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Optimal carrying capacity in rural tourism: Crowding, quality deterioration, and productive inefficiency

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ABSTRACT

This paper introduces a novel framework for characterizing destination overcrowding in rural tourism using a production approach. We build upon destination life cycle, carrying capacity, and consumer preference theories to characterize optimal levels of overnight stays in the presence of disutility from crowding. Using panel data for rural tourism in Spanish provinces, we model crowding non-linearly as a demand shifter within a service production function. To deal with plausible endogeneity, we use a control function approach within a Stochastic Frontier regression. Consistent with our theoretical predictions, we show there is a non-linear concave relationship between overnight stays and crowding. We calculate optimal carrying capacity levels (turning points) for each province and illustrate which regions are exhibiting negative externalities from overcrowding.

1. Introduction

Tourism development has been shown to foster economic growth and to produce positive demand effects on related sectors (Faber & Gaubert, 2019). However, these economic gains generally come at the cost of negative externalities in the form of congestion (Canale & De Siano, 2021). Consistent with destination life cycle theories (Butler, 1980; Marsiglio & Tolotti, 2024), word-of-mouth effects and social interactions contribute to the discovery and popularity of destinations, which translates into smooth increases in tourism demand over time. Nevertheless, when tourism arrivals exceed the destination's carrying capacity, further increases in demand produce negative externalities to both residents and tourists through overcrowding, congestion, and noise (Neuts, 2016; Santana–Jiménez & Hernández, 2011).

The goal of this article is to study how crowding level affects subsequent tourists' overnight stays, and how this relationship varies depending on the level of crowding. Whereas most studies have evaluated the tolerance of the host population in terms of deterioration of quality-of-life indicators (Tokarchuk et al., 2021), feelings of solastalgia (Lalicic, 2020) or anti-tourism sentiment (Gössling et al., 2020), we investigate optimal crowding levels from the tourists' viewpoint. Rooted on well-established theories on utility deterioration with visitors' density and crowding (Saveriades, 2000), we postulate that overnight stays exhibit a concave relationship with the number of tourists at the destination relative to residents. During early phases of development, increases in demand positively enhance consumers' utility and demand through bandwagon effects (Boto-García & Baños–Pino, 2022) and herding behaviour (Lim et al., 2023). However, as arrivals continue to grow, overcrowding deteriorates the quality of services (Alvarez & Brida, 2019) and creates discomfort among tourists (Ruiz et al., 2021), which subsequently decreases demand through reduced destination attractiveness (Jacobsen et al., 2019). Therefore, the paper revisits optimal social carrying capacity, defined as the maximum number of tourists that a destination can accommodate without causing negative effects on residents and visitors themselves (Saveriades, 2000).

We first develop a theoretical framework that integrates crowding as a non-linear demand shifter within a standard production function of accommodation services (e.g., Assaf & Josiassen, 2016). Building upon De Witte and Geys (2011), we make a distinction between *service potential* and *observed* output levels in the accommodation sector. Service potential is given by a (Cobb-Douglas) production function that depends on labor and capital inputs plus possible technical change. Actual output levels (overnight stays) are modelled as the sum of service potential, demand shocks associated with crowding (which shift the production

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frontier), managerial inefficiency, and random noise. Crowding enters the model non-linearly as explanatory of the wedge between actual output and the service potential predicted by the production function.

Next, we perform an empirical analysis in the context of rural tourism, which has experienced a sustained increase in recent years (Albadalejo & Díaz–Delfa, 2021; Campón–Cerro et al., 2017). We use a panel dataset of overnight stays, workers, and bed places in rural accommodation establishments in Spanish provinces (NUTS 3) during the period 2007–2019. Rural tourism has a long tradition in Spain and has been subject of great interest (Albadalejo & Díaz–Delfa, 2009; An & Alarcón, 2021; Barke, 2004; Campón–Cerro et al., 2017). We adopt a crowding indicator defined as the ratio of visitors to the rural population and estimate a True Random Effects model (Greene, 2005) with random parameters that allows for province-specific threshold points in social carrying capacity.

The paper makes three contributions to the tourism literature. Firstly, we add to the growing literature on carrying capacity by investigating potential crowding-out effects in rural areas. Most studies have evaluated sun-and-beach destinations (Papadopoulou et al., 2023; Santana–Jiménez & Hernández, 2011) or urban areas and city centers (Hagemans et al., 2023; Neuts & Nijkamp, 2012; Tokarchuk et al., 2022). However, the disutility arising from congestion is particularly problematic for rural and nature-based tourism. People seeking peace and relaxation in nature present the greatest aversion to crowding (Marsiglio, 2015, 2016) and over-tourism deteriorates the brand image of green areas (Insch, 2020). The calculation of optimal threshold points in rural areas thus emerges as a key facet to achieve long-run sustainable development goals (Marsiglio, 2017). As discussed by Butler (2020), little academic research has evaluated overcrowding in rural areas. Although some studies have evaluated the crowding-satisfaction nexus in natural environments (Luque-Gil et al., 2018; Pikkemaat et al., 2020), there is a need to examine how crowding influences rural stays. Pulido-Fernández et al. (2024) have recently studied how crowding perceptions influence intentions to return to protected natural areas. In contrast to their study, we assess how crowding impacts actual subsequent stays.

Secondly, most works evaluate the influence of crowding on different stated measures of tourists' satisfaction and sentiment (Tokarchuk et al., 2021, 2022). We, instead, investigate crowding effects on realized levels of overnight stays as an output measure reflecting *revealed* preferences. We consider a quadratic relationship between crowding and stays, so that social carrying capacity corresponds with the vertex of the parabola (i.e., level of crowding for which the marginal effect is zero). From this perspective, the paper is close to those by Albadalejo and González–Martínez (2019) and Albadalejo et al. (2016), who evaluate how the effect of lagged demand on current levels is moderated by congestion. Whereas they consider tourists divided by the squared kilometers of the area as a physical measure of carrying capacity, we use the ratio of tourists to rural population as the measure of social crowding. Moreover, our analysis is framed in a service production setting rather than in a demand context.

Thirdly, several works have investigated productive efficiency in the hospitality industry using Stochastic Frontier Analysis modelling, mainly for the case of hotels (e.g., Assaf et al., 2010; Assaf & Tsionas, 2018b) and peer-to-peer accommodations (e.g., Pérez–Rodríguez & Hernández, 2023a; 2023b). Yet few works have examined productive inefficiency in rural accommodations, with Martínez–Roget and Rodríguez–González (2006) and Fleischer and Tchetchik (2005) being a few exceptions. We therefore add new evidence on productive efficiency in rural tourism.

2. Literature review

2.1. Destination life cycle and carrying capacity

Butler's Tourism Area Life Cycle Model (Butler, 1980) posits that tourist destinations follow the same demand principles as products: their visitors slowly grow at first, followed by rapid expansion, stabilization, and eventual decline. Consequently, tourism arrivals typically exhibit a S-shaped curve over time.[1] Initially, lesser-known destinations lacking tourist attractions and public recognition attract few visitors, mainly those drawn to exotic or undiscovered destinations. As visitor numbers gradually increase and local communities begin to benefit from tourism activities, destinations enhance their tourism infrastructure, becoming more discoverable through word-of-mouth recommendations or marketing campaigns. The popularity of a destination further amplifies tourism demand through repeat visits from satisfied tourists (Jarvis et al., 2016) and the establishment of a positive destination image (Park et al., 2021).

Eventually, a threshold point is reached, beyond which additional arrivals have negative effects (i) on residents, in the form of congestion and noise leading to decreased well-being (e.g., Gössling et al., 2020), (ii) on tourists themselves, due to a decline in experienced utility caused by overcrowding (e.g., Jacobsen et al., 2019), and (iii) on the environment, in terms of pollution and degradation of resources (e.g., Insch, 2020). Beyond this threshold, arrivals start to decline due to the deterioration of quality, leading the destination into a stagnation phase.

The stagnation of the tourist destination is closely linked to the concept of carrying capacity, understood as the number of visitors that an area can accommodate without causing excessive environmental degradation or a decline in visitor satisfaction (Saveriades, 2000). This concept has also been referred to as 'overtourism', tourism intensity, or territorial pressure. Carrying capacity has been conceptualized from both the visitors' and the residents' perspective, yet there is no universally accepted definition (Zekan et al., 2022). From the residents' viewpoint, the hosting capacity of a destination becomes depleted when additional arrivals start to cause disutility among residents. Excess tourism often leads to anti-tourism sentiments (Gössling et al., 2020) and feelings of solastalgia (Lalicic, 2020), and some studies show that residents in tourist areas are willing to pay to alleviate congestion caused by tourists (Neuts, 2016; Neuts et al., 2012). Alternatively, carrying capacity can be seen as the threshold at which negative externalities for potential visitors promopt them to seek alternative destinations.

At the empirical level, carrying capacity has been quantified using physical measures like the number of tourists per squared kilometer (Albadalejo & González–Martínez, 2019) or the ratio of tourists to hotspots in the area (Albadalejo et al., 2016). However, this method of measuring crowding poses challenges when comparing areas of the same size but with differing population densities. Alternatively, other researchers have utilized metrics such as the number of overnight stays over population (Tokarchuk et al., 2021) or the ratio of arrivals to residents per squared kilometer (Canale & De Siano, 2021).

In the following section, we review and describe the theoretical mechanisms underlying the emergence of negative externalities on tourists' utility (and consequently on destination arrivals).

2.2. Tourists' disutility from overcrowding

Individuals select their travel destination by comparing the utility and associated costs of visiting each destination within their budget constraints. Destination-specific characteristics, coupled with individual preferences, determine choice probabilities and the influx of tourists to destinations (Boto-García et al., 2021). In a dynamic framework, the utility function incorporates a social externality component that captures the influence of other travelers' characteristics, creating a social externality (Marsiglio & Tolotti, 2024). In the early phases of development, marginal increases in demand for a particular destination enhance

[1] A similar conceptualization has been proposed by Marsiglio and Tolotti (2024).

its utility for other consumers through conspicuous consumption and bandwagon effects (e.g., Boto-García & Baños–Pino, 2022), herding behaviour associated with popularity, and positive online reviews (e.g., Lim et al., 2023).

However, as demand continues to rise, the influence of the social externality component on consumers' utility shifts from positive to negative. This shift occurs because a relatively high number of other people consuming tourism services in the area leads to overcrowding, deteriorating service quality (Alvarez & Brida, 2019; Brida et al., 2010), and causing discomfort through space violations and diminished feelings of uniqueness (Jacobsen et al., 2019).

At the empirical level, numerous studies have investigated how crowding impacts tourists' utility and identified potential threshold points. Existing research indicates that social overstimulation and perceptions of inappropriate behavior by others interact with the physical characteristics of destinations, producing discomfort among tourists (Ruiz et al., 2021). Crowding perception tends to be more pronounced among visitors from neighboring areas (Schuckert & Wu, 2021) and is correlated with noise and obstruction by other tourists while taking photos (Neuts & Nijkamp, 2012). An important implication is that crowding diminishes satisfaction with a destination (Liang et al., 2021) and decreases the willingness to revisit it in the future (Papadopoulou et al., 2023). This issue is particularly problematic for rural tourists, as those seeking tranquility and relaxation in natural settings are likely to have the strongest aversion to crowding (Marsiglio, 2015, 2016).

2.3. Rural tourism

Rural tourism is a form of tourism that "takes place in non-urban areas with low population density, traditional social structure and density and landscape and land-use dominated by agriculture" (UNWTO, 2023). In rural areas, tourism development often complements agricultural income (Fleischer & Tchetchik, 2005), stimulates economic activity, and influences urbanization patterns (Yang et al., 2021). Research by Fleischer and Felsenstein (2000) demonstrates that public support for rural tourism generates net welfare benefits for local communities.

Rural tourism typically attracts individuals interested in nature-based activities, agriculture, and the rural lifestyle (Molera & Albadalejo, 2007). While factors like staff hospitality, outdoor activities, facilities, quality certifications, and location are important considerations for tourists when choosing rural accommodations (Albadalejo & Díaz–Delfa, 2009; An & Alarcón, 2021), the pursuit of tranquility emerges as the most significant aspect (Han, 2019). Albadalejo and Díaz–Delfa (2021) show that although some rural tourists enjoy socializing and interacting with locals, the desire for a calm and peaceful stay remains a primary motivation for choosing rural accommodations. Evidence by Martínez–Roget and Rodríguez–González (2006) underscores the importance of prestige and reputation as key factors influencing overnight stays. Consequently, crowding is a significant deterrent that negatively impacts future demand because destination loyalty among rural tourists is highly contingent on the perceived quality of the stay experience (Campón–Cerro et al., 2017).

2.4. Productive efficiency in hospitality accommodations

A growing body of research has investigated productive inefficiency and total factor productivity growth in tourist accommodation establishments, utilizing data from samples of countries (Assaf & Tsionas, 2018a; Chatzimichael & Liasidou, 2019; Hadad et al., 2012), regions (Algieri & Álvarez, 2023; Cracolici et al., 2008; Li & Liu, 2022; Pérez–Granja & Inchausti–Sintes, 2023; Sellers–Rubio & Casado–Díaz, 2018), or individual firms (Assaf et al., 2010; Assaf & Tsionas, 2018b; Bernini & Galli, 2023; Cordero & Tzeremes, 2017). While hotels have been the primary focus, in recent years scholars have increasingly evaluated performance efficiency in Airbnb apartments (Pérez–Rodríguez & Hernández, 2023a; 2023b). However, studies on productive efficiency in rural accommodations are comparatively scarcer (Martínez–Roget & Rodríguez–González, 2006). The paper thus aims to broaden the limited evidence.

Most studies on performance modelling in tourism assume that the production process can be characterized as a parametric function of inputs plus a stochastic term, typically employing Stochastic Frontier Analysis (Algieri & Álvarez, 2023; Assaf & Tsionas, 2019; Bernini & Galli, 2023; Pérez–Granja & Inchausti–Sintes, 2023). Alternatively, other scholars opt for non-parametric methods like Data Envelopment Analysis (Benito et al., 2014; Li & Liu, 2022). As discussed in Assaf and Josiassen (2016), neither approach is definitely superior, with each possessing its own set of advantages and disadvantages. In this study, we choose Stochastic Frontier Analysis. While most studies using this method typically assume constant parameters for all units (e.g., Cracolici et al., 2008; Pérez–Granja & Inchausti–Sintes, 2023), recent applications have shifted towards the adoption of random parameter models, allowing for heterogeneous output elasticities (Pérez–Rodríguez & Hernández, 2023a).

3. Theoretical framework

3.1. Potential versus actual outcomes in services production

The provision of tourist accommodation services can be conceptualized as a specific production process in which various inputs are combined to deliver accommodation services to consumers, according to a predefined production function:

$$Output = f(Inputs) + v - u \tag{1}$$

where f (.) represents the functional form that describes how the inputs are transformed into the final output, and $v - u$ is a stochastic term composed of random noise v and an asymmetric inefficiency component u that captures inefficiencies in service provision.

Usually, the inputs considered are capital (number of bed places or other types of infrastructure investments) and labor (number of workers), whereas the nights spent by tourists is the most used output measure (Algieri & Álvarez, 2023; Chatzimichael & Liasidou, 2019). Nevertheless, some studies have used alternative performance indicators such as profits, value added, tourist expenditure and number of tourists (e.g., Bernini & Galli, 2023).

Using the same input quantities, some accommodation establishments attract more consumers than others, a pattern that can be attributed to differences in managerial efficiency. Fig. 1 presents a scatter plot of potential and actual output on inputs using simulated data for illustrative purposes. Filled dots represent the potential output for

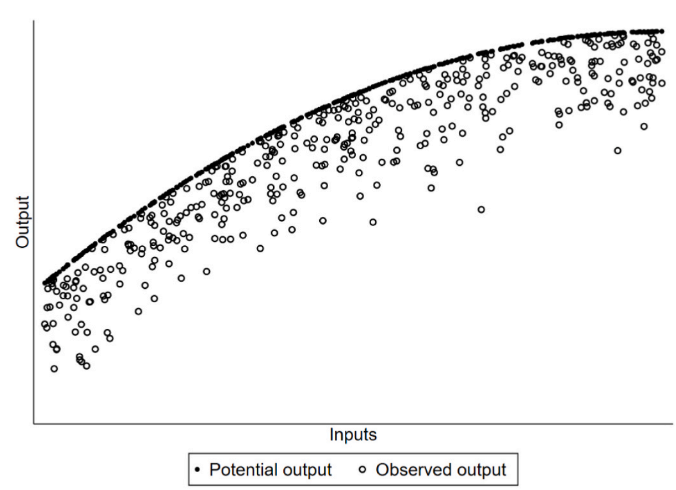

Fig. 1. Graphical representation of potential and actual output.

each combination of input levels (frontier points), determined by the production function in (1). Empty dots represent observed output levels for each combination of input level. The distance between filled and empty points represents productive inefficiency (excluding random noise), which is the gap between potential (frontier) and observed production for each input level combination (also referred as the output gap). The greater the distance, the greater the inefficiency.

3.2. Demand shocks in productive inefficiency

In contrast to other industries, observable outcomes in hospitality and tourism (e.g., arrivals, overnight stays) are not strictly 'produced' in the traditional sense and cannot be stored. Instead, tourist areas and hospitality firms use a combination of inputs to facilitate the *potential production* of a certain level of output. Here potential production refers to the total units that can be sold given inputs and technology available. Departures from this attainable output level are primarily driven by demand factors, as is typical in service-based industries. Consider rural accommodation establishments in a region that hire workers and make several bedrooms available to accommodate an expected number of tourists during a specific period. If there is a positive (negative) demand shock, the potential output achievable will increase (decrease) for the same use of inputs (i.e., causing a parallel shift in the production frontier). This is graphically illustrated in Fig. 2. In the event of a negative shock that discourages demand, the production frontier shifts downwards (blue line).

Given these considerations, we follow Hammond (2002) and De Witte and Geys (2011) and postulate that accommodation services can be conceptualized as a *two-stage* production process. Firstly, inputs are combined to produce what we can label as the *service potential* (production function), as described by equation (1). That is, the maximum output attainable with a set of input factors and technology. Next, the service potential is converted into *actual* output, and this process is affected by external factors/shocks beyond the control of the accommodation firm (also known as 'environmental' factors), random factors (noise) and managerial inefficiency (u) as follows:

$$Actual\ output = Potential\ Output - u = \underbrace{f(Inputs) + Shocks + v}_{potential\ output} - u \qquad (2)$$

Equation (2) thus expands Equation (1) with demand-driven environmental shocks.

3.3. Overcrowding as a demand shifter in service provision

As discussed previously, crowding represents a significant shock that

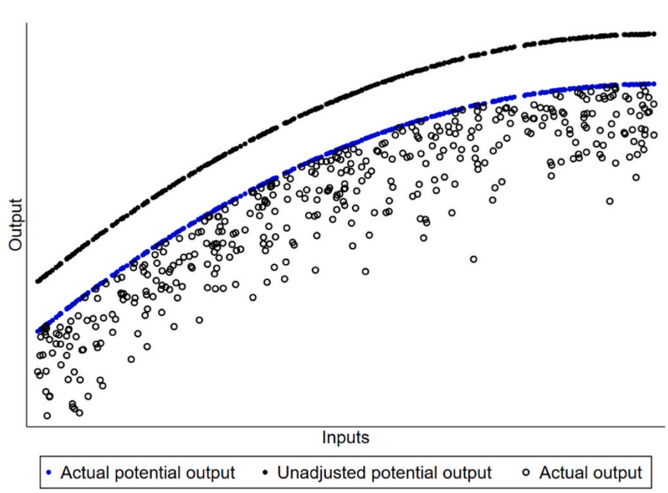

Fig. 2. Graphical representation of potential and actual output under a negative demand shock.

can nonlinearly impact actual output levels. At lower levels of crowding, positive externalities emerge through bandwagon (Boto-García & Baños–Pino, 2022) and word-of-mouth influences (Book et al., 2016; Park et al., 2021), resulting in increased choice probabilities (and hence observed output levels) with greater crowding. However, beyond a certain threshold, crowding transitions into a dis-amenity, diminishing tourists' individual utilities due to the deterioration of service quality and discomfort (Alvarez & Brida, 2019; Jacobsen et al., 2019; Neuts, 2016; Neuts et al., 2012). The reduction in choice probabilities relative to alternative destinations leads to a drop in aggregate output (given inputs). Therefore, we anticipate that the conditional-on-input-use potential output ($E(output|inputs)$) will exhibit a concave relationship with crowding, as depicted in Fig. 3. The crowding level at which maximum output occurs ($E(output|inputs)$) serves as an indicator of social carrying capacity, beyond which further increases in crowding decreases the output.

4. Data & empirical model

4.1. Dataset and variable definition

We collected a panel dataset at the province level (N = 50) encompassing the number of tourists, overnight stays, workers, and bed places in rural accommodation establishments in Spain from 2007 to 2019. The data was sourced from the *Rural Accommodation Survey* conducted by the Spanish National Statistics Institute (INE) on an annual basis.[2] The number of overnight stays is selected as the output metric and the number of workers and bed places as the labour and capital inputs, respectively. This follows common practice in the literature on productive efficiency in the accommodation sector (Chatzimichael & Liasidou, 2019; Pérez–Granja & Inchausti–Sintes, 2023).

Our measure of crowding is constructed as the ratio between the number of tourists that stay at rural accommodations and the population size of rural areas for each province and year. Specifically, the denominator encompasses the total population residing in municipalities with fewer than 30,000 inhabitants and less than 100 inhabitants per squared

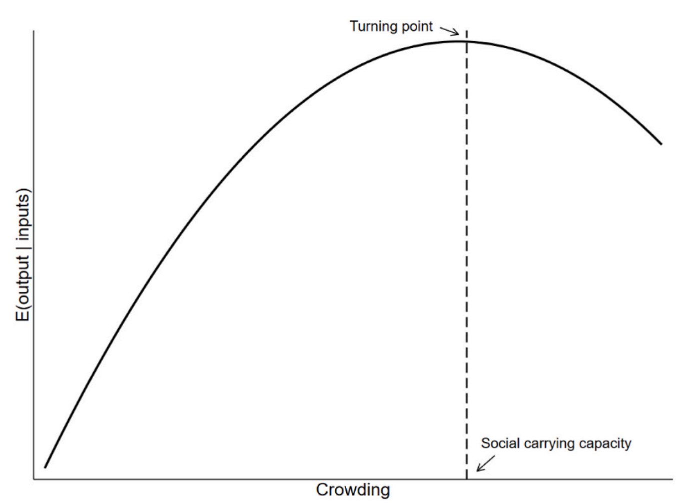

Fig. 3. Non-linear relationship between conditional-on-input use output and crowding.

[2] The Rural Accommodation Survey does not consider peer-to-peer accommodations. Nonetheless, Airbnb and platforms alike are a relatively recent phenomenon and their penetration in Spain mainly concentrates in urban areas (Jiménez et al., 2022). We do not envisage this should represent a concern in our study period and rural setting.

kilometer in each province, which is the definition of a rural municipality in Spain.[3] This information was retrieved from the population census conducted by the Spanish Statistics Institute (INE) at the municipality level and subsequently aggregated at the provincial level.

This method of defining crowding is reminiscent of that used by Tokarchuk et al. (2021), who employed the ratio of overnight stays to population size for explaining residents' satisfaction. It is also similar to the ratio of arrivals to inhabitants per squared kilometer adopted by Canale and De Siano (2021) to measure territorial pressure and overtourism. Note that because province size is time invariant, this dimension will be captured in our model by the province individual effects.

Importantly, our crowding indicator is lagged one year. Destination quality is not directly observable at the time of booking, so consumers infer it from previous experiences, recommendations, and online reviews. Social learning via online and offline word-of-mouth channels, which influence destination image, occurs over time (Liu, 2011; Robb & Fishman, 2005). We therefore posit that current stays are influenced by the level of crowding in the previous year.

4.2. Summary statistics

Table 1 presents summary statistics of the variables. The average number of overnight stays at rural establishments is 175,785, with 440 workers and 2787 bed places. Nonetheless, the high standard deviations in these variables indicate significant variations in the prevalence of rural tourism across Spanish provinces. Fig. 4 plots the number of overnight stays per province in the first (2007) and last (2019) year of the sample. We observe that the provinces of Asturias, Cantabria, the Balearic Islands and Girona have the highest levels of rural demand, exceeding 500,000 overnight stays during the study period. Overall, overnight stays in rural accommodations have shown an upward trend over time, particularly in Northern provinces.

For descriptive purposes, Fig. 5 displays a box plot of the distribution of *Crowding* in rural areas across the 50 Spanish provinces over the sample period. Provinces such as Cantabria (2.19), Gipuzkoa (2.01), Soria (1.14), Ávila (1.11), Girona (0.99) and Segovia (0.98) exhibit the highest average levels of rural tourists per rural resident. Conversely, provinces like Almería (0.05), Sevilla (0.05), Badajoz (0.05), Jaén (0.06) and Granada (0.07) display the lowest figures.

Fig. 6 presents a scatter plot showcasing the unconditional relationship between *Crowding* and the number of overnight stays (Y, in logs). As hypothesized, there exists a positive yet non-linear (concave) association between the two: as crowding levels remain low, rural overnight stays steadily rise. However, when the number of tourists reaches approximately 1.5 times the rural population, additional increases deter the number of stays. It is important to note that this plot is merely descriptive; this link might be confounded by other factors. Therefore, we proceed to a formal econometric analysis.

4.3. SFA econometric modelling

In line with equation (2) and assuming a Cobb-Douglas production function (Fleischer & Tchetchik, 2005), the model to be estimated is the following:

$$\ln Y_{it} = \alpha_i + \beta_1 \ln L_{it} + \beta_2 \ln K_{it} + \gamma_1 Crowding_{it-1} + \gamma_2 Crowding^2_{it-1} + \delta Z_{it} + v_{it} - u_{it} \tag{3}$$

where α_i are destination individual effects capturing time-invariant unobserved heterogeneity across areas (tourism attractiveness, hedonic characteristics, endowment of natural resources), $\ln L_{it}$ and $\ln K_{it}$ are the log of workers and bed places per province and period, Z_{it} are additional control variables that affect the output frontier, v_{it} is the error term and u_{it} captures productive inefficiency.[4] We include a time trend and a dummy variable for the year 2013 as control variables in Z_{it}. The former captures potential Hicks-neutral technical change in overnight stays, while the dummy variable aims to account for a common drop in rural demand in that year detected in preliminary descriptive analyses (see Figs. A1–A4 in the Supplementary Material).

The total variance of the composite error term is given by $\sigma^2 = {\sigma_u}^2 + {\sigma_v}^2$. If the signal-to-noise ratio ($\lambda = \sigma_u/\sigma_v$) is statistically different from zero, that means that part of the error term is due to the one-sided inefficiency term, and therefore the Stochastic Frontier model is preferred over a deterministic frontier. An estimate of productive inefficiency ($\widehat{u_{it}}$) can be obtained following Jondrow et al. (1982) from the composite error term ($\epsilon_{it} = v_{it} - u_{it}$) as follows:

$$\widehat{u_{it}} = E(u_{it}|\epsilon_{it}) = \frac{\sigma\lambda}{1+\lambda^2}\left[\frac{\varphi(a_{it})}{1-\Theta(a_{it})} - a_{it}\right] \tag{4}$$

where $a_{it} = \epsilon_{it}\lambda/\sigma$, $\varphi(.)$ denotes the standard normal density function and $\Theta(.)$ indicates the cumulative density function.

Equation (3) is a Stochastic Frontier model that is estimated using a True Random Effects (TRE) model (Greene, 2005) under the assumption that $\alpha_i \sim N(0, \sigma_\alpha)$ and the composed error term $v_{it} - u_{it} = \varepsilon_{it}$ follows a normal-half normal distribution. It can be seen as a random intercept model that offers the advantage that it separates unobserved heterogeneity (α_i) from time-varying inefficiency (u_{it}) by making some distributional assumptions and by postulating that α_i is orthogonal to the inefficiency u_{it} and the noise term v_{it}.

One shortcoming of equation (3) is that we are assuming a common concave relationship between *Crowding* and observed output for all provinces. However, the curvature in Fig. 6 likely varies across provinces. For instance, Albadalejo and González–Martínez (2019) document that congestion is more deterrent for inland than for coastal areas. Relatedly, Assaf and Tsionas (2018b, 2018c) discuss that the analysis of tourism productivity and performance needs to consider cross-sectional heterogeneity in production technology. To allow for more flexibility, we also estimate a random parameter version of equation (3) (Greene, 2012) that allows γ_1, γ_2 and the time trend parameter capturing technical change to vary across provinces following a normal distribution. The reader is referred to Pérez–Rodríguez and Hernández (2023a) for a recent application of this econometric model.

Given inputs, the partial derivative of the observed output with respect to our measure of crowding is given by:

$$\frac{\partial \ln Y_{it}}{\partial Crowding_{it-1}} = \gamma_{1i} + 2\gamma_{2i} Crowding_{it-1} \tag{5}$$

Accordingly, the level of social carrying capacity will be given by $\frac{\gamma_{1i}}{-2\gamma_{2i}}$. Since γ_{1i} and γ_{2i} are province-specific estimates, we can estimate province-specific optimal thresholds.

Because overnight stays are the product of tourists times their length of stay, γ_1 and γ_2 might suffer from endogeneity bias in the case of serial correlation in the error terms because the crowding measure is computed based on the ratio of tourists to rural population one year before. To deal with this potential source of bias, we construct a Bartik-type instrumental variable W_{it-1} (Goldsmith–Pinkham et al., 2020) defined as follows:

[3] Because crowding stems from interpersonal interactions, we believe the same number of tourists per squared kilometer might produce distinct crowding effects depending on population size.

[4] We assume that natural resources are time invariant in the study period and captured by α_i. These individual effects are treated as 'random' in the baseline model and as 'fixed' effects in auxiliary regressions in Appendix (subsection 5.4.).

Table 1
Summary statistics of the variables (NxT = 650).

Label	Variable	Mean	SD	Min	Max
Y	Overnight stays in rural accommodations	175,785.9	166,255.7	9314	1,251,746
L	Number of workers in rural accommodations	440.5	337.5	33.5	1973.4
K	Bed places in rural accommodations	2787.3	2013.8	172.3	13,738.5
Tourists (t-1)	Tourists in rural accommodations in t-1	59,974.3	47,758.0	1972	333,896
Rural pop (t-1)	Rural population in t-1	175,728.5	85,943.7	28,547	399,313
Crowding	Ratio of tourists in rural accommodations in t-1 over rural population in t-1	0.465	0.454	0.005	2.849

Note: to compute the values for variables lagged one period, we use data for 2006 so that all the variables have 650 observations.

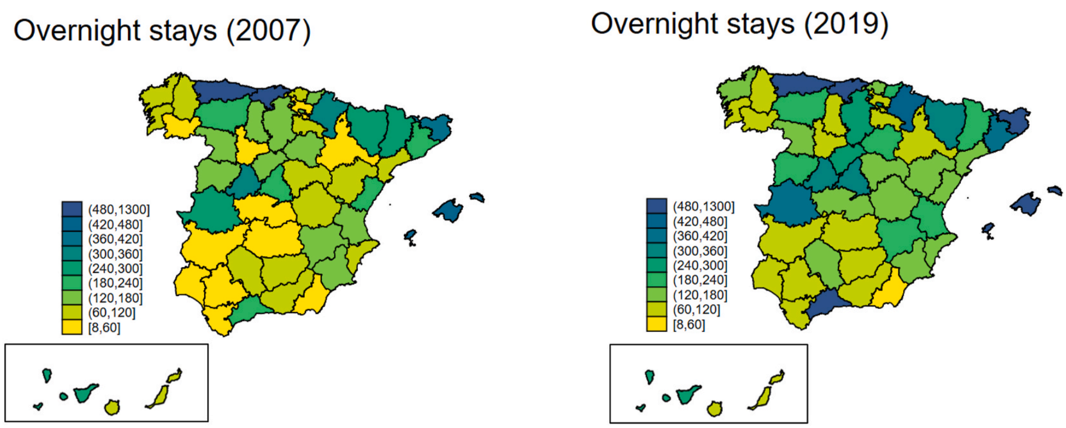

Fig. 4. Overnight stays per province (thousands) in rural accommodations.

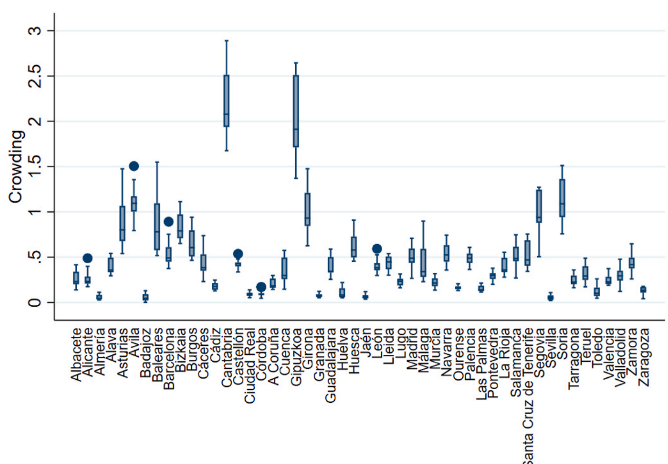

Fig. 5. Box plot of levels of crowding in rural areas per province.

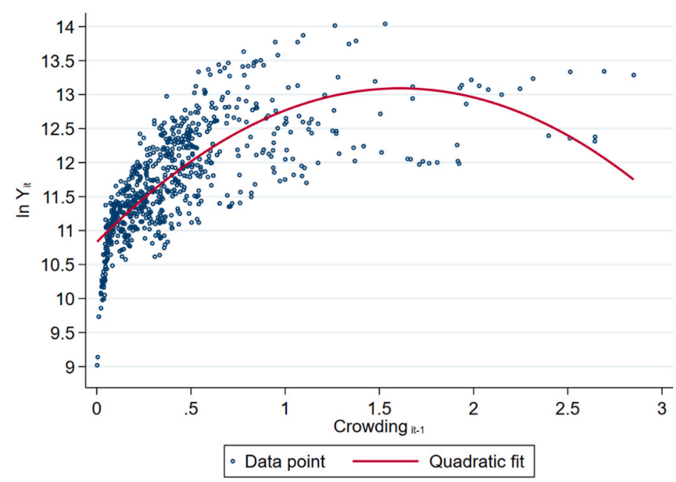

Fig. 6. Descriptive scatterplot of the relationship between crowding and overnight stays (Y, in logs) in the sample.

$$W_{it-1} = \frac{tourists_{it-2} \times (1 + \dot{g}_{it-1})}{population_{it-1}} \tag{6}$$

where $\dot{g}_{it-1}$ is the annual rate change in total tourists in the country excluding region i between *t-2* and *t-1* computed in the following manner:

$$\dot{g}_{it-1} = \ln\left(\sum_{j=1}^{N} tourists_{it-1}\right) - \ln\left(\sum_{j=1}^{N} tourists_{it-2}\right) \; \forall j \neq i \tag{7}$$

That is, W_{it-1} is created by leveraging the exogenous rate change between two consecutive years in all remaining provinces $j \neq i$ multiplied by the level of tourists in province i at time *t-2*. The identifying assumption is that the overall growth in the total number of rural tourists in the country, excluding province *i,* is partially correlated with the growth experienced by province *i* through common temporal shocks, but uncorrelated with the *level* of overnight stays in province *i* in period *t+1*. The way of constructing the instrumental variable closely resembles that used by Coulson et al. (2020).

Fig. A5 in Supplementary Material presents a binned scatterplot (100 quantiles) of the positive correlation between individual growth rates in *Crowding* and the average growth rates of all other provinces. Fig. A6 in the Supplementary Material illustrates the positive correlation between $Crowding_{it-1}$ and the generated instrument W_{it-1} following equations (5) and (6). We observe the instrument strongly correlates with our crowding measure, thereby meeting the relevance condition for the application of Instrumental Variable (IV) modelling.

5. Results

5.1. Estimation results

As a first step of the empirical analysis, we estimated the model in (3) without the inefficiency component by Two Stage Least Squares using W_{it-1} and $W_{it-1}{}^2$ as instruments for $Crowding_{it-1}$ and $Crowding_{it-1}{}^2$ (Supplementary Material, Table A1). The F from first stage is largely above the common threshold value of 10 (F (2,593) = 542.57), implying that we do not suffer from a weak instrument problem. Wu-Hausman test does not reject the null hypothesis of exogeneity (F (2, 592) = 1.866, p-value = 0.155), implying that, in principle, $Crowding_{it-1}$ would not be endogenous.

Table 2 reports the coefficient estimates from the model in equation (3). Column (1) presents the results of a baseline True Random Effects (TRE) model treating $Crowding_{it-1}$ as exogenous. Column (2) presents the control function estimates that expand the baseline specification with the residuals from an auxiliary first-stage regression of $Crowding_{it-1}$ on the instrument W_{it-1} plus the rest of explanatory variables (Wooldridge, 2015). Columns (3) and (4) report the estimates from a Random Parameter Stochastic Frontier model (RPM) model that allows for province-specific estimates of the crowding variable (and its square) and the time trend without and with the endogeneity correction, respectively. Notably, columns (2) and (4) miss one observation due to the unavailable of information for the province of Bizkaia in the year 2005, which is needed for the calculation of W_{it-1}.

Table 2
Stochastic Frontier Analysis estimation results.

Dependent variable: Ln Y	(1) TRE	(2) TRE + control function	(3) RPM	(4) RPM + control function
Ln K	0.375[a]	0.378[a]	0.220[a]	0.298[a]
	(0.053)	(0.011)	(0.028)	(0.072)
Ln L	0.319[a]	0.315[b]	0.455[a]	0.326[a]
	(0.051)	(0.155)	(0.024)	(0.056)
Trend: Mean	0.005[a]	0.005[c]	0.006[a]	0.007[a]
	(0.002)	(0.003)	(0.001)	(0.002)
Trend: SD			0.020[a]	0.014[a]
			(0.001)	(0.001)
Crowding (t–1): Mean	1.039[a]	1.053[a]	1.242[a]	1.214[a]
	(0.088)	(0.060)	(0.037)	(0.109)
Crowding (t–1): SD			0.035[a]	0.152[a]
			(0.010)	(0.011)
Crowding^2 (t–1): Mean	−0.232[a]	−0.233[a]	−0.321[a]	−0.299[a]
	(0.032)	(0.023)	(0.018)	(0.065)
Crowding^2 (t–1): SD			0.026[a]	0.042[a]
			(0.009)	(0.009)
Residuals (t–1)		−0.0657		−0.006
		(0.089)		(0.099)
Residuals^2 (t–1)		−0.267		−0.071
		(0.207)		(1.568)
Year 2013	−0.190[a]	−0.189[a]	−0.183[a]	−0.190[a]
	(0.022)	(0.018)	(0.023)	(0.057)
Constant	−0.320[a]	−0.339[a]	−0.391[a]	−0.293[a]
	(0.099)	(0.037)	(0.022)	(0.044)
Lambda	0.568[a]	0.458[a]	1.373[a]	1.553[a]
	(0.118)	(0.104)	(0.215)	(0.398)
σ_u	0.078	0.064	0.135	0.148
σ_v	0.137	0.139	0.098	0.096
Log– Likelihood	250.66	250.13	279.76	272.62
Number of provinces	50	50	50	50
Number of periods	13	13	13	13
Observations	650	649	650	649

Columns (3) and (4) reports the means of the random parameters for Crowding (t–1), Crowding^2 (t–1) and Trend.
Note: bootstrapped standard errors in parentheses.
[a] $p < 0.01$.
[b] $p < 0.05$.
[c] $p < 0.1$. TRE stands for True Random Effects model. RPM refers to the Random Parameter Stochastic Frontier model.

Starting with the TRE model in column (1), the output elasticities have the expected positive sign and are significant at 99 per cent confidence level. Rural overnight stays increase on average by 0.375% and 0.32% per each percentage increase in the number of bed places and workers, respectively. Accordingly, our estimates indicate that the rural tourism sector exhibits diminishing returns to scale (RTS $= \frac{\partial \ln Y}{\partial \ln L} + \frac{\partial \ln Y}{\partial \ln K} =$ 0.694). A test for whether $\beta_1 + \beta_2 = 1$ clearly rejects the null hypothesis ($\chi^2_1 = 106.65$, p-value <0.001). The time trend parameter is also positive and statistically significant, indicating the existence of technical change in the sector. The dummy variable for the year 2013 is nonetheless negative and significant, capturing the average drop in stays in that year documented in the preliminary descriptive analyses.

Importantly, we confirm the hypothesized non-linear (concave) relationship between overnight stays and our crowding indicator illustrated in Fig. 6. Initially, stays increase with the ratio of previous year visitors to the local population during the early stages of development, but they begin to decrease as crowding continues to grow. Specifically, the turning point (i.e., vertex of the parabola where $\frac{\partial \ln Y}{\partial Crowding} = 0$) locates at Crowding = 2.239. This turning point serves as the threshold value of social carrying capacity (Tokarchuk et al., 2021). In other words, when the number of visitors exceeds 2.24 times the local population, subsequent stays start to decrease (contingent upon input factors, individual heterogeneity, and temporal dynamics). During the sample period, the provinces of Cantabria (years 2018 and 2019) and Gipuzkoa (2016–2019) are found to surpass this turning point.

When we implement the control function approach in Column (2), our results remain robust; the turning point is very similar (2.26). The auxiliary residuals are nonetheless not statistically significant. Consistently with the Wu-Hausman test abovementioned, this suggests that there would not be an endogeneity problem (Wooldridge, 2015). Moving to Columns (3) and (4) where we allow for random parameters, we find that although the estimates remain similar, the output elasticity with respect to labor increases whereas that for capital decreases. Furthermore, the results still indicate that the sector operates under decreasing returns to scale (RTS = 0.675). Most importantly, these regressions allowing for province heterogeneity point again to a concave relationship between crowding and overnight stays. The average turning points are 1.93 and 2.03, respectively. These values are slightly lower than those from the constant-parameter specifications in Columns (1) and (2).

Finally, the lambda parameter (the ratio of the variance of the inefficiency term to the variance of the random noise) is always positive and statistically significant. This result supports the need for estimating a Stochastic Frontier with asymmetric errors. It is lower than one when considering constant parameters, but above the unity in the random parameter specifications. In the latter case, the estimates indicate that the inefficiency term is quantitatively more important than the random noise in explaining the non-explained variation in output across provinces.

5.2. Heterogeneity in social carrying capacity by province

Based on the province-specific estimates from Column (3) in Table 2 ($\widehat{\gamma_{1i}}$ and $\widehat{\gamma_{2i}}$), we calculate the turning points for each province. Fig. 7 maps the estimated values. Although the turning points concentrate in the 1.8–2 interval, certain provinces can accommodate a larger ratio of visitors to residents before experiencing congestion effects. These provinces include Salamanca (2.15), Cantabria (2.20) and Zamora (2.23). In contrast, the provinces of Baleares (1.68) and Badajoz (1.71) present the lowest turning points, implying that their overnight stays in rural accommodations are more sensitive to crowding effects. The specific point estimates can be found in Table A2 in the Supplementary Material.

Figs. 8 and 9 illustrate the observed levels of crowding versus the

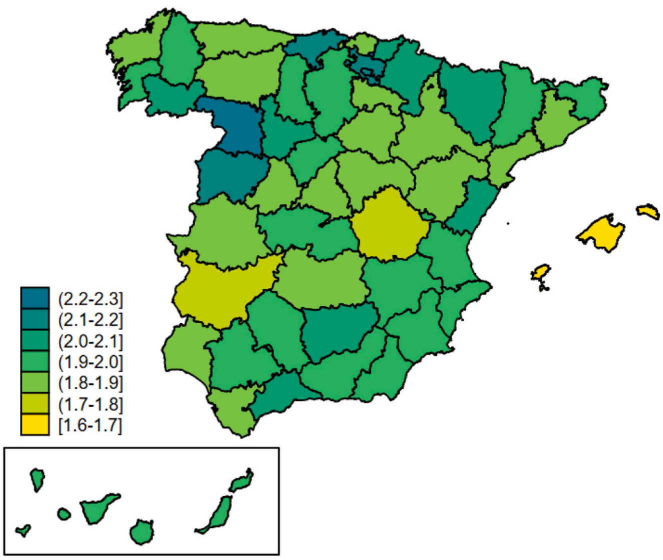

Fig. 7. Map of province-specific turning points for crowding based on the estimates from Column (3) in Table 2.

indicating that the province is fully efficient and lies in the production frontier) using $E_{it} = \exp(-\hat{u}_{it})$. Fig. 10 presents a kernel density plot of these estimates for the TRE and the RPM models in Columns (1) and (3) in Table 2.

The average efficiency under the TRE model is relatively high (0.94), with a highly leptokurtic distribution. On the contrary, the RPM model displays a more platykurtic profile; the corresponding efficiency scores exhibit greater variability around the mean (0.90). On average, the provinces with the highest productive efficiency are Lleida (92.26%), Madrid (91.57%) and Cantabria (91.04%). Auxiliary analyses of the evolution of efficiency scores over time suggest a slight decrease in efficiency levels (Supplementary Material, Figs. A9 and A10).

5.4. Robustness checks

We conducted some robustness checks on our main analysis. Firstly, we re-estimated the four model specifications presented in Table 2 using Bayesian methods.[5] Some authors have indicated that Bayesian modelling performs better with small samples and allows for parameter uncertainty through posterior distributions (Assaf & Tsionas, 2018b, 2019). We document that the estimates are consistent across model specifications and similar to Table 2. We nevertheless find again that the capital output elasticity is much lower in the random parameter regressions, highlighting the importance of considering province-specific trends plus heterogeneity in the influence of our crowding indicator to obtain unbiased estimates.

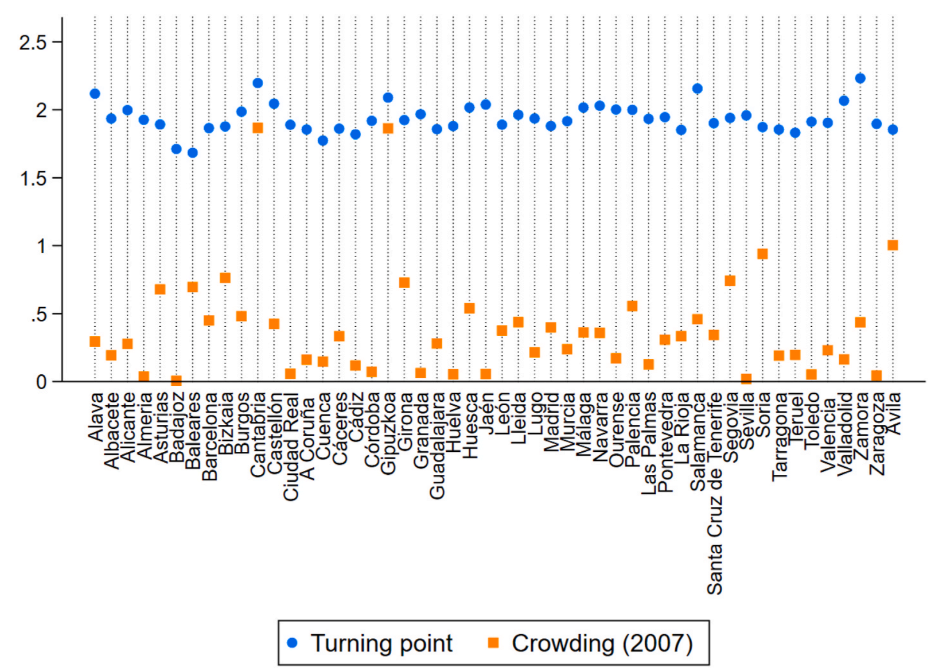

Fig. 8. Observed levels of crowding (blue) versus turning points (orange) in 2007. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

estimated turning points for each province in the first (2007) and last (2019) year in the sample. We see that the gap has narrowed down over time. Interestingly, two out of the fifty provinces have surpassed their optimal levels of carrying capacity during the study period: Cantabria (2017–2019) and Gipuzkoa (2016–2019). These provinces are thus experiencing drops in overnight stays associated with congestion (see Fig. A8 in Supplementary Material). Furthermore, others like Baleares and Girona are close to surpass their estimated turning points.

5.3. Estimates of productive efficiency

We use Jondrow et al. (1982) estimator to obtain the predictions of the inefficiency term $(-\hat{u}_{it})$ following equation (4). Subsequently, we compute the efficiency scores (bounded between 0 and 1, with 1

Secondly, we have estimated (i) a True Fixed Effects Stochastic Frontier (Greene, 2005) that, unlike the TRE model, allows for arbitrary correlation between the province-specific effects and the rest of covariates, and (ii) the models in columns (2) and (4) in Table 2 replacing the actual values by their fitted values from the auxiliary first stage regression and omitting the residuals (i.e., two-stage procedure). The results are shown in Table A4 in the Supplementary Material. We see

[5] A brief overview of the method together with the regression output is presented in the Supplementary Material, Table A3.

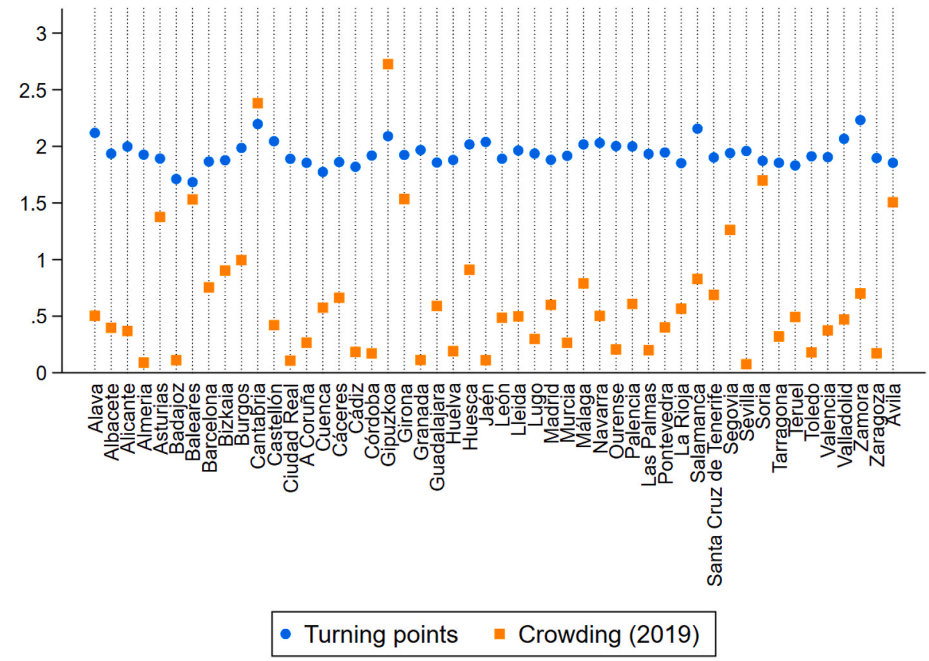

Fig. 9. Observed levels of crowding (blue) versus turning points (orange) in 2019. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

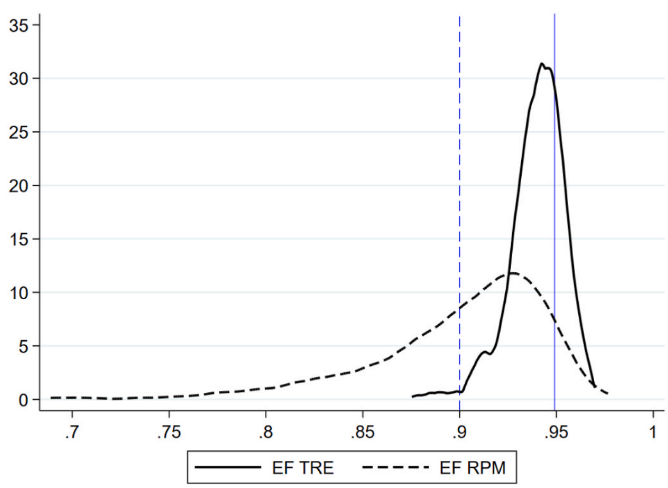

Fig. 10. Kernel density plot of efficiency scores from TRE model (solid line) and RPM model (dashed line).
Note: Vertical lines in blue indicate mean values. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

that the estimates remain largely unchanged under these checks, offering great robustness. Thirdly, we have included our crowding indicator as explanatory of the inefficiency term under a Battese and Coelli (1995) formulation (Supplementary Material, Table A5). It was not statistically significant for explaining the mean of inefficiency, thereby affecting the production frontier only. Finally, we have considered a translog production function instead of Cobb-Douglas (Supplementary Material, Table A6). Because most interaction terms are not significant, we have kept the Cobb-Douglas formulation for the sake of parsimony. Nonetheless, the output elasticities and coefficient estimates for the crowding indicator remain robust.

6. Discussion

6.1. Discussion of findings

In line with our theoretical predictions, our regressions show there is a non-linear (concave) relationship between crowding levels and stays one year after. On average, the turning point is around 2, implying that stays start to decrease when past year visitors are twice the local population. Our findings for Spain align with Albadalejo and González–Martínez (2019) and Albadalejo et al. (2016), who document that congestion moderates the positive effect of demand dynamics. When we consider distinct turning points by province, we find that Cantabria and Gipuzkoa have already surpassed their threshold points in the last years of the sample. Nonetheless, other regions like Baleares or Girona are about to surpass their threshold points.

In our preferred specifications (columns (3) and (4) in Table 2), the output elasticity of labor is higher than that for capital. Like Fleischer and Tchetchik (2005), we thus document that the output is more sensitive to the labor than to the capital input. Our analysis also reveals that rural accommodations operate under decreasing returns to scale. This result aligns with the findings of Chatzimichael and Liasidou (2019) on hotel efficiency in Europe. Other works, however, have documented increasing (e.g., Bernini & Galli, 2023) returns to scale in other settings.

Furthermore, rural accommodations show relatively high levels of productive efficiency. This relatively high efficiency levels are consistent with Assaf and Josiassen (2012), who documented a mean efficiency of 98% in the Spanish tourist sector. As compared to previous studies on the Spanish accommodation sector (Benito et al., 2014; Sellers–Rubio & Casado–Díaz, 2018), rural accommodations seem to be more efficient than hotels. Nevertheless, comparing both sectors is challenging because they differ in many dimensions like the type of target tourists or seasonality patterns. Crucially, efficiency scores under a common parameter specification (TRE) seem to be upward biased, which reinforces the argument by Assaf and Tsionas (2018a; 2018b; 2019) on the need to appropriately modelling technology heterogeneity.

We find positive technical change in the sector, a result that is consistent with Bernini and Galli (2023) for the case of Italy. Nevertheless, there is no evidence of *catching up*: efficiency change exhibits a negative trend implying that provinces are becoming less efficient in their input management over time.

6.2. Theoretical contributions

The paper has presented a novel theoretical characterization of how overnight stays follow an inverted U-shaped relationship with past levels of tourism arrivals. Specifically, the social externality component in consumers' utility switches from positive to negative as demand smoothly grows. We have conceptualized crowding as a demand factor that produces inward and outward shifts in the production function of accommodation services depending on the stage of tourism development of the destination. Our framework posits that crowding explains the wedge between observed output levels and the service potential predicted by input use. Our crowding measure is thus understood as a relevant environmental factor that needs to be considered when analyzing the performance efficiency of the accommodation sector (Assaf & Tsionas, 2019).

This study has offered an alternative view of the well-known concept of social carrying capacity. Whereas most works on this issue focus on how high levels of tourism demand damage residents (Tokarchuk et al., 2021) or produce visitor dissatisfaction (Saveriades, 2000), we have looked at threshold points at which the stay duration of tourists themselves diminishes with additional tourism arrivals. This represents a novelty in the literature: how long tourists travelling to the destination is thus used as a *revealed* (rather than stated) preference measure of destination utility. Moreover, instead of using a physical measure of tourist density (Albadalejo & González–Martínez, 2019; Albadalejo et al., 2016), we have used a social measure that relates tourists to local population. This has been done in the context of rural accommodations, for whom evidence on crowding effects is scarcer than in urban settings. Our work thus enriches theoretically and empirically the knowledge about acceptable crowding levels in rural tourism settings. Moreover, whereas most related works analyse crowding effects at the local level using data for a single city (Lalicic, 2020; Neuts & Nijkamp, 2012; Tokarchuk et al., 2021, 2022) or a point in time (Papadopoulou et al., 2023), our paper adds novel evidence considering the 50 Spanish provinces during a thirteen-year time span.

From a methodological standpoint, we have estimated a True Random Effects Stochastic Frontier model (Greene, 2005) with both constant and random parameters. In line with the arguments posited by Assaf and Tsionas (2018a; 2019) on the need to properly model technology heterogeneity, we allow for heterogeneity in the intercept, the time trend, and the variable measuring crowding. To deal with the plausible endogeneity of our crowding indicator, we have implemented a control function approach (Wooldridge, 2015) using a Bartik-type instrumental variable (Goldsmith–Pinkham et al., 2020) that exploits exogenous sources of variation in crowding in other provinces as external temporal shocks for identification.

6.3. Implications

Our results raise relevant managerial and policy implications for regional sustainability. Rural tourism is nowadays a popular type of tourism that has experienced a substantial growth in recent years, particularly among those looking for relaxation (Albadalejo & Díaz–Delfa, 2021; Han, 2019). Exceeding optimal crowding levels should be a major concern for rural hospitality and destination managers (Zekan et al., 2022), as crowding reduces satisfaction (Liang et al., 2021) and the willingness to come back (Papadopoulou et al., 2023). This seems to be particularly worrying for rural tourism because destination loyalty is highly sensitive to quality deterioration (Campón–Cerro et al., 2017). Our analysis has revealed that the provinces of Gipuzkoa and Cantabria have already surpassed their estimated turning points, entering a stagnation phase in which excessive arrivals are deterring subsequent overnight stays (*ceteris paribus*). Destination managers and policymakers in these provinces are urged to implement tailor-made actions aimed at reducing their levels of crowding. As discussed in Ma and Su (2024), local governments need to behave pro-actively to deal with tourism-related rural gentrification.

One valuable strategy could be to restrict the concession of new licences for rural accommodations in those provinces experiencing congestion. Those areas surpassing their optimal carrying capacity levels (e.g., Gipuzkoa and Cantabria) should temporarily limit accommodation supply and focus on quality over quantity dimensions to ensure pleasant experiences. This closely resembles the tourism moratoria policy implemented in the Canary Islands in the early 2000s (Hernández-Martín et al., 2015; Inchausti-Sintes & Voltes-Dorta, 2020). This sort of de-growth measure could be potentially effective at the goal of fixing the service potential at levels close to the optimal carrying capacity threshold.

From a broader perspective, our study has also important environmental implications. Rural tourism is intensive in natural resources, and excessive arrivals to rural areas might compromise environmental quality. Public authorities must balance the economic benefits of further tourists with the costs imposed on the environment and control whether destinations are surpassing optimal thresholds (Marsiglio, 2017). Similar studies in different countries and using our methods can be useful for destination managers to monitor destination crowding levels relative to the optimal.

7. Concluding remarks

This work has studied optimal levels of social carrying capacity in rural tourism. This seems to be particularly timely as COVID-19 has increased consumers' disutility from crowding (Park et al., 2021). Our theoretical framework posits that at first stages of development, overnight stays in rural destinations increase with the number of previous visitors due to word-of-mouth effects and increased popularity (Marsiglio & Tolotti, 2024). However, as long as arrivals continue to grow, negative externalities from crowding and congestion emerge (Saveriades, 2000), producing quality deterioration and discomfort (Alvarez & Brida, 2019; Jacobsen et al., 2019) that lead to subsequent drops in demand.

Using panel data for Spanish provinces in the period 2007–2019, we have estimated the quadratic relationship between overnight stays and the ratio of past year tourists to local population in the context of a production function using Stochastic Frontier Analysis. In doing so, we have allowed for province-specific turning points over which crowding deters overnight stays.

Our main findings can be summarized as follows. First, there is a nonlinear relationship between the crowding level of a rural destination and the overnight stays made by tourists the following year. On average, the turning point is around 2, meaning that overnight stays begin to decrease when the number of tourists doubles that of residents. Second, there is significant heterogeneity in social carrying capacity among Spanish provinces. Two of the fifty provinces are found to exceed their optimal carrying capacity level (Cantabria in 2017 and Guipuzkoa in 2016), with some others being close to their threshold points. Finally, the average estimated efficiency is relatively high (exceeding 0.90), and the rural tourism sector in Spain operates under diminishing returns to scale.

The paper has some limitations that constitute valuable avenues for future research. First, our analysis has been done for the case of Spain, a leading country in rural tourism. Nonetheless, results for Spain might not be generalizable to other countries, which calls for more country-specific studies on social carrying capacity. Second, we do not consider spatial spillover effects by which overnight stays exhibit spatial dependence, an issue that is receiving increasing attention in recent years (e.g., Bernini & Galli, 2023). We leave the analysis of crowding effects in the presence of spatial autocorrelation as an avenue for future work. Third, we have worked at the annual level without examining how crowding effects vary within the year. Future works could investigate the linkages between social carrying capacity and seasonality. Fourth, our analysis has considered the role of crowding as an environmental factor within a service production function. Algieri and Álvarez (2023) propose to examine the role of congestion on regional efficiency in tourism arrivals using a Stochastic Frontier Demand Model. Future studies could expand our work by investigating crowding effects on inefficiency from the demand side. A final limitation is that we have considered the pool of rural visitors to each province without considering heterogeneity by sociodemographic profile. In this vein, it would be fruitful to investigate distinct turning points depending on the origin (e.g., Albadalejo et al., 2016), since some works argue that crowding perceptions are greater among those travelling from nearby areas (Schuckert & Wu, 2021).

Declaration of generative AI and AI assisted technologies in the writing process

NONE. AI technology was NOT used during the writing process.

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Impact statement

This research on crowding from the visitors' perspective in rural tourism carries significant implications beyond the academic realm for various economic stakeholders. Given that this sector has experienced substantial growth in recent years, surpassing its optimal crowding levels should be a major concern for rural hospitality and destination managers, as crowding diminishes tourists' perceived satisfaction and their likelihood of returning. Our measure of crowding is thus a relevant environmental factor that must be considered when analyzing the performance efficiency of the accommodation sector. Importantly, it emerges as a crucial tool in ensuring the long-term sustainability of rural tourism. By examining the threshold points for each Spanish province over several years, we can determine which destinations have exceeded their optimal carrying capacity levels, resulting in a decline in subsequent overnight stays. Based on our findings, we discuss the potential need to consider implementing restrictions on accommodation supply in congested areas.

CRediT authorship contribution statement

José Francisco Baños-Pino: Writing – review & editing, Writing – original draft, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **David Boto-García:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis. **Emma Zapico:** Writing – review & editing, Validation, Investigation, Data curation, Conceptualization. **Matías Mayor:** Writing – review & editing, Supervision, Investigation, Funding acquisition, Formal analysis.

Declaration of competing interest

None.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tourman.2024.104968.

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