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Estimation of staff use efficiency: Evidence from the hospitality industry☆

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ABSTRACT

We analyze the extent to which hospitality firms overuse staff using a production function model which considers firm heterogeneity and accounts for environmental variables in staff use. We decompose overall staff use inefficiency into transient and persistent inefficiency. To do this, we employ a state-of-the-art stochastic frontier model, which is estimated using daily data on 94 Norwegian hospitality firms from 2010 to 2014. The environmental variables, especially the annual time trend, seasonality, and days of the week are found to exert heterogeneous effects on staffing. The mean transient, persistent, and overall efficiencies of the hospitality firms are 69%, 67%, and 46%, respectively. We find that seasonality (days of the week) decreases (increases) transient inefficiency by about 4%, suggesting significant room for improvement in hospitality staff use.

1. Introduction

Getting staffing levels right is at the crux of productivity and service quality because of its vital role in service and specifically hospitality operations. Edvardsson (1997), for instance, describes the staff in a service setting as "beyond a resource" [emphasis added] because staff inputs determine service quality and customer satisfaction. More broadly, these practices have wide-ranging implications for employee welfare and the firm's profitability, image, and competitiveness (Anand et al., 2011; Ernst et al., 2004; Huselid, 1995). The staff employment is increasing in the from time to time and the service sector plays a leading role in the European economies (Santos-Vijande et al., 2021). At the same time, service companies aim to cut staff expenses as it covers the largest share of operating costs (Van den Bergh et al., 2013; Choi et al., 2009; Tan and Netessine, 2014a; Tsai et al., 2009). That is why striking a balance with the staffing practices is the key concern. For instance, the service productivity dilemma (See; Aspara et al. (2018); Calabrese (2012)) deals with the trade-off between the service outcomes and staff costs. Therefore, the current article drives the concept of right staff levels from this balance and Botta-Genoulaz and Millet (2006), who defines staffing practices as the relationship between staff and activity levels while accounting for the staff skills and service quality implications. However, the balance between staffing cost and a given service quality level is a difficult one, and especially for a manager worried about bad guest reviews, it is easy to err on the side of overstaffing. Thus, the key research questions in this area are the extent to which staff use practices are inefficient (over use of staff), if any, and what are the sources of inefficiency, and the determinants.

Despite its importance, the overstaffing issue (staff use efficiency) has received relatively scant attention in the hospitality literature. The empirical literature on staff scheduling in service industries and those facing stochastic demand is dominated by applications in healthcare, specifically nursing and emergency units (Arisha and Abo-Hamad, 2013; Gul and Guneri, 2012; Maier-Rothe and Wolfe, 1973) and call centers (Chevalier and Van den Schrieck, 2008; Defraeye and Van Nieuwenhuyse, 2016; Gurvich et al., 2010; Koçağa et al., 2015) and police departments (Kaplan, 2013; Liu et al., 2019). Rocha et al.(2012) show a clear need for more research in this area given the small amount of empirical research in hospitality compared to transport and nursing.

The scant empirical literature in the hospitality sector are mostly conceptual, are focused on an ex-ante approach for planning staff levels and are limited to the investigation of the historical evaluation of staffing practices and its relationship with service performance. A series of staff scheduling and rostering articles by Thompson (1998a; 1998b;

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1999a; 1999b) describe the steps in the staff scheduling process, viz., (i) forecasting demand, (ii) determining staff requirement, (iii) optimizing the staff level and (iv) adapting this to real-time arrangements. The review article by Ernst et al. (2004) also has a conceptual discussion of similar staff scheduling steps in the service sector. Fujita et al. (2016) argue that although these conceptual discussions are useful, they have to a little degree been translated into empirical work in the hospitality sector. The ex-ante studies provided empirical applications that optimized staff levels used mathematical programming and simulation, aiming to give rules for optimizing staff levels. For example, Choi et al. (2009) did so in a Korean restaurant using integer programming, Fujita et al. (2016) included the permanent versus temporary staff dichotomies into the staff optimization model, while Kadry et al. (2017) accounted for work shifts in the optimization of housekeeping and front-desk service staffs. These analyses are important to account for the tour scheduling practices a 24-7 staff assignment (Van den Bergh et al., 2013). A few studies dealt with evaluating the 'historical performance of hospitality managers' staffing practices. These studies, (e.g.,Tan and Netessine (2014a,b)) have evaluated restaurant chains' actual staffing practices and the impact of sub-optimal staffing on firm performance. These studies, however, use a different methodological approach and they do not allow identification of inefficiency in staff use. That means, they overlooked the estimation of efficiency in staff use, the identification of inefficiency types and their determinants.

The current study fills these gaps in evaluating staffing performance in the hospitality sector, with a focus on staff overuse. To analyze managers' staffing practices, the study uses panel data of 94 companies in Norway from 2010 to 2014. The degree of overstaffing is defined as the difference between the actual and optimal (benchmark) staff levels. An input distance function (IDF) is used to determine the benchmark staff level. In particular, our IDF is specified as a semiparametric smooth coefficient (SPSC) stochastic frontier (SF) function. The staff overuse (labeled as inefficiency following the nomenclature used in SF models) is determined by the difference between the observed and the benchmark staff level, estimated from the frontier. In defining the benchmark (frontier), the statistical noise is taken into consideration. Technically speaking, a company's staff use is optimal when both persistent and transient inefficiency components associated with staff use are zero. We also allow firm heterogeneity and separate them from time-varying (transient) and persistent (permanent) inefficiencies and random noise. Thus, our primary focus is on estimating overall staff overuse and decomposing it into persistent and transient components. We also examine factors affecting transient staff overuse.

The current study provides several contributions to tourism and hospitality literature. First, the study provides a broader and in-depth view of staffing performance in hospitality operations. Second, as far as we know, this is the first attempt in identifying firm-specific heterogeneity from the transient and persistent inefficiencies and the random noise while also estimating the effects of environmental variables in hospitality operations using the Semiparametric Smooth Coefficient (SPSC), barring an unpublished conference presentation by Kumbhakar, Sun and Tveterås (2019). Zhang et al. (2012) argue that this methodology provides more precise estimates than the standard regression. Besides, earlier studies have not estimated the inefficiency of staffing performance, and the bulk of studies that estimated the technical inefficiency (Assaf and Josiassen, 2016; Baker and Riley, 1994; Sigala, 2004) hold few managerial and policy implications for staff scheduling practices because the studies dealt with measuring cost (productivity) across firms and time. Finally, the current study provides both policy and managerial lessons to improve hospitality operations. As Lien et al., (2018) argue, the transient component is an issue of concern for managers, while the persistent inefficiency is dealt with by policymakers because such an inefficiency results from structural rigidity.

