CONTAGION EFFECT ON BUSINESS FAILURE: A SPATIAL ANALYSIS OF THE HOTEL SECTOR

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ABSTRACT

This paper analyzes the contagion effect on business failure, focusing on the Spanish hotel sector. The sample consists of 3,948 hotel MSMEs in the 2012–2015 period and includes variables related to characteristics of the hotel and tourist destination. The results show that the contagion effect is significant, increasing the explanatory capacity of the model. Moreover, the results show that the analysis of the contagion effect should consider not only its simultaneous impact but also deferred over time on the probability of failure. Thereby, this paper found that after the initial shock, the contagion effect decreases and changes its sign from negative to positive in the fourth year.

KEYWORDS

failure; hotel; contagion; location; coordinates

JEL CODES

M21, L83, Z30.

1. INTRODUCTION

The destruction of a significant percentage of companies has serious consequences on the economy, negatively influencing the welfare of economic agents such as workers, suppliers, and customers (Vivel-Búa, Lado-Sestayo, & Otero-González, 2018). A line of research initiated in the last ten years is analyzing the importance of the contagion effect among economic agents when studying business failure, that is, the probability that the failure of a company is influenced by the bankruptcy of another company. These papers analyze the extent to which the probability of failure increases or decreases when a company with which other companies have some kind of relationship fails. For example, there is evidence that a company that is bankrupt or close to bankruptcy may influence the financial stability of other companies with which it has commercial relationships

(Barro & Basso, 2010; Battiston, Delli, Gallegati, Greenwald, & Stiglitz, 2007; Egloff, Leippold, & Vanini, 2007; Giesecke & Weber, 2006; Hertzel, Li, Officer, & Rodgers, 2008; Kolay, Lemmon, & Tashjian, 2015). In addition, the failure of a company can also influence its competitors, generating a redistribution of the market share and/or eroding prestige and confidence towards the sector, which can make access to financial resources difficult (Hertzel & Officer, 2012; Lang & Stulz, 1992). Finally, the most recent studies have identified that the geographical location is also a transmission channel of the contagion effect (Maté-Sánchez-Val, López-Hernandez, & Rodríguez-Fuentes, 2018). In particular, there is evidence that geographical proximity between companies is a channel through which business failure can spread (De Silva & McComb, 2012; Rodríguez-Fuentes, Maté-Sánchez-Val, & López-Hernández, 2016; Staber, 2001). In fact, Addoum, Kumar, and Le (2014) found that companies close to a failed one reduce their levels of investment and indebtedness. However, this evidence is still scarce, and it is necessary to deepen the analysis of the effect of geographical proximity on failure because it has an important impact on the current and future competitiveness of companies. In addition, this is relevant because geographic location plays a key role in certain sectors (Vivel-Búa et al., 2018).

In this context, the study of business failure and how it can be spread among companies is important to prevent and mitigate its economic impact, especially considering micro, small, and medium-sized enterprises (MSMEs). Information asymmetries between lenders and MSMEs make it difficult to access credit, as well as a prudential credit policy that financial institutions have applied in recent years (Yoshino & Taghizadeh-Hesary, 2015). Consequently, it is important to analyze specifically the business failure in these types of companies, developing specific methodologies for them (Altman & Sabato, 2007; Barreto & Artes, 2016). In fact, financial companies that assess credit risk have stressed that these methodologies should consider their particularities in relation to their legal status, financial structure, and competence, which are different from large companies (Lado-Sestayo, Vivel-Búa, & Otero-González, 2018).

The objective of this paper is to analyze the existence and effects of spatial interaction related to geographical proximity when analyzing business failure in companies in the same sector of activity. The economic crisis of 2008 showed that the inclusion of a factor related to the business cycle to capture the dependency structure is not enough, but that other types of modeling or adjustments are needed to assess business failure (Duffie, Eckner, Horel, & Saita, 2009). Therefore, this paper applies a spatial econometrics

approach. Moreover, it focuses on the Spanish hotel sector using a sample of 3,948 MSMEs in 2015. According to IET (2019), the tourism sector is internationally relevant as an engine of economic growth, and the hotel sector represents its main component of expenditure. This helps to justify this choice as a research focus. In fact, UNWTO (2020) indicates that the direct contribution of the tourism industry to global GDP exceeded $2.7 trillion, which, according to Standard and Poor's (2014), needs a specific analytical framework to evaluate its credit risk. In this context, Spain is one of the main tourist markets in the world, ranking as one of the top five countries in Europe (Vivel-Búa et al., 2018). In addition, MSME hotels are around 90% of the hotel offer in Spain.

The main contribution of this paper is that it models spatial dependence in the Spanish hotel sector. That is, how the probability of failure of a hotel can be influenced by the failure of other hotels that are geographically close. The analysis of the contagion effect in hotel failure at the geographic level is important because location plays a key role in this sector. The hotel service can only be consumed where it is generated, and location is one of the main attributes that customers value from the hotel activity (Lado-Sestayo, Otero-González, Vivel-Búa, & Martorell-Cunill, 2016a). In this sector, the location is a strategic decision, and it is not possible to modify it, at least in the short and medium term, due to the high real investments. In addition, this paper considers a very broad geographic area (all of Spain) in the empirical analysis, evaluating the contagion effect of failure using geographic coordinates. This helps to control the effect of location variables related to the tourist destination where the hotel is located. Likewise, the availability of geographic information at the hotel level (coordinates) to reference companies geographically avoids possible spatial aggregation biases, for example, due to the aggregation at the level of postal code, municipality, or tourist destination used in other studies for other markets and/or sectors.

Another important contribution of the paper is the temporal evaluation of spatial interaction. None of the few previous studies that have considered spatial interdependence in the analysis of business failure has evaluated the extent to which a failed company at a time will influence failure at later times. In our opinion, this makes it difficult to evaluate and quantify the spatial impact of failure completely, so this paper considers the temporal effect in its empirical study.

This paper is organized into four sections. After this introduction, the second section presents the theoretical framework, providing a review of the papers related to business failure and, specifically, those that have considered the contagion effect. Subsequently,

the third section presents the empirical study. The paper concludes with a fourth section that synthesizes the main conclusions.

2. FRAMEWORK

Business failure is a traditional and broad line of research in the academic literature, which has had two main objectives: i) quantify the probability of failure of a company proposing predictive models and ii) identify the best determinants of business failure (Rodríguez-Fuentes, Maté-Sánchez-Val, & López-Hernández, 2017). This literature is presented below, paying particular attention to the contagion effect as a determinant of business failure as this is the focus of this research. As noted in the introduction, the contagion effect refers to the fact that the probability of failure of one company is influenced by the failure of one or more others. Previous literature has studied business and competitive relationships between companies as the two main transmission channels of this contagion effect in business failure. Recently, a few studies have obtained evidence that geographical proximity between companies is a channel through which business failure can also spread.

This paper fill three main gaps in the previous literature. Firstly, this empirical research models spatial dependence in a sector where location plays a key role as hotel sector and using geographic coordinates, so it controls the effect of location variables related to the tourist destination where the hotel is located. Secondly, this paper quantifies the time evolution of the contagion effect to identify how the failure of one company at one point in time may influence the failure of another or others at later points in time. Thirdly, this analysis of the contagion effect focuses on MSMEs, which have been little explored to date although they play a very important role in many economies.

2.1. Methodology and determinants of business failure

The methodology applied to quantify the bankruptcy probability consisted of different statistical and econometric techniques: from the univariate analysis applied in the pioneering research of Fitzpatrick (1932) and Beaver (1966), to the use of a multivariate approach through the Z-score model proposed by Altman (1968), and the logistic regression used by Martin (1977), Ohlson (1980), and Zmijewski (1984) from the 1970s. Subsequently, artificial intelligence techniques became popular as of the 1990s (Ciampi & Gordini, 2013).

Regarding the determinants of failure, firstly, it should be noted that there are two theoretical perspectives that explain the causes of business failure: deterministic and voluntarist (Vivel-Búa, Lado-Sestayo, & Otero-González, 2019). The deterministic

perspective highlights that business failure is related to environmental or industry-level factors. There are exogenous factors that managers cannot fully control, so they influence their ability to respond to changes in the environment (Barron, 2001). The voluntarist perspective highlights the role of firm-level factors, so business failure is related to the activity of managers. This perspective considers variables such as strategy, resources, and leadership, which are controlled by the managers (Mellahi & Wilkinson, 2004). Recent studies have shown that both perspectives must be considered together, because the factors related to both the company and the environment are relevant to explain the failure (Heracleous & Werres, 2016). In particular, the previous literature has proposed a broad set of economic and financial variables obtained from the accounting information published by the company, especially accounting ratios related to profitability, indebtedness, liquidity, and economic structure. Also, according to Vivel-Búa et al. (2018), the study of failure in some sectors cannot only be based on the use of accounting indicators, but also consider factors related to their environment, such as macroeconomic variables.

2.2. The contagion effect in business failure

A line of research developed in the last decade provides evidence on the importance of considering a new determinant of failure called the contagion effect (Hertzel et al., 2008; Hertzel & Officer, 2012; Kolay et al., 2015). The concept of "contagion" refers to the probability that the failure of a company is influenced by the bankruptcy of another company. The contagion effect on business failure has been analyzed considering different channels through which this effect is generated or enhanced.

Firstly is the supply chain, so the failure of a company influences the companies with which it has business relations. In general, the previous literature concludes that the effect is positive; that is, the failure of a company increases the probability of failure of the companies with which it has commercial relations. This can be related to liquidity problems among suppliers generated by the failed company (Giesecke & Weber, 2004). In fact, Hertzel et al. (2008) find that this contagion effect is more significant among suppliers than among clients.

A second transmission channel of the contagion effect is related to the competing companies, so the failure of a company influences the companies with which it competes and shares the same sector of activity. This effect can be positive or negative (Lang & Stulz, 1992) and is applicable to those companies listed on a stock market. Competing companies can increase their probability of failure because the failed company generates

a climate of distrust of the sector that erodes the value of its shares. In addition, financial providers may impose more restrictions and requirements to obtain new financial resources, increasing the financial cost in these companies (Hertzel & Officer, 2012). On the other hand, competing companies can reduce their probability of failure because they increase their market share as a result of the failure of a company in their sector; that is, failure generates a redistribution of wealth within the sector.

Finally, the geographical proximity between companies can also spread the contagion effect, so the failure of a company influences companies that are geographically close to it, at least in the medium and long term. This contagion effect related to geography could be explained by the existence of a good flow of information between the failed company and other companies in its environment as a result of managers working in several of these companies or simply that they are operating in a more local environment (Haunschild & Beckman, 1998; Lee, 2012). Therefore, knowledge of the financial situation of these companies helps to make decisions that neutralize the negative impact of a bankruptcy. In other words, the failure of a company reduces the probability of failure of companies that are geographically close. However, authors such as Parsons, Sulaeman, & Titman (2018) also indicate that companies that are close tend to have a similar behavior, which contributes to this contagion effect having the opposite sign, increasing the probability of failure of nearby companies.

There is a theoretical framework that justifies the importance of geography in business performance by relating it to transportation costs and external economies, which has been extrapolated to failure. The geographical proximity between companies facilitates the access and exchange of financial resources, labor, and raw materials, among other things, which contributes to reduce transaction costs, generating a positive effect on performance, and, at the same time, a reduction can be expected of the probability of failure (Weber, 1909). Likewise, the interaction between companies and the environment contributes to industrial specialization and can generate knowledge spillovers, also positively influencing performance (Marshall, 1920). In relation to business failure, this paper considers that the effects of industrial specialization are inconclusive. Consequently, being part of a cluster can have positive and negative effects on the likelihood of failure (Khelil, 2016; Weterings & Marsili, 2015). According to Bernstein et al. (2019), the negative effects of competitor failure are larger in agglomerate environments for firms in the non-tradable and service sectors. The failure of a competitor would reduce knowledge spillovers and could also reduce the overall demand for the

cluster in net terms, increasing the probability of failure. This positive relationship between agglomeration and failure is also posited by organisational ecology studies, due to the greater competition in highly-concentrated locations and the existence of negative externalities (Shaver & Flyer, 2000; Sorenson & Audia, 2000; Staber, 2001; Folta et al., 2006). In contrast, Buehler et al. (2012) and Buenstorf & Klepper (2009) find that firms with higher agglomeration economies are less likely to fail, which is supported by the lower transaction costs, industrial specialization and access to knowledge spillovers by incumbent firms, all of them positively influencing performance.

Supplement Table 1 summarises the previous literature on business failure considering, on the one hand, the chronology of its origin and, on the other hand, differentiating methodology and determinants. Thus, the table shows how this paper focuses on the most recent developments in this line of research: the application of spatial econometrics and the inclusion of the contagion effect as a determinant of failure at the geographical level.

2.3. Business failure in MSMEs: the role of geographic distance

Geographic distance as a factor that should be considered in the spread of credit risk among MSMEs is still little explored (Petersen & Rajan, 2002). Likewise, there could be important differences in the role that location plays depending on the sector considered. For example, in the service sector, Rodríguez-Fuentes et al. (2016, 2017) find a significant spatial colocalization pattern in the failure of SMEs in the Region of Murcia in Spain. Specifically, they confirm that the probability of failure of an SME depends on its internal characteristics and the characteristics of geographically close companies. In the industrial sector, Maté-Sánchez-Val et al. (2018) evaluate SMEs of the Madrid metropolitan area (Spain) and find that the proximity to a failed company increases the probability of failing. In addition, these authors show that the proximity to external economic agents, such as logistics centers and industrial estates, reduces the probability of failure, so that factors related to location and proximity to failed businesses seem to be determining factors of business failure.

According to Calabrese, Andreeva, and Ansell (2017), distance could be a relevant factor in MSMEs because their customers are usually located close to their geographical location. In addition, in our opinion, this is also relevant because there are activity sectors where location is a strategic factor. For example, in the hotel sector, location is a very important attribute for the selection of the company by the customer (Lado-Sestayo, Vivel-Búa, & Otero-González, 2016b). At the same time, previous literature has shown that hotel location significantly influences not only the probability of hotel failure but also

its profitability and efficiency (Lado-Sestayo & Fernández-Castro, 2019). Due to the importance of geographical location, this sector is especially interesting to assess the contagion effect on business failure.

Calabrese et al. (2017) propose the integrated analysis of spatial dependence and the standard methodology for credit risk assessment, evaluating SME defaults in London. These authors do not find evidence of spatial dependence at the postcode level. In our opinion, this may be related to the modifiable area unit problem (MAUP), which means that a discrete point of view of space based on aggregate data (e.g., postcodes) could bias results. Pablo-Martí and Muñoz-Yebra (2009) show the lack of sturdiness of results under discrete (or aggregate) considerations. Fotheringham and Wong (1991) also warn about this problem in multivariate analysis because they found strong evidence of the unreliability of multivariate analysis in a context of the MAUP. A summary of implications of MAUP is presented in Supplement Figure 1. The first square shows a clear concentration in the center of the figure, considering space in a continuous way. However, if space is discretized and data are aggregated to different levels, spurious conclusions can be reached. Consequently, the use of hotel coordinates is always preferable to aggregate alternatives such as postcodes, municipalities, or regions. Thus, this research applies this approach because it evaluates the spatial interaction in the MSMEs of the hotel sector, considering the entire Spanish market and hotel coordinates. In addition, it analyzes the temporal evolution of this interaction, which, to our knowledge, has not been explored in previous empirical studies.

3. EMPIRICAL STUDY

3.1. Sample, variables, and methodology

The objective of this paper is to determine if it is important to consider the spatial interaction between observations when analyzing business failure in a specific sector of activity. Therefore, this paper analyzes the contagion effect to identify if spatial interdependence is a significant determinant of failure in the Spanish hotel sector. In addition, to evaluate the temporal evolution of spatial interaction, the paper uses information on failed hotels in 2014, 2013, and 2012. The identification of MSMEs is based on the official definition proposed by Recommendation 2003/361/EC of the European Commission.

The sources of information are i) the SABI (Analysis System of Iberian Balances) and Alimarket databases, to obtain indicators related to the characteristics of the hotel; ii) the

databases of the Spanish National Institute of Statistics, to obtain indicators related to the tourist destination where the hotel is located; and iii) the Eurogeographics database, to obtain indicators on the means of transport.

The sample consist of 3,948 hotel MSMEs. There are 2203 micro (55.80%), 1438 small (36.42%) and 307 medium (7.77%) hotel MSMEs. All hotel MSMEs with complete and accessible information in the databases used have been considered.

Table 1 identifies the variables used in the empirical analysis. The dependent variable is business failure, which is defined from a legal point of view. According to Vivel-Búa, Lado-Sestayo, and Otero-González (2016), failure is usually identified through compliance with legal requirements that verify a legal bankruptcy situation in the companies that are studied. Specifically, this paper defines a failed firm when it is in a state of financial insolvency currently or in the short term, and therefore, the value of its assets is not sufficient to meet its payment obligations.

The independent variables were selected using the previous literature as a reference (Table 1). According to Lado-Sestayo et al. (2016b), the study of business failure in the hotel sector should simultaneously consider variables at the hotel and tourist destination levels to avoid biased results. Therefore, this paper includes both variables. Regarding the tourist destination where the hotel is located, the paper includes the occupancy rate, the average number of rooms in the tourist destination, the seasonality, and the competitive concentration level. Focusing on the variables related to the characteristics of the hotel, the paper uses size, indebtedness, liquidity, asset efficiency, and market share. Recently, Lado-Sestayo et al. (2018) showed that accessibility to centers of interest, such as airports and train stations, also plays an important role in hotel profitability, so this paper also considers this type of variable in the analysis of failure.

Table 1. Variables

	Label	Definition
Dependent variable	Failure	Dummy variable that takes the value of 1 when the hotel has failed and 0 otherwise. According to Spanish law, a firm is failed when it is in a state of financial insolvency (currently or in the short term)
Independent variables related to hotel characteristics	Size	Logarithm of total assets in thousand euros$_i$
	Leverage	Total liabilities$_i$ / total assets$_i$
	Liquidity	Cash$_i$ / current liabilities$_i$
	Near_dist_air_km	Distance in kilometers to nearest international airport$_i$
	Near_dist_train_station_km	Distance in kilometers to nearest train station with medium distance services$_i$
	Asset_efficiency	Income$_i$ / total assets$_i$
	Market_share	[Hotel revenues$_{ij}$ / total revenues$_j$] X 100
Independent variables related to tourist destination where hotel is located	Concentration	Concentration of the lodging market in each tourist destination calculated as the logarithm of Herfindahl–Hirshman Index
	Rooms	Hotel rooms$_j$ / number of hotels $_j$
	Occupancy_rate	Average of monthly occupancy rate in the tourist destination
	Seasonality	Variance of average monthly occupancy rate in the tourist destination

Note: According to the Spanish Statistic Institute, a tourist destination is a municipality where the concentration of tourism is significant. There were 116 tourist destinations in Spain in 2015. *i* represents each hotel, and *j* represents each tourist destination.

The analysis of the effect of the characteristics of the hotel, the tourist destination, and the spatial interaction (or contagion effect) consists in the estimation of a spatial probit model using the following equation:

$$y' = \rho W y' + X\beta + \varepsilon \qquad \text{[Equation 1]}$$

$$y' = \begin{cases} 1 \; if \; y \geq 0 \\ 0 \; if \; y < 0 \end{cases}$$

$$\varepsilon \sim N(0, I_n)$$

Where,

y is a vector nx1 that identifies the observed variable relative to failure. It has the value of 1 if the company has failed and 0 otherwise.

ρ is the parameter that measures the strength of spatial dependence of firm failure.

W is an nxn neighborhood matrix, which reflects the spatial structure of the data. Each row reflects the effect of neighbors (in columns) over hotel. The matrix is row-

standardized, and each value is calculated as the inverse distance between hotels (closer hotels have higher impact than distant ones) (see Supplement Table 2).

X is an nxk matrix that measures the hotel and tourist destination variables considered as determinants of firm failure.

β is a kx1 vector of parameters associated with the firm failure determinants.

The model is estimated following the Bayesian estimation of LeSage & Pace (2009) using the package *spatialprobit* in R software (Wilhelm & Godinho-de-Matos, 2015). According to Calabrese et al. (2017), the empirical study of spatial failure must consider different alternatives in the distance matrix. Thus, in order to evaluate the robustness of the results to the spatial weight matrix, this paper evaluated 10 models, considering different spatial weight matrixes from 10 to 100 neighbors in intervals of 10. Each matrix evaluates different strengths of spatial relation. According to Akaike information criterion (AIC) and Bayesian information criterion (BIC), the best fitting model uses a spatial weight matrix of 30 neighbors.

3.2. Results

Table 2 shows the descriptive statistics of the variables included in the empirical study in 2015 and the join-count spatial correlation test, considering a neighborhood matrix with 30 neighbors. As shown, 12.8% of the hotels failed during that period, with a debt ratio of around 60%. The liquidity ratio indicates that the Spanish hotel sector generates quite a lot of cash, since this allows the payment of around 25% of all short-term obligations of the company. Likewise, asset turnover confirms that it is a sector that requires high investment, because it presents a value very close to the unit.

In general, hotels are closer to airports than to train stations, which can be explained by the existence of more than 50 international airports in Spain. All regions are connected by at least one airport, while this does not happen with train stations that have long-distance rail transport services available. Moreover, the plane is the means of transport most used by international tourists who come to Spain (NSI- FRONTUR, 2019).

The market share indicates that each hotel represents a very small part of the sales of the tourist destination, so that its influence on the variables of the tourist destination is limited. Considering the number of rooms, the average size is around 181 rooms, with important differences between the hotels. This could be explained by the coexistence of sun and beach destinations with historical, cultural, and urban destinations in the Spanish tourist offer. The variation in the occupancy rate and the high seasonality are also

indicative of this heterogeneity. Finally, although the high average size of the hotels may indicate the existence of a monopolistic competition market, the Herfindahl index values indicate that the Spanish hotel sector is a competitive market.

Finally, the join-count test indicates that the colocalization patterns of active and failed companies are positive. Therefore, the probability of finding geographically active companies close to failed companies is reduced.

Table 2. Descriptive statistics

Variable	Obs.	Mean	St. Dev.
Failure	3,948	0.128	0.335
Size*	3,948	4,526.918	12,481.208
Leverage	3,948	0.621	0.347
Liquidity	3,948	0.263	0.393
Near_dist_air_km	3,948	52.391	50.323
Near_dist_train_station_km	3,948	137.540	333.880
Asset_efficiency	3,948	1.065	2.803
Market_share	3,948	1.305	2.805
Concentration*	3,948	0.035	0.037
Rooms	3,948	181.016	153.445
Occupancy_rate	3,948	58.733	13.051
Seasonality	3,948	13.073	4.396

	Observed counts value	Expected counts value	Variance (Z Statistic)
Join-count test: healthy/healthy	1518.404	1499.498	19.781 (4.251***)
Join-count test: failed/failed	46.223	32.498	4.150 (6.738***)
Join-count test: healthy/failed	409.373	442.003	26.838 (-6.299***)

Notes: “Obs.” means the number of observations. “St.Dv.” is the standard deviation. * The values of the mean and standard deviation are refereed to total assets in thousand euros and Herfindahl–Hirshman Index respectively without logarithm transformation. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Then, two models are presented in Table 3. The first model is a non-spatial probit model, so it omits the inclusion of $\rho W y'$ in equation 1, and it only includes the variables related to the hotel characteristics in 2015 (firm-level model). The second model is also a non-spatial probