \tilde{y}_j}$, $\beta_{\tilde{x}_2 \tilde{M}} = \beta_{\tilde{M} \tilde{x}_2}$, etc. See Kumbhakar and Lovell (2000) for the construction of a translog stochastic frontier analysis. Equation 1 shows the extended empirical model, where the βs are the coefficients of the respective variables indicated in the subscripts.

$$
\begin{aligned}
-\ln x_{1it} &= \beta_0 + \beta_{\tilde{x}_2} \ln \tilde{x}_{2it} + \sum_{j=1}^{3} \beta_{y_j} \ln y_{jit} + \beta_M M_{it} + \beta_t t + \frac{1}{2} \beta_{\tilde{x}_{22}} \left(\ln \tilde{x}_{2it} \right)^2 + \\
& \frac{1}{2} \sum_{j=1}^{3} \sum_{j'=1}^{3} \beta_{y_{jj'}} \ln y_{jit} . \ln y_{j'it} + \frac{1}{2} \beta_{MM} \left(M_{it} \right)^2 + \frac{1}{2} \beta_{tt} \left(t \right)^2 + \sum_{j=1}^{3} \beta_{y_j \tilde{x}_2} \ln y_j . \ln \tilde{x}_2 + \\
& \sum_{j=1}^{3} \beta_{y_j M} \ln y_j . M_{it} + \sum_{j=1}^{3} \beta_{y_j t} \ln y_j t + \beta_{\tilde{x}_2 M} \ln \tilde{x}_{2it} . M_{it} + \beta_{x_2 t} \ln \tilde{x}_{2it} . t + \beta_{Mt} M_{it} . t + \\
& Chain + \upsilon_{it} - \mu_{it}
\end{aligned}
\qquad (1)
$$

Kumbhakar et al. (2015) show in more detail how to construct stochastic frontier analysis models with multiple inputs and/or outputs. The IDF assumes that the cost elasticities of the input ratio, $\partial \ln x_{1it} / \partial \ln \tilde{x}_{2it}$, must be negative and that the cost elasticities of outputs, $\partial \ln x_{1it} / \partial y_j$, must be positive. The stochastic noise is regarded as part of the distance function and the conditional technical inefficiency term (u_{it}) is calculated from a probability density function of $u_{it} | v_{it} - u_{it}$ (Kumbhakar et al., 2015). The inefficiency term (u_{it}) is assumed to be half normally distributed and (v_{it}) is assumed to be identically and independently distributed (i.i.d.). The half-normal distribution of the technical inefficiency term implies that it is distributed with a mean of zero and a variance of $\sigma^2_{\mu_{it}}$ and the potential determinants of (u_{it}) will be estimated from the variance $\left(\sigma_{\mu_{it}}{}^{2}\right)$. The determinants include management practices $\left(M_{it}\right)$ and chains (*Chain*) to control for the effect of differences in management styles on inefficiency. Hotel/restaurant dummies (hid_i) are also included as one of the determinants of inefficiency to control for the remaining firm-specific inefficiency differences.

$$\sigma_{\mu_{it}}{}^{2} = \exp\left(\varphi_M M_{it} + \sum_{k=1}^{2}\varphi_k Chain + \sum_{i=1}^{91}\varphi_i hid_i\right) + \varepsilon_{it} \qquad (2)$$

Based on the three assumptions discussed in the conceptual model, M_{it} enters the model as the determinant of production technology (I), technical efficiency (II), and both production technology and inefficiency (III). The model specifications described in equations (1) and (2) represent III but we implement Models I and II by including and excluding management practice.

The maximum likelihood estimation method is used to identify the conditional inefficiency term and estimate the effects. The key parameters of interest in this study are the effects of management practice on cost, $\partial \ln x_{1it} / \partial M_{it}$ and the effect on the technical inefficiency, $\partial\sigma_{\mu_{it}}^{2} / \partial M_{it}$. In addition, we need to estimate the coefficients of the cost elasticity of outputs, $\partial \ln x_{1it} / \partial y_j$, the technical change, $\partial \ln x_{1it} / \partial t$, the coefficients of the chain dummies for both the IDF and inefficiency, and the efficiency scores to understand the context of these hotels and restaurants. These coefficients are estimated from derivatives of $\ln x_{1it}$ and $\sigma_{\mu_{it}}^{2}$ from equations 1 and 2 with respect to the variables as follows.

$$\frac{\partial \ln x_{1it}}{\partial M_{it}} = \beta_M + \beta_{MM}.M_{it} + \beta_{\tilde{x}_2 M}.\ln \tilde{x}_{2it} + \beta_{y_j M}.\ln y_j + \beta_{Mt}.t \tag{3}$$

$$\frac{\partial \ln x_{1it}}{\partial y_j} = \beta_{y_j} + \beta_{y_{jj'}}.\ln y_j + \beta_{y_j \tilde{x}_2}.\ln \tilde{x}_2 + \beta_{y_j M}.M_{it} + \beta_{y_j t}.t \tag{4}$$

$$\frac{\partial \ln x_{1it}}{\partial t} = \beta_t + \beta_{tt}.t + \beta_{y_j t}.\ln y_j + \beta_{\tilde{x}_2 t}.\ln \tilde{x}_{2it} + \beta_{Mt}.M_{it} \tag{5}$$

$$\frac{\partial \sigma_{\mu_{it}}^{2}}{\partial M_{it}} = \varphi_M \tag{6}$$

Thus, the marginal effects of management practice are further graphically illustrated by the relationship between these effects and the levels of management practice.

3.2.Data and summary statistics

The empirical framework was implemented using daily data on 92 hospitality firms from 2012 to 2014. The data were received from a productivity management software system provider for hotels and restaurants in the Nordic countries. The variables described in the empirical model are defined as follows.

Capital, the measure of distance to the frontier, is proxied by the number of available rooms in this study because it approximates the level of other complementary inputs in physical terms. The area of meeting space is a potential measure of capital, but we were unable to use this because of insufficient observations. Outputs were measured as revenue in Norwegian kroner (NOK), following previous studies (Syverson, 2011). There were three measures of output, based on revenues from food and beverages sales (y_1), accommodation service (y_2), and sales of other goods and services (y_3). Taking the sum of labor hours used in the production of hotel/restaurant services might be misleading because heterogeneous groups of labor are common in these firms. We accounted for such heterogeneity by calculating the number of quality-adjusted labor hours (x_2) using the *Divisia index*, where the average wage rate in each department is used as proxy to measure the labor quality. Table 1 provides the summary statistics.

Management practice is the key variable of interest. The supplier of the software scheduling system has developed an index that measures how well the firms have implemented good managerial "habits" in terms of following the recommended procedures for using the system, based on 10 observable criteria. The criteria include the frequency with which the software was accessed and how often the relevant information was updated (e.g., forecasts of key performance indicators, such as budgets, labor hours, etc.). The credibility levels of indicators such as productivity, food costs, sales, and others are also included. Each criterion was given a score from 0 to 10, where 1 represents the "worst" and 10 represents the "ideal" usage. Thus, the productivity management index (M_{it}) is an index that summarizes the information from these 10 indicators on how managers use the software. This serves as the measure of our management practices index.

Variable	**Definition**	**Mean**	**SD**	**Min**	**Max**
x_1	No. of available rooms	151.78	78.83	23.00	435.00
M	Management practices index	8.02	1.14	1.96	10.00
x_2	Labor hours	166.41	140.39	0.54	872.67
y_1	Food and beverages	24398.41	26920.90	1.69	237333.10
y_2	Room service	87511.34	62947.94	158.00	509812.40
y_3	Other sales	42460.80	49950.30	112.51	457481.60
y	Total revenue	154370.50	117852.40	733.46	701577.10

Notes: In total, there are 52,358 observations. The variables were transformed into natural logarithms for use in the empirical model.

Table 1: Summary statistics.

4. Results and discussion

4.1. Empirical results

Table 2 reports the empirical results in terms of the three theoretical constructions of management practices. Models II and III show that all the determinants of inefficiency were statistically significant at less than 1%. This finding implies that we can reject the null hypothesis of the stochastic frontier model—no inefficiency exists among the hospitality firms—and supports stochastic frontier analysis as the right approach to address this issue.

Table 2: Estimation results from the maximum likelihood stochastic frontier analysis.

	(I)	**(II)**	**(III)**
VARIABLES	**IDF**	**IDF**	**IDF**
Constant	5.719***	5.877***	–0.037**
	(0.1560)	(0.0960)	(0.0184)
$\ln \tilde{x}_{2it}$	–0.658***	0.661***	–0.655***
	(0.0185)	(0.0154)	(0.0185)

$\left(\ln \tilde{x}_{2it}\right)^2$	–0.071***	–0.072***	–0.071***
	(0.0021)	(0.00212)	(0.0021)
$\ln y_{1it}$	–0.080***	–0.146***	–0.079***
	(0.0158)	(0.0108)	(0.0159)
$\ln y_{2it}$	–0.331***	–0.499***	–0.335***
	(0.0204)	(0.0157)	(0.0203)
$\ln y_{3it}$	–0.095***	0.104***	–0.100***
	(0.0214)	(0.0162)	(0.0215)
$\left(\ln y_{1it}\right)^2$	0.024***	0.023***	0.023***
	(0.0014)	(0.0014)	(0.0014)
$\left(\ln y_{2it}\right)^2$	0.068***	0.070***	0.069***
	(0.0015)	(0.0015)	(0.00149)
$\left(\ln y_{3it}\right)^2$	–0.017***	–0.017***	–0.017***
	(0.0017)	(0.0017)	(0.00171)
$\ln \tilde{x}_{2it} \ln y_{1it}$	–0.022***	–0.023***	–0.022***
	(0.0019)	(0.0019)	(0.0019)
$\ln \tilde{x}_{2it} \ln y_{2it}$	0.031***	0.034***	0.031***
	(0.0015)	(0.0015)	(0.00154)
$\ln \tilde{x}_{2it} \ln y_{3it}$	0.038***	0.038***	0.038***
	(0.0021)	(0.0021)	(0.0021)

M_{it}	–0.034*		–0.037**
	(0.0183)		(0.0184)
$\left(M_{it}\right)^2$	0.011***		0.011***
	(0.0014)		(0.0014)
$M_{it} \ln \tilde{x}_{2it}$	0.0031**		0.003**
	(0.0014)		(0.0014)
$M_{it} \ln y_{1it}$	–0.0099***		–0.0098***
	(0.0018)		(0.0018)
$M_{it} \ln y_{2it}$	–0.020***		–0.020***
	(0.0015)		(0.0015)
$M_{it} \ln y_{3it}$	0.027***		0.028***
	(0.0020)		(0.0020)
t	0.094***	0.064***	0.092***
	(0.0235)	(0.0209)	(0.0235)
t^2	0.0009	0.0007	0.0010
	(0.0023)	(0.0023)	(0.0023)
$\ln \tilde{x}_{2it}\, t$	–0.010***	–0.009***	–0.010***
	(0.0018)	(0.0018)	(0.0018)
$\ln y_{1it} t$	0.006***	0.002	0.007***
	(0.0023)	(0.0022)	(0.0023)
$\ln y_{2it} t$	–0.005***	–0.006***	–0.005**

	(0.0019)	(0.0019)	(0.0019)
$\ln y_{3it}t$	–0.008***	–0.001	–0.008***
	(0.0026)	(0.0025)	(0.0026)
$M_{it}t$	–0.003**		–0.003**
	(0.0015)		(0.0015)
$2.pcomp$	0.222***	0.223***	0.223***
	(0.0037)	(0.0037)	(0.0038)
$3.pcomp$	–0.178***	–0.176***	–0.179***
	(0.0074)	(0.0071)	(0.0074)
Usigma			
Constant	–2.076***	–1.610***	–1.555***
	(0.0683)	(0.1200)	(0.1310)
M_{it}		–0.061***	–0.063***
		(0.0117)	(0.0135)
$2.pcomp$	–0.494***	–0.511***	–0.534***
	(0.1010)	(0.1020)	(0.1020)
$3.pcomp$	2.108***	2.253***	2.148***
	(0.0984)	(0.0989)	(0.0989)
Vsigma			
Constant	–3.338***	–3.331***	–3.338***
	(0.0109)	(0.0108)	(0.0109)
Observations	52,358	52,358	52,358

Notes: Firm dummies are included as the determinant of the variance in inefficiency in each of the three models. Standard errors are presented in parentheses where *, **, and *** represent p<0.10, p<0.05, and p<0.01, respectively.

The empirical results provide consistent estimates in terms of sign, statistical significance, and coefficient size in most cases, especially in Models I and III. The differences in Model II might be attributed to the different specifications, that is, the exclusion of M_{it} from the IDF.

The key determinants of IDF were significant at the conventional significance levels, except for the coefficient of the time trend squared, t^2. The coefficients of management practices in Models I and II were found to be the same, and the effect on inefficiency in Models II and III was quite similar (Table 2). In addition, the coefficient estimates of the chain dummies for both the IDF and inefficiency were consistent across the models. The cost elasticity of outputs and the technical changes were similar in Models I and III, but the estimates differ from the specification in Model II. Figures 1 and 2 illustrate the cases. This is because the interactions of the time trend with y_1 and y_3 were not significant at one of the conventional levels in Model II. However, the coefficient of M_{it}

was significant at less than the 10% level and its interactions with the inputs ratio $\left(M_{it}\ln \tilde{x}_{2it}\right)$ and the time trend $\left(M_{it}t\right)$ were significant at less than the 5% level in Model I. The coefficients of M_{it} and its interactions with $\ln y_{1it}$, $\ln y_{3it}$, and t were significant at less than the 5% level in Model III. Therefore, in this article, we base the interpretation of our main results on Model III.

4.1.1. Effects of management practice on cost and technical inefficiency

Our aim was to test if improved management routines can assist in better management of inputs and reduce the frequency and magnitude of input overuse, as well as inefficiency. The key variables to study in relation to this aim are the effect of the cost elasticity of M_{it} on cost, $\left(Ec_m\right)$and the effect of M_{it} on inefficiency, $\left(Eu\_m\right)$. The empirical results reveal that the coefficient of Ec_m becomes positive, supporting the argument that improved management practices increase the cost, on average; that is, a one-point increase in M_{it} will increase the cost of production by 1.17%. This indicates that implementing a proper management procedure has the potential to increase cost. However, a closer examination of the results reveals that M_{it} has heterogeneous effects on costs, Ec_m. See the illustration in figure 3(a). The result shows a one-point improvement in management practices reduces the cost of production by 0.66% for the first quartile, but it increases cost for the remaining quartiles by 1.12%, 2.93%, and 5.65%. Thus, the effect on cost, Ec_m becomes positive, on average. The finding implies that better management routines initially reduce costs through the better use of other inputs but once the initial gains have been achieved, more improvements in management routines require a greater increase in management inputs. In summary, the finding reveals that management practices have heterogeneous effects on the cost of hospitality operations.

The results also show that the effect of M_{it} on inefficiency Eu_m is negative and significant at the 1% level. This supports the null hypothesis that improved management practices reduce technical inefficiency. For example, a one-point increase in M_{it} yields a 0.88% decline in inefficiency. Figure 3(b) shows that Eu_m is negative throughout, but its size gradually declines from about 1.33% (first quartile) to 0.18% (third quartile) and ultimately drops to zero (fourth quartile). This pattern suggests efficiency gains from improved management practices, as the most effective management practices yield zero inefficiency.

Peng et al. (2008) provide support for this finding, as they argue that better organizational routines can be a source of competitive advantage. The results of the management practice in general are in line with these findings (Bloom et al., 2017; Bloom et al., 2013a; Bloom et al., 2016; Bloom and Van Reenen, 2007, 2010).

4.1.2. Technical change and group differences

As well as the firm fixed effects, the heterogeneity of hospitality firms was reflected in terms of the differences in technical progress, cost, and technical inefficiency among chains and, hence, in their efficiency scores.

The mean technical change was found to be 2.06% over the study period (2012–2014), with variations across the hotels and restaurants. The distribution of the density plot depicts a negative technical change suggesting technical regress up to the 50% distribution. Nevertheless, the remaining 50% experience positive technical change. On average, the technical progress tends to be slightly larger than the technical regress; see the kernel density plot in Figure 3 for details. Therefore, the results imply that, on average, the input usage of the hospitality firms increasingly improved over time.

The results comparing chains of hotels show that *Chain 2* and *Chain 3* differed from *Chain 1* in terms of both production technology and technical inefficiency, with significance at less than the 1% level. These results suggest that the cost and technical inefficiency of *Chains 2* and *3* vary compared with those of the reference chain. *Chain 2* is 0.22% more costly than *Chain 1*, but 0.53% less inefficient; whereas *Chain 3* is 0.18% less costly than *Chain 1* but 2.15% more inefficient. Thus, *Chain 3* is the least costly of all three chains, but also the least efficient, and *Chain 2* is the costliest but the most efficient.

4.1.3. Technical efficiency and scale economies

The hospitality firms examined are quite efficient, as indicated by the average efficiency score of 77%. The efficiency scores are quite dispersed; for instance, the 25% and the 75% distributions cover 63% and 97%, respectively. The fourth quartile covers hospitality firms that are fully efficient. Therefore, the findings suggest that the firms are inefficient in about 75% of the cases, that is, they have some room to improve their input usage.

The findings also show that the hospitality firms were far from the optimum scale. The scales of production of their outputs were found to be very small relative to one, which indicates the optimum scale. On average, the cost elasticities of y_1, y_2, and y_3 were 0.08, 0.24, and 0.02%, respectively. Figure 2 shows the distribution of the cost elasticities of outputs. The sum of these cost elasticities was 0.34% on average, which is still very small relative to the best scale of operation. Comparing the cost elasticities, we find that y_2 is in a better position than y_1 and y_3 but even y_2 is very small relative to the optimum.

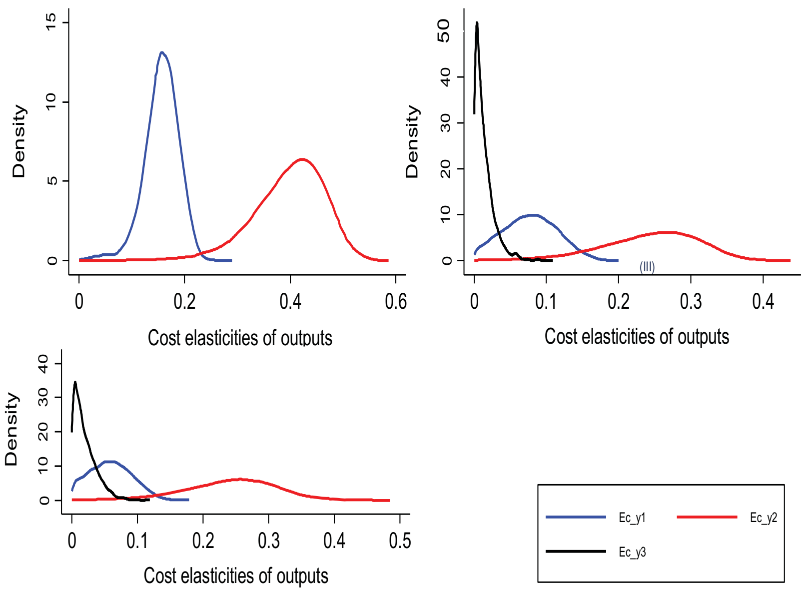

Fig. 1: Distributions of Cost Elasticities of Outputs

The figure shows the cost elasticity of three outputs; food and beverages (Ec_y1), accommodation service (Ec_y2) and other goods and services (Ec_y3). The three figures correspond to the empirical models reported in Table 2.

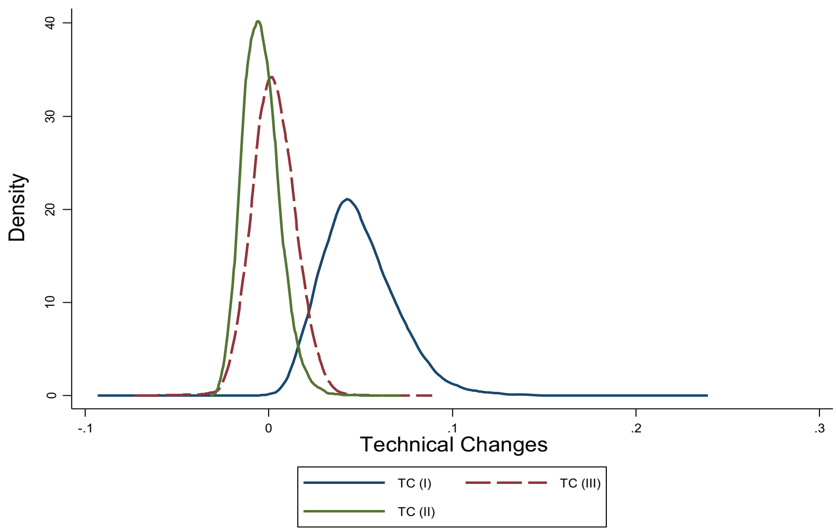

Fig. 2 : Distributions of Technical Changes (TC) 2012–2014

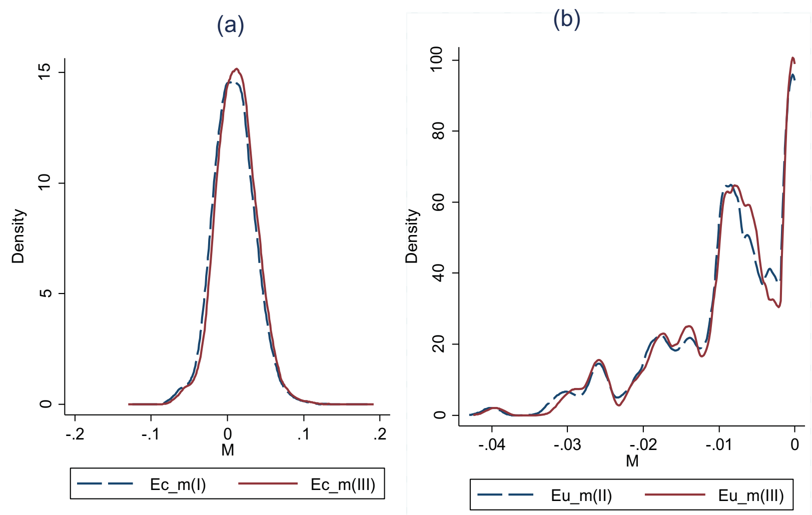

Fig. 3: The density of the effect of management practices (M) on cost and inefficiency.

In these figures,Ec_m and Eu_m represent the effects of management practices on cost and on inefficiency respectively. The numbers (I, II, and III) stand for the empirical models in Table 2.

4.2. Discussion and implications

The findings show that, on average, improved management practices increase the cost of hospitality operations but reduce the technical inefficiency. These effects are heterogeneous and, hence, the marginal effects vary for the different levels of management practices. The 95% linear prediction of the marginal effects of M_{it} on cost (a) and technical inefficiency (b) are illustrated in Figure 4. The effect on cost is U-shaped, as the marginal effect was negative for smaller indices, becomes zero at an index of approximately 7, and then becomes positive. That is, the cost reduction from improved management practices is realized up to the minimum threshold level (i.e., the zero marginal effect), which refers to the first quartile only. Nevertheless, the efficiency benefits resulting from improved management practices continue, at a cost, after this point.

The findings on the cost elasticity of management practices can be attributed to various mechanisms. Inspired by the finding on scale economies, the cost benefits of improved management practices might be reaped quickly, but are then reversed—that is, improved management increases costs—because maintaining good management routines requires management time and expertise. If this is the case, hospitality firms need to improve the scale of operations or modify the software so that it requires less management time, for instance through further automation. However, even if it is tempting to conclude that the benefits of management practices are exhausted at some level, we believe another explanation for the U-shaped costs is more convincing.

As the cost represents the production technology of hospitality services, quality characteristics also come into play in determining the cost level. All hospitality firms have a defined service quality level and a trade-off exists when optimizing staffing levels, as productivity improvements can come at the expense of the service quality level. For example, Bloom et al. (2013b) suggested that improved management practices enhance quality in the Indian manufacturing industry. The optimal trade-offs between service quality and the cost of production are the focus of a number of productivity studies in the service industry (Baker and Riley, 1994; Brown and Dev, 2000; Choi et al., 2015; Curtis and Sydney, 1990; Grönroos and Ojasalo, 2004; Klingner et al., 2015; Parasuraman, 2002; Rust and Huang, 2012; Singh, 2000).

Tan and Netessine (2014a) suggest that an inverted U-shaped relationship exists between productivity and staffing levels, which implies that the desirable staff level is achieved by the joint optimization of cost and quality (i.e., a U-shaped curve with a flatter bottom); that is, service companies seem to strike a balance between the two (Anderson et al., 1997). Although this interpretation goes beyond the scope of the model's results, we believe that those managers who achieve high management practice scores in terms of using the staff scheduling software have a strong focus not only on productivity but also on quality, which places limits on cost savings.

The effect of M_{it} on inefficiency was consistently negative and declining over the different levels of M_{it}, as shown in Figure 4(b). The figure indicates that improved management practice reduces inefficiency, but the marginal effect declines as the management practice improves. This suggests that hospitality firms that implement better management routines can reduce inefficiency to zero, that is, avoid wasting resources in hospitality service production. Earlier studies have shown that demand fluctuations increase inefficiency in service industries (e.g. Morikawa, 2012). However, as that study and others show, revenue management is not the only means for service firms to mitigate the negative effects of demand fluctuations. Improved management practices that result in proper management in proper management of inputs are important because of the effect on cost and inefficiency. Now that economic benefits from revenue management are eroding for hospitality firms as a result of the price transparency offered by online booking, more precise decisions on the volumes of variable inputs, such as staffing, materials, and outputs, are increasingly important as a potential source of competitive advantage. In situations with a high degree of demand uncertainty, active management practices are presumed to be particularly important to mitigate the negative effects on cost (to some extent) and technical inefficiency.

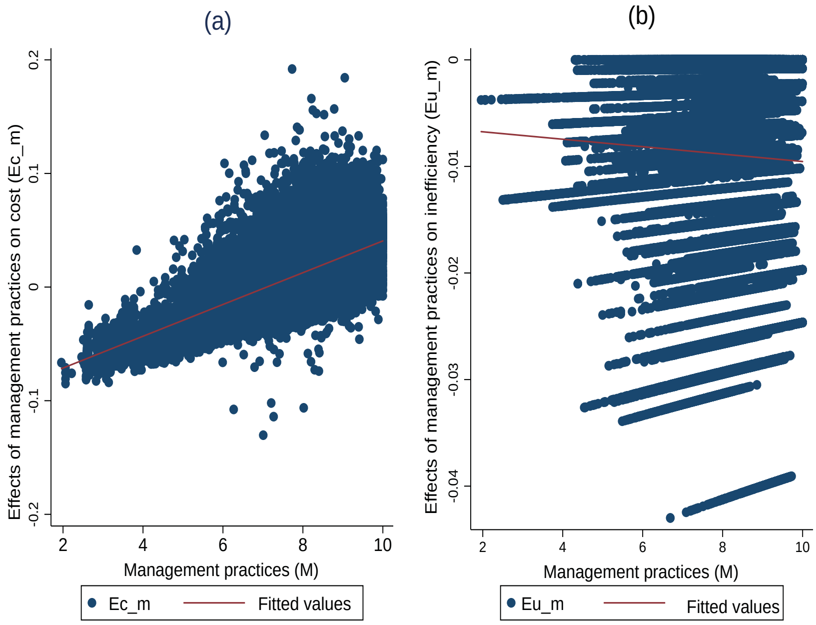

Fig. 4: Marginal Effects of Management Practices (M) on Cost and Inefficiency

5. Conclusions

Globalization and tougher competition have forced service firms to become ever more streamlined and efficient in their operations, leading to a continuous search for new ways of improving efficiency and productivity. For instance, it is becoming increasingly common for service firms to rely on machine learning and soft technologies to forecast demand and optimize inputs accordingly. However, decision support systems on their own are not helpful for minimizing production costs and inefficiency unless they are supported by good management practices.

This study used data on 92 hospitality firms from Norway that implemented the same software system over the period 2012–2014 to evaluate the impacts of managerial habits on cost and technical inefficiency. The results show that there are substantial efficiency gains to be obtained from having improved managerial routines in place to manage the operations of hospitality firms. The results highlight that organizations are rewarded by proper managerial use of the productivity management software in terms of efficiency gains; that is, implementing good routines can mitigate the inefficiency that results from input and output decisions, but the effect in reducing cost is limited, as improved management practices gradually increase cost. As discussed, it is likely that this occurs because a focus on maintaining a certain service quality level places constraint on potential cost savings. Thus, the key managerial implication of our findings is the importance of implementing proper managerial routines to reduce technical inefficiency in service organizations. However, the exact role of service quality in mitigating the effect of management practices on cost requires further investigation.

For the same reason, the effects of improved managerial practices in this study might be underestimated. Improved management affects not only costs and technical inefficiency, but also service quality, employee and customer satisfaction, and profitability, factors that are not reflected in this analysis (See Inoue and Lee (2011) for a review of the literature on these issues). One can speculate, for instance, on whether improved management practices reflect more precise input decisions (e.g., staffing decisions), but also more predictable work situations for employees, which may then be a source of increased employee satisfaction and motivation. However, this conclusion is beyond the scope of this study and represents a topic for future research.

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