The rest of the paper is organized as follows. Section 2 explains the theoretical model of staffing in an IDF framework and explains the steps in the modeling approach and the estimation procedure. Section 3 provides information on the data source, variable construction, and descriptive statistics. Section 4 provides the empirical results, discussion, and implications, and finally, section 5 provides concluding remarks.

2. Conceptual model and methodology

As operational performance plays a central role in hospitality, it is usual to measure staffing hours against different outputs. These include, for example, sales to staff hours, number of sold rooms to staff hours, and similar ratios. Nevertheless, these measures are only partial and potentially play another important role other than measuring the amount of output per unit of staff. Baker and Riley (1994) [p. 258] put the issue like this: "productivity management is essentially a function of accurate sales forecasting and accurate manipulation of the supply of all types of resources to match demand" . In other words, it emphasizes the role of forecast information as an essential input in service production. Collecting the relevant information, forecasting the demand, and determining the required inputs ahead of time are then essential aspects of hospitality operations.

In forecasting demand, seasonality and daily demand fluctuations are among the most critical factors determining tourism and hospitality staffing. Barlow (2002) argues that a portion of hospitality demand tends to vary systematically over seasons and the days of the week. The daily demand fluctuations, for instance, depend mainly on customer groups' characteristics dominating on specific days. Typically, hotels receive business guests (e.g., those coming for a business meeting, conference, or training course) on weekdays but leisure guests dominate the market on weekends. For instance, Liu et al. (2018) finds higher tourist arrivals on weekends and holidays. Besides, several other factors, such as location, determine hospitality firms' performance (Lado-Sestayo and Fernández-Castro, 2019) and hence whether leisure or business customers dominate the market.

Moreover, repeated events like holidays, conferences, sporting events, and other special days influence the demand for hospitality service and staffing requirements. Uncertainties like economic fluctuations, terrorism, climate changes, etc., also influence staffing decisions. The ability to forecast demand and translate it into resource requirements and the pace at which managers develop experience through learning by doing varies among firms and influences the staffing decision through its impact on manager intuition.

Therefore, the environmental variables, Z_{it} in our model, which include three variables: the annual trend $\widetilde{t}$ to reflect annual variations, measured in the number of years since 2009; m is a measure of seasonality measured in months; and d is the day of the week ($d = 1, 2, 3\ldots7$).

Here, the relevant operational problem is to optimize staff levels, x_{1it}, for a given level of y_{jit}, and the other exogenous variables, for j number of outputs, hospitality firms i and time in days t. We assume that hospitality firms' production process is a multi-output, multi-input process that we can characterize by a transformation function or an IDF. The IDF is defined as $D_{it} = f(x_{1it}, x_{2it}, y_{jit})$, where D_{it} is the distance function, x_{1it} is the staff level, and x_{2it} is the level of capital for the j^{th} output, y_{jit}. For details on the construction of the IDF, see Kumbhakar et al., (2015). Because an IDF is homogeneous of degree one in input quantities, we impose a linear homogeneity condition by dividing both sides of the IDF by x_{1it} and replacing the capital, x_{2it}, by the ratio of x_{2it} to x_{1it}. We then take the logs and write the IDF as $\ln x_{1it} = f(\ln\widetilde{x}_{2it}, \ldots, y_{Jit})$ with a typical element $y_{jit}, \forall j = 1, \ldots, J)$. Finally, we use the following SPSC specification with input-oriented inefficiency:

$$\ln x_{1it} = \beta_0(Z_{it}) + \beta_1(Z_{it})\ln\widetilde{x}_{2it} + \beta_2(Z_{it})\ln y_{1it} + \beta_3(Z_{it})\ln y_{2it} + \beta_4(Z_{it})\ln y_{3it} + \varepsilon_{it} \quad (1)$$

where Z_{it} are environmental variables, and

$$\varepsilon_{it} = b_i + v_{it} + \eta_i + \mu_{it} \quad (2)$$

where b_i are the mean-zero random firm effects, v_{it} is the mean-zero noise term, $\eta_i \geq 0$ is persistent inefficiency, and $\mu_{it} \geq 0$ is transient inefficiency. All the coefficients are non parametric functions of the Z_{it} variables. Note that if the functional coefficients $\beta(.)$ are constants, the SPSC IDF becomes a standard IDF. Now we show that the model in (1) and (2) is identified in the sense that we can not only estimate the functional coefficients, $\beta(Z_{it})$ but can also predict η_i and μ_{it}. For this we assume that η_i is mean-independent from Z_{it}, i.e., $E(\eta_i|Z_{it}) = E(\eta_i) = a_1$, but μ_{it} is determined by the Z variables, i.e., $E(\mu_{it}|Z_{it}) = a_2(Z_{it})$. If $E(b_i|Z_{it}) = 0$and$E(v_{it}|Z_{it}) = 0$,then clearly, $E(\varepsilon_{it}|Z_{it}) = E(\eta_i|Z_{it}) + E(\mu_{it}|Z_{it}) = a_1 + a_2(Z_{it}) \neq 0$. To correct for the non-zero conditional mean problem, we first take $E(.|z_{it})$ on both sides of (1), and obtain:

$$\begin{aligned} E(\ln x_{1it}|Z_{it}) &= \beta_0(Z_{it}) + \beta_1(Z_{it})E(\ln\widetilde{x}_{2it}|Z_{it}) + \beta_2(Z_{it})E(\ln y_{1it}|Z_{it}) + \\ &\quad \beta_3(Z_{it})E(\ln y_{2it}|Z_{it}) + \beta_4(Z_{it})E(\ln y_{3it}|Z_{it}) + E(\varepsilon_{it}|Z_{it}) \end{aligned} \quad (3)$$

Subtracting (3) from (1), we obtain:

$$\ln\breve{x}_{1it} = \beta_1(Z_{it})\ln\breve{x}_{2it} + \beta_2(Z_{it})\ln\breve{y}_{1it} + \beta_3(Z_{it})\ln\breve{y}_{2it} + \beta_4(Z_{it})\ln\breve{y}_{3it} + \breve{\varepsilon}_{it} \quad (4)$$

where $\ln\breve{x}_{1it} = \ln x_{1it} - E(\ln x_{1it}|Z_{it})$, $\ln\breve{x}_{2it} = \ln\widetilde{x}_{2it} - E(\ln\widetilde{x}_{2it}|Z_{it}), \ln\breve{y}_{jit} = \ln y_{jit} - E(\ln y_{jit}\Big|Z_{it}), j = 1, 2, 3$, and

$$\breve{\varepsilon}_{it} = \varepsilon_{it} - E(\varepsilon_{it}|Z_{it}) = \varepsilon_{it} - E(\eta_i|Z_{it}) - E(\mu_{it}|Z_{it}) = \varepsilon_{it} - a_1 - a_2(Z_{it}). \quad (5)$$

Equation (4) is similar to the Robinson (1988) transformation (Kumbhakar et al., 2019). It is clear that $E(\breve{\varepsilon}_{it}|Z_{it}) = 0$ and it must be uncorrelated with the right-hand-side variables, including input ratio, outputs and Z_{it}. The conditional means $E(\ln x_{1it}|Z_{it})$, $E(\ln\widetilde{x}_{2it}|Z_{it})$, and $E(\ln y_{jit}\Big|Z_{it})$ can be estimated using the Nadaraya-Watson kernel estimator (Nadaraya, 1965; Watson, 1964) available for the npreg function of the np package (Hayfield and Racine, 2008) in R. The transformed model in (4) is the standard SPSC model, which is estimated using the np package in R. After estimating the functional slope coefficients, we rewrite (1) as

$$R_{it} = \beta_0(Z_{it}) + \varepsilon_{it} \equiv \theta_0(Z_{it}) + \breve{\varepsilon}_{it} \quad (6)$$

where $R_{it} = \ln x_{1it} - \beta_1(Z_{it})\ln\widetilde{x}_{2it} - \beta_2(Z_{it})\ln y_{1it} - \beta_3(Z_{it})\ln y_{2it} - \beta_4(Z_{it})\ln y_{3it}$ and $\theta_0(Z_{it}) = \beta_0(Z_{it}) + a_1 + a_2(Z_{it})$. A non-parametric regression of (6) yields the estimates of $\theta_0(Z_{it})$ and its gradients as well as $\breve{\varepsilon}_{it}$. We can now use the residuals $\breve{\varepsilon}_{it}$ to estimate the persistent and transient inefficiency (staff overuse) components. Using the relationship between $\breve{\varepsilon}_{it}$ and ε_{it} in (7), we write:

$$\breve{\varepsilon}_{it} = \chi_{0i} + \chi_{it}, \quad (7)$$

where $\chi_{0i} = b_i + \eta_i - a_1$, and $\chi_{it} = v_{it} + \mu_{it} - a_2(Z_{it})$. In practice, we first replace the $\breve{\varepsilon}_{it}$ in (7) with the residual from (6), and then estimate (7) as either a fixed or random effects panel model without any regressors and obtain $\widehat{\chi}_{0i}$ and $\widehat{\chi}_{it}$ which are then used to obtain the transient and persistent inefficiencies. For persistent inefficiency, we use the relationship:

$$\chi_{0i} = b_i + \eta_i - a_1, \quad (8)$$

where χ_{0i} in practice is replaced by $\widehat{\chi}_{0i}$. We treat (8) as a SF model and estimate its parameters using the distributional assumptions $b_i = iidN(0, \sigma_b^2)$, $\eta_i = iidN^+(0, \sigma_\eta^2)$ (half-normal), and b_i and η_i are independent from each other. Note that for half-normal distribution of η_i, $a_1 = E(\eta_i) = \sqrt{(2/\pi)}\sigma_\eta$, so that the SF model in (8) estimates σ_η^2 and σ_b^2. We then use the Jondrow et al., (1982) estimator to predict persistent inefficiency and Battese and Coelli (1988) to estimate the persistent technical efficiency. See Kumbhakar and Lovell (2000) for details. For transient inefficiency, we use the relationship (Kumbhakar et al., 2019):

$$\chi_{it} = v_{it} + \mu_{it} - a_2(Z_{it}), \quad (9)$$

where χ_{it} is replaced by $\widehat{\chi}_{it}$. We use distributional assumptions $v_{it} = iidN^+(0, \sigma_v^2), \mu_{it} \sim iidN^+(0, \sigma_\mu^2(Z_{it}))$ (half-normal), v_{it} and μ_{it} are independent from each other. The latter gives $a_2(Z_{it}) = E(\mu_{it}|Z_{it}) = \sqrt{2/\pi}\sigma_\mu(Z_{it}) = \sqrt{2/\pi}\exp(c_1 + \gamma' Z_{it})$. This is the standard but nonlinear SF model. We use the estimated $E(\mu_{it}|Z_{it})$ to predict transient inefficiency and the estimate of $a_2(Z_{it})$ to recover $\beta_0(Z_{it})$ using the estimates of a_1 and $a_2(Z_{it})$ from the relationship $\theta_0(Z_{it}) = \beta_0(Z_{it}) + a_1 + a_2(Z_{it})$.

Once the functional coefficients $\beta_0(Z_{it}), \cdots, \beta_4(Z_{it})$ are estimated, we compute the marginal effects of the environmental variables on staffing in (1) using:
$\frac{\partial \ln x_{1it}}{\partial Z_{pit}} = \frac{\partial\beta_0(Z_{it})}{\partial Z_{pit}} + \frac{\partial\beta_1(Z_{it})}{\partial Z_{pit}}\cdot\ln\widetilde{x}_{2it} + \frac{\partial\beta_2(Z_{it})}{\partial Z_{pit}}\cdot\ln y_{1it} + \frac{\partial\beta_3(Z_{it})}{\partial Z_{pit}}\cdot\ln y_{2it} + \frac{\partial\beta_4(Z_{it})}{\partial Z_{pit}}\cdot\ln y_{3it}$, $\forall p = 1, 2, 3$ where $\beta_0(Z_{it}), \cdots, \beta_4(Z_{it})$ in the above equations are replaced by their estimates.

3. Data and descriptive statistics

For the analysis, we employ a data set consisting of daily observations for 94 hospitality firms from 2010 to 2014. We received the data from d20, a staff forecasting software provider for hospitality companies. The software provider automatically reports the key performance variables of clients on a daily basis to use the data as an input for the next period's forecast. The variable construction is as follows. Capital is measured using the number of available rooms following several studies on hospitality productivity and efficiency (e.g., Barros (2005); Sigala (2004)). Moreover, the measure of inputs and outputs should account for heterogeneous qualities because Fox and Smeets (2011) recommend weighting staff quality when a severe bias is perceived. In hospitality companies, the various departments such as administration, bar and restaurant, front office, housekeeping, etc., require groups of staff with different skills and experience. To account for these quality differences, the department level average wage rate is used to calculate the weights using the Divisia index (Solow, 1957). Alternatively, the actual staff educational qualifications skills and experience could control for quality differences, but this information is not included in our data set.

Therefore, we measure the staff level in terms of quality-weighted staff hours. One drawback of this approach is that weighted staff hours implicitly assume that staff hours can substitute for one another. We agree that this assumption is rather strong but not entirely implausible in the context of the Nordic hospitality industry, where permanent staff typically undertake multiple tasks and perform different roles because of the high salary level (Alemayehu and Tveteraas, 2020).

Similarly, the heterogeneity of output is also an issue in measuring hospitality services. Measuring outputs in terms of natural units (rooms

Table 1
Descriptive Statistics

Notation	Variable	Mean	SD	Min	Max
x_1	Staff hours	250	469.24	0.21	17863
x_2	Available rooms	157	88.61	23	435
y_1	Food and beverages	29498	68,016.14	0.37	11,234,382
y_2	Room service	83973	77604	4.79	6,077,041
y_3	Other sales	53610	117544	1.46	16,811,844

occupied or the number of food orders) might yield misleading results as this does not account for heterogeneity. For instance, Anderson and Xie (2016) observe that rooms could be of different types (standard and deluxe rooms, suites), and even the same type of rooms could vary depending on the amenities included. A similar differentiation exists in food orders in a restaurant. That is why the existing literature (e.g., Grönroos and Ojasalo (2004); Syverson (2011)) recommends using the revenue to measure differentiated outputs like these. Gronroos and

Table 2
Summary of the Functional Coefficients.

	Robinson	Semiparametric Smooth Coefficient (SPSC)				
	$\beta_0(Z_{it})$	$\beta_0(Z_{it})$	$\beta_1(Z_{it})$	$\beta_2(Z_{it})$	$\beta_3(Z_{it})$	$\beta_4(Z_{it})$
Q1	0.3887	0.6432	2.1163	0.0403	0.2192	0.1316
		(0.211)	(0.1610)	(0.0066)	(0.0082)	(0.0097)
		[0.3840 1.265]	[3.0657 1.4640]	[0.0267 0.0555]	[0.1941 0.2431]	[0.1116 0.1520]
Median	0.3216	1.7026	1.5532	0.0576	0.2345	0.1704
		(0.4323)	(0.3325)	(0.0085)	(0.0104)	(0.0135)
		[0.8380 2.567]	[2.2182 0.8883]	[0.0406 0.0746]	[0.2137 0.2553]	[0.1434 0.1974]
Mean	0.2891	1.4641	1.4156	0.0589	0.2424	0.1639
		(0.4082)	(0.2320)	(0.0075)	(0.0092)	(0.0128)
		[0.3232 3.167]	[2.5319 0.5090]	[0.0408 0.0720]	[0.2224 0.2592]	[0.1288 0.1852]
Q3	0.2332	2.3684	0.6739	0.0695	0.2593	0.1979
		(0.5893)	(0.4789)	(0.0104)	(0.0124)	(0.0156)
		[1.5390 3.592]	[1.3570 0.1153]	[0.0519 0.0860]	[0.2408 0.2738]	[0.1787 0.2520]

Notes: The data consists of 130,707 observations. 95% confidence intervals reported under coefficient estimates and standard errors in brackets. In Robinson's model, the elasticity of inputs ratio β_1 and the staff elasticities of outputs (β_2,β_3, and β_4) were 0.0032, 0.0762, 0.2160, and 0.2168, while the return to scale (RTS) was 0.509. The p-values are not directly reported in the table but inferred from the 95% confidence intervals. The criterion is to accept the null hypothesis that a given coefficient equals zero at less than 5% level if the confidence interval includes zero, but to reject the null hypothesis if the confidence interval does not include zero.

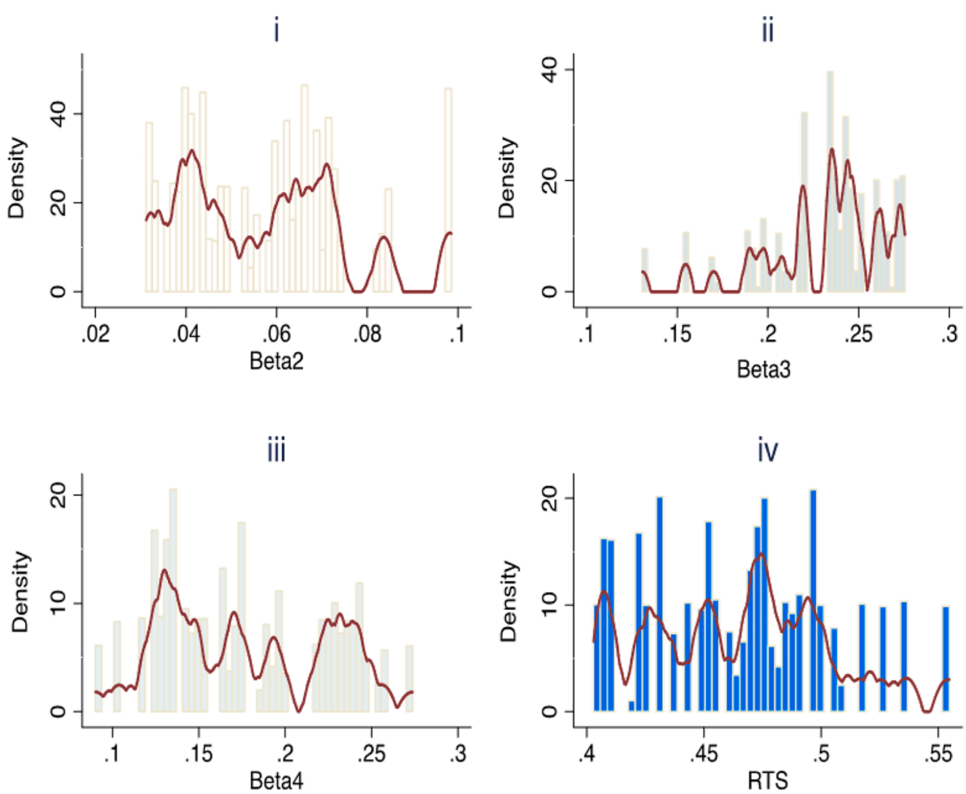

Fig. 1. The distributions of staff elasticities of outputs and the returns to scale (RTS).

Table 3
Summary of Marginal Effects of Environmental Variables.

	Robinson		SPSC		
	$\frac{\partial \ln x_{1it}}{\partial t_{it}}$	$\frac{\partial \ln x_{1it}}{\partial m_{it}}$	$\frac{\partial \ln x_{1it}}{\partial d_{it}}$	$\frac{\partial \ln x_{1it}}{\partial \widetilde{t_{it}}}$	$\frac{\partial \ln x_{1it}}{\partial m_{it}}$
Q1	0.0009	0.0021	0.0038	0.2096	0.0024
Median	0.0050	0.0001	0.0050	0.3789	0.0006
Mean	0.0039	0.0005	0.0006	0.0972	0.0001
Q3	0.0081	0.0036	0.0107	0.8942	0.0032

Notes: Marginal effects of days of the week, $\frac{\partial \ln x_{1it}}{\partial d_{it}}$, are zero and not reported in the table for SPSC

Table 4
Transient and Persistent Efficiency Parameter Estimates.

	Transient	Persistent
σ_μ		
Constant	− 1.72***	− 1.082*
	(0.098)	(0.526)
Months	− 0.040***	
	(0.009)	
Days of the week	0.037**	
	(0.014)	
σ_v		
Constant	− 1.010***	− 1.760***
	(0.012)	(0.345)
N	130,707 93	

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$ Notes: The annual time trend is dropped from the environmental variables in this case because of the modeling difficulty. Standard errors under the respective coefficient estimates in parentheses.

Ojasalo (2004) also argues that a measure of outputs using revenue better addresses the changes in service quality over time and the customers' willingness to pay for these changes than using physical units. Therefore, we measure the outputs in terms of the deflated revenue (in NOK) by the consumer price index to account for the differences in service quality and hence customer's willingness to pay for it.

The sample summary statistics show that the typical hospitality firm hires 250 staff hours daily and has 157 rooms available. On average, the sample firms generate total revenue of NOK 167,081, comprising sales of food and beverages (18%) and room service (50%) with the remaining 32% of revenues from the sale of other goods and services. Table 1 details the full summary statistics.

4. Empirical results, discussion, and implications

4.1. Results

In addition to the SPSC model outlined in the previous section, we consider a simple model in which the variables affect staff use ($\ln x_{1it}$) only directly. Thus, this model assumes that environmental variables such as the annual time trend, seasonality and days of the week affect ($\ln x_{1it}$) in a neutral fashion (independently of the levels of outputs and other inputs). The resulting model is:

$$\ln x_{1it} = \beta_0(Z_{it}) + \beta_1 \ln \widetilde{x}_{2it} + \beta_2 \ln y_{1it} + \beta_3 \ln y_{2it} + \beta_4 \ln y_{3it} + \varepsilon_{it}. \tag{10}$$

This is Robinson's (1988) model, in which the intercept function is non-parametric in Z_{it}. All other coefficients are fixed. The model in (10) following the transformation used for (1) becomes:

$$\ln \breve{x}_{1it} = \beta_1 \ln \breve{x}_{2it} + \beta_2 \ln \breve{y}_{1it} + \beta_3 \ln \breve{y}_{2it} + \beta_4 \ln \breve{y}_{3it} + \breve{\varepsilon}_{it} \tag{11}$$

This is a standard regression model that we can estimate using Ordinary Least Squares, with the residuals used to estimate $\beta_0(Z_{it})$.

Note that the environmental variables, Z_{it} in our model include $\widetilde{t}$ (the annual time trend), m (seasonality measured in months) and d (the day of the week). Under the Robinson's neutral-effect model in (10), the marginal effects of the environmental variables Z_{it} on staff level are calculated as $\frac{\partial \beta_0(Z_{it})}{\partial \widetilde{t}}$, $\frac{\partial \beta_0(Z_{it})}{\partial m_{it}}$ and $\frac{\partial \beta_0(Z_{it})}{\partial d_{it}}$ by replacing the derivatives by their estimates. Note that as $\theta_0(Z_{it}) = \beta_0(Z_{it}) + a_1 + a_2(Z_{it})$, we can obtain $\beta_0(Z_{it}) = \theta_0(Z_{it}) - a_1 - a_2(Z_{it})$, and the first column is comparable to the second column in Table 2. The table provides summary statistics of these results because the functional coefficients,βs are observation specific.

Table 2 shows the estimated parameters for the determinants of IDF. These coefficient estimates make sense both statistically and theoretically in most cases except for a few outliers. Statistically, all the coefficient estimates differ from zero at less than the 5% level, except for the first quartile of β_0 and the third quartile of β_1. In addition, the coefficient estimates are consistent with our expectation from production theory, i.e., the staff elasticities of outputs are positive while the elasticity of the ratio of the inputs is negative in both models. The sizes of the coefficient estimates are consistent for both models. The coefficient estimates for the staff elasticity of each output y_{1it}, y_{2it} and y_{3it} average 0.06%, 0.23%, and 0.18% in the SPSC model, respectively, and indicates low responsiveness in staffing based on output changes in the different departments. The coefficient estimates of the Robinson model are like the SPSC model. This indicates that the results are robust with respect to the two estimation methods. Summing over staff elasticities of outputs for the three departments, we find the overall returns to scale (RTS) of about 0.5%, on average, for the hospitality companies irrespective of the differences in the assumptions in SPSC and the Robinson model. The finding implies that the capacity utilization of the sample of hospitality companies is at a sub-optimal level and they need to consider more capacity utilization. See figure 1 for the density distributions of the elasticities of outputs and returns to scale.

While the results in Table 2 shows the responsiveness of staffing to the changes in output, Table 3 relates to how environmental variables influence staffing performance through the staff elasticities. These include variables that potentially can be linked to forecasting staff requirements, such as seasonality and days of the weeks. Specifically, Table 3 provides a summary of the marginal effects of the environmental variables on staffing, using both the neutral (Robinson) and non-neutral (SPSC) assumptions. In the Robinson model, the positive marginal effect of the annual time trend on staffing, $\frac{\partial \ln x_{1it}}{\partial t}$, implies staffing (i.e., inefficiency) increases with time, but that the marginal impact of seasonality on staffing, $\frac{\partial \ln x_{1it}}{\partial m_{it}}$, is negative for only about 50% of observations. In contrast, the marginal effect of days of the week, $\frac{\partial \ln x_{1it}}{\partial d_{it}}$, are positive except for observations in the first quartile. This implies that hospitality companies are more able to adjust staffing to top optimal levels between months than between days. In the SPSC, the marginal effect of the annual time trend is also positive. In contrast to the Robinson model, the effect of seasonality is positive, and of the days of the week is zero.

Table 4 details the determinants of transient and persistent inefficiency after controlling for the effects of firm-specific heterogeneity. As shown, for the determinants of transient inefficiency, both potential variables, i.e., seasonality and days of the week, are statistically significant at the 1% and 5% level, respectively. On average, seasonality decreased transient staffing inefficiency while the days-of the-week variable increased it by about 4%. These results are the opposite of the

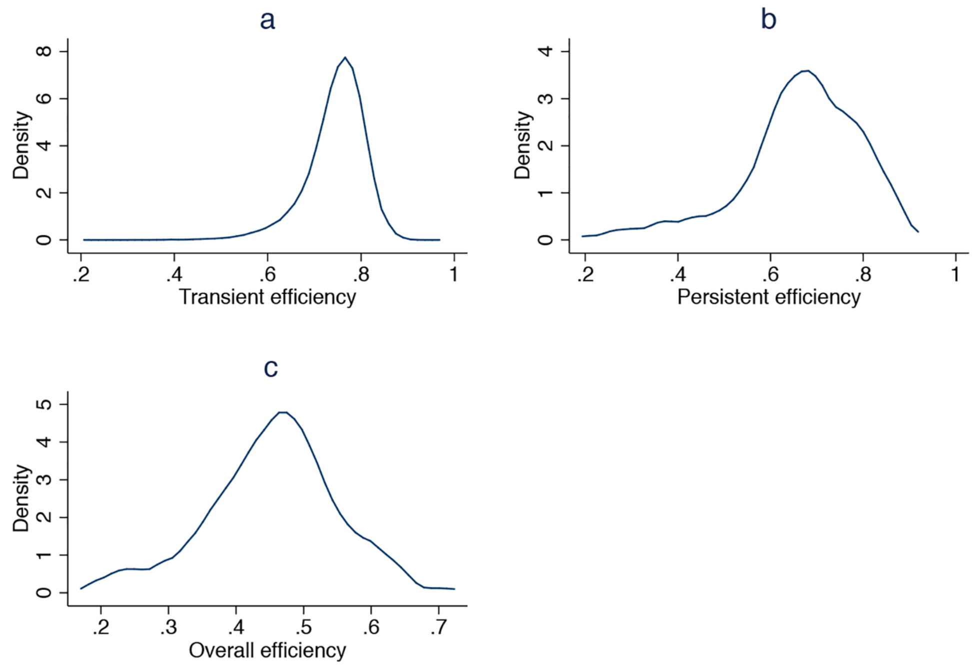

Fig. 2. The distributions of transient(a), persistent(b) and overall(c) efficiencies.

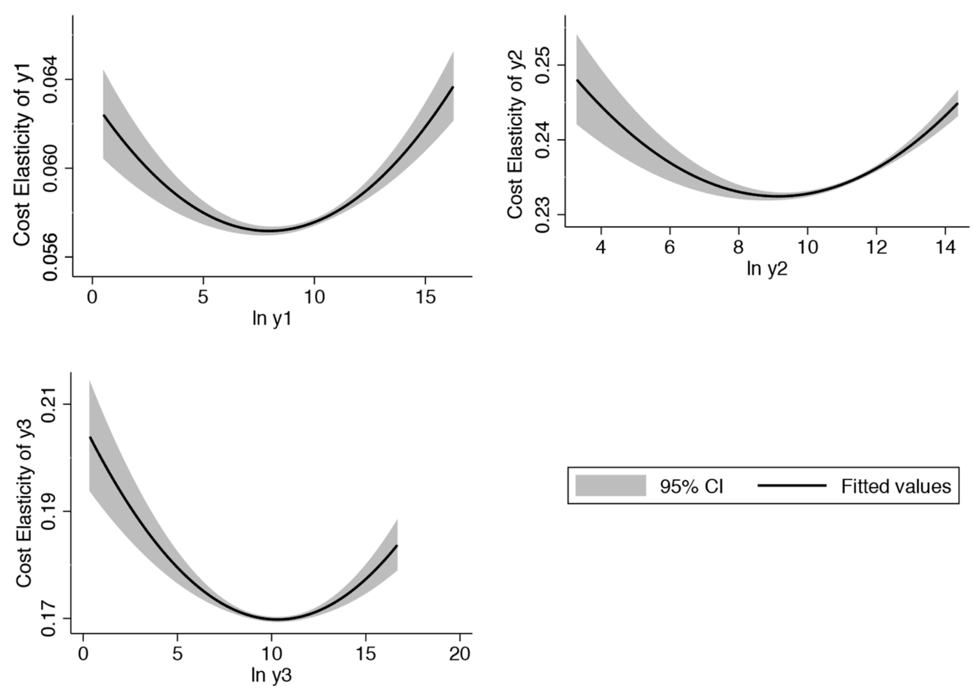

Fig. 3. The distribution of Marginal Staff Elasticities of Outputs.

impact on firm heterogeneity, i.e., seasonality increased firm-specific heterogeneity by about 0.6%, whereas the days of the week decreased it by about 0.7%.

We also summarize the efficiency scores. These show that the transient and persistent efficiency of staffing decisions are almost the same, with the former being about 69% and the latter about 67%. These findings are consistent with Alemayehu and Tveteraas (2020), who found that hospitality firms average about two-thirds of the profit-maximizing staff level. Overall, the efficiency scores of staffing performance average 46%. Note that overall efficiency is the product of the transient and persistent efficiencies, where efficiency is defined as exp(-inefficiency). Fig. 2 illustrates the distributions of these efficiency scores. As depicted, the transient and persistent efficiency scores skew to the left and have heavy tails, whereas the distribution of the overall

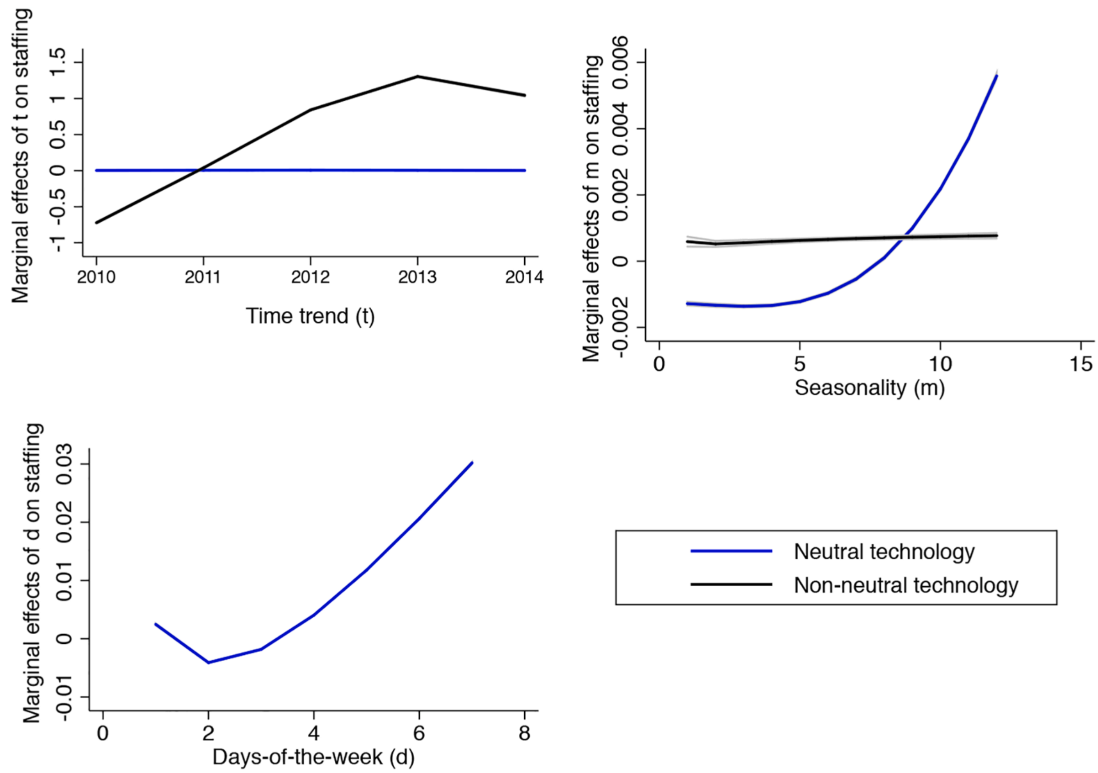

Fig. 4. Marginal Effects of Environmental Variables.

efficiency scores is almost symmetric and less leptokurtic.

The wider distribution of persistent compared to the transient efficiency scores indicates that fixed effects linked to, e.g., capital investment and location lead to large differences in the persistent efficiency scores related to how efficiently hospitality companies can employ its staff. On the other hand, the relative tight distribution of transient efficiency scores suggest that hospitality companies tend to struggle equally with some degree of staff inflexibility, i.e., an inability to adjust staffing at the same rate that demand changes.

4.2. Discussion and implications

We have presented the empirical results from some measures based on the estimated IDF, the impacts of some exogenous variables, and inefficiency. Now, we move to a discussion of the implications of these empirical findings.

4.2.1. Output elasticities and returns to scale.

Based on the estimated IDF, we find that the average staff elasticity of food and beverage output is almost completely inelastic, while the response to output changes in room service and other sales is slightly higher. This suggests that staffing in food and beverage can be viewed as a semi-fixed input, which implies that there are scale economies, and to a lower extent in room services. Efficiency in staff use increase with the number of rooms to clean and prepare.

The returns to scale are about 50% across the sample. The findings show that changes in the overall staff level move only half relatively to changes in all outputs. That means that efficiency improves at higher output levels, entailing that the sample firms operate at sub-optimal capacity utilization. In fact, the results suggest that these firms have never operated at an optimal scale during the sample period. To exploit demand variations, hospitality firms need to carry a surplus capacity of rooms. Add that hospitality markets often are monopolistic, on top of the ‘overcapacity by default’ characteristic, makes it even more challenging to raise occupancy to the capacity limit (Balaguer and Pernías, 2013). Strong competition in the hospitality industry also appears to have motivated tacit collusion in some markets (Gan and Hernandez, 2013). The incentives for tacit collusion are clear from both revenue and efficiency perspectives. The endemic overcapacity characterizing the industry means that staffing will never reach maximum efficiency. However, within those constraints of hospitality markets, managers can influence many aspects of efficiency.

Fig. 3 depicts the 95% confidence intervals for the relationship between the marginal staff elasticities and output levels after sorting them in terms of output in ascending order. As shown, the marginal staff elasticities for the three outputs, i.e., food and beverages, accommodation service, and other sales, are U-shaped. This behavior makes sense because when demand is low, the basic staff functions is already in place, manning the reception, room cleaning, breakfast and so forth. The need to increase staff when guest visitation increases from low levels is modest because employed staff hours have slack capacity. As discussed earlier, this is especially the case for the food and beverage department that can handle large increases in guest volume without any change in staffing.

In contrast, staffing needs linked to room cleaning increase more monotonously to increasing output. But even here, there can be some slack in the available employed staff hours that allow smaller increases in output without increasing staffing hours. However, as guest volume grows, the available slack in the employed staff hours will gradually be exhausted and the rate of additional staff hours needed starts to rise more quickly. Also, note that due to labor laws and regulations, it is impossible to reduce the employment of permanent staff to match demand, which can also explain the observed pattern of staffing elasticities.

4.2.2. Marginal effects of environmental variables on input distance function.

We examined the impact of the environmental variables (Z_{it}) on the staffing in terms of the IDF. This section focuses on the transient and persistent efficiencies, which were 69% and 67%, respectively. These findings imply that hospitality firms can improve the efficiency of their staff use substantially. However, the overall staff use efficiency, on average, is only 46%. This indicates that there is substantial scope to improve staff levels in the context of Norwegian hospitality firms.

Given that the environmental variables such as seasonality, days of the week trend also affect the technology, we now focus on their effect via the beta parameters, namely, $\frac{\partial \ln x_{1it}}{\partial Z_{it}}$ based on the formula already provided. The results show that each environmental variable influences staffing decisions differently in terms of both magnitude and sign, as reflected in figure 4. Specifically, figure 4(a) plots the distribution of the marginal effects of the annual time trend on staffing for both models. These effects are often labeled as technical change, although these changes might be influenced by external factors (2011). For this study, the external factors can be demand, or firms' innovativeness and application of decision support systems that can influence staff utilization and efficiency. Under Robinson's neutral formulation, the marginal effects are generally constant and close to zero, while under the non-neutral SPSC model, the figure displays negative, zero, and positive technical change. This implies that the firms underwent some technical progress in 2010 (a decrease in staff required to produce a given vector of outputs), but this effect leveled out in 2011 and then turned to technical regress, reaching a peak in 2013. Fig. A.5(a) in the Appendix suggests a similar story but with more detail. Thus, the impact of technical change on staffing decisions was almost constant and close to zero under the neutral model but U-shaped under the non-neutral SPSC model.

Fig. 4 (b) illustrates the distributions of the marginal effects on staffing under both the neutral and non-neutral models of seasonality. Under the neutral model, the figure shows the marginal effects of seasonality on staffing to be negative, zero, and positive. Specifically, December is the low point for staff efficiency, which makes sense as it corresponds to a period where the guest volume is at a low. Fig. A.5(b) in the Appendix displays a similar staffing trend and provides evidence of more specific monthly fluctuations. The figure shows that the marginal effects are relatively higher in March. This could be because of two reasons: (a) there is unutilized staff capacity during this period because firms hire new staff in March to train for the summer season, and (b) hospitality demand is low during the Easter season because, in Norway, Easter is typically celebrated in family summer houses and at camping sites in the mountains. Also, note that June or July are relatively low or medium effects on staff efficiency, reflecting that the business segment is relatively more important than the holiday segment for hospitality demand. In November, the demand for hospitality services is again high because of Christmas dinner parties (Julebord). Therefore, the marginal effect of seasonality on staffing displays a U-shape under the neutral assumption but is close to zero under the non-neutral model. Fig. 4(c) depicts the distribution of the marginal effects of the days of the week on staffing under Robinson's neutral model. Again, the pattern of staff efficiency reflects a hospitality industry which most important customer segment is business travelers. This feature is particularly clear in figure A.5(c) in the Appendix, where we can see how efficiency drops on Friday and Saturdays, as demand drops, while picks up again on Sunday as business travelers start arriving for next week's work appointments. Another explanation for the improved efficiency on Sundays is that labor regulation in Norway requires firms to pay an additional wage rate on Sundays, which may encourage managers to schedule fewer staff hours.

4.2.3. Staffing inefficiency and the effects of environmental variables.

Next, we focus on the effect of the environmental variables on transient efficiency and discuss hospitality management implications. We found that seasonality decreased transient inefficiency while the days of the week increased it by about 13.6% ($\sqrt{2/\pi}\exp(-1.72-0.04)$), applying the marginal effects formula (i.e., $\sqrt{2/\pi}\exp(c_1+\gamma' Z_{it})\gamma_p$, where γ_p is the coefficient of $Z_{pit}, \forall p=1,2.$) on the results reported in Table 4. An explanation for these opposing effects is that adjusting the overall staffing level to monthly demand variations is easier than intra-week demand variations. Labor laws and regulations limit the day-to-day flexibility that are incorporated in work contracts. This is less of a binding restriction for staffing with respect to seasonal demand variations. The efficiency estimates imply that hospitality firms can improve the staff use efficiency substantially, with the improvements to their transient and persistent inefficiencies of up to 31% and 33% of their efficient level, respectively. Overall, the firms analyzed could improve their efficiency by up to 54% of the most efficient level. Thus, the findings imply that getting staff levels right could yield more than a 100% improvement in current overall staffing efficiency. Obviously, a 100% improvement will be unrealistic for most cases, as the persistent inefficiencies often are linked to fixed effects such as location (e.g., local demand and competition characteristics) and hotel building (i.e., sunk investments). However, the transient component is more within the grasp of staff managers to influence as this is more directly linked to the staff rostering.

5. Conclusion

This study investigates the degree of overstaffing in hospitality firms while also identifying the varying impact of firm-specific heterogeneity, transient and persistent efficiency, and random noise. We used daily data for 94 hospitality firms in Norway over the period from 2010 to 2014 to conduct the empirical estimations. The fact that these 94 firms represent only part of the Norwegian hospitality firms might not affect the study's ability in addressing the research purpose as these firms belong to three popular chains in Norway. The data serves the current purpose as these firms work under the same regulations, labor markets and other institutional settings, in addition to the attempts to open the door for further generalizations of the conclusions.

Based on the input distance function framework, we used the state-of-the-art Stochastic Frontier approach to identify the four components while considering seasonality and days of the week as potential determinants of firm-specific heterogeneity and transient inefficiency. The empirical model also included the impact of environmental variables such as the annual time trend, seasonality, and days of the week using Robinson's neutral specification and the non-neutral SPSC.

The study provides different findings and, in doing so, suggests ways to reduce the overstaffing problem in the hospitality sector. First, the staff elasticities of outputs are very low, which implies that the employed staff hours to some extent are idle. These findings suggest that, with the current technology, staff adjustment downwards is constrained when demand is already is at low levels. This can explain why hotels are introducing an increasing array of self-service technologies, like automatic check-ins, food vending machines, etc. Of course, the firms must weigh the trade offs of changing the technology, and hence the product, on how it influences efficiency versus its influence on demand. This link between demand and operations also suggests that further integration of revenue management and operations can be beneficial; the marginal cost of increasing demand depends on the output level and the concurrent slack in the capacity of staff hours already employed.

Second, the sample hospitality firms exhibit transient, persistent, and overall efficiency of 69%, 67%, and 46%, respectively. In particular, the presence of transient inefficiency suggests that these hospitality firms still have room to improve their staff use. Thus, it seems that the main challenge in hospitality operations is how to deal with within week variations in demand, i.e., how to increase staffing flexibility between days. These issues seem difficult in economies like Norway, where strong labor regulations exist, but some exceptions should still be possible similar to non-standard working hours and third-party providers regulations for the hospitality industry (Underthun and Aasland, 2018).

CRediT authorship contribution statement

Fikru K. Alemayehu: Conceptualization, Formal analysis, Writing – original draft. **Subal C. Kumbhakar:** Conceptualization, Writing – original draft, Methodology, Writing – review & editing. **Sigbjørn Landazuri Tveteraas:** Conceptualization, Writing – review & editing.

Appendix A. Marginal effects

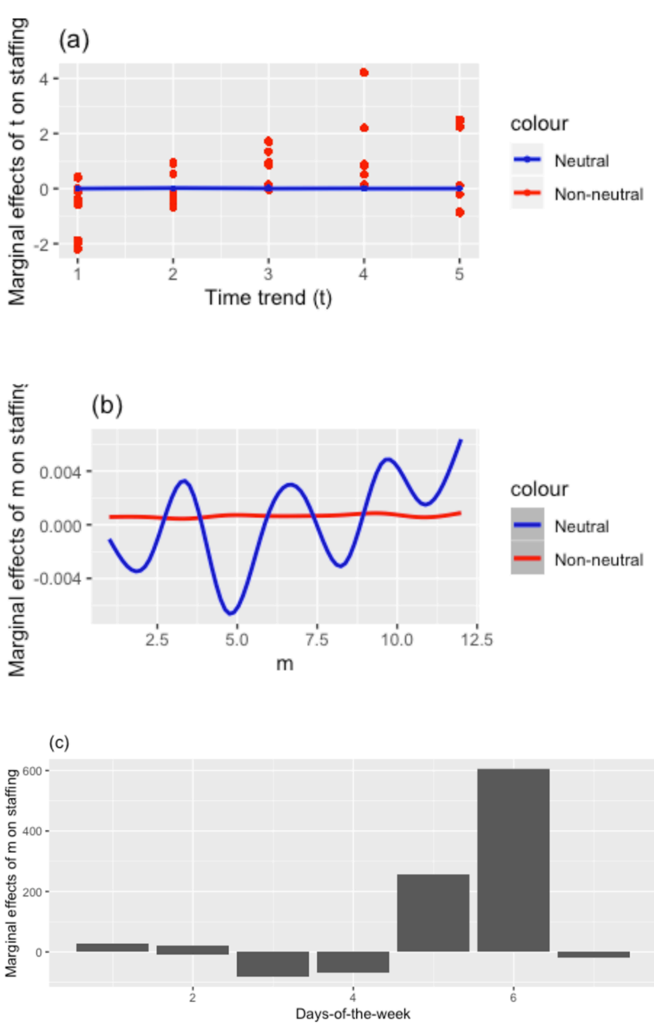

Fig. A1. Marginal Effects of Environmental Variables.

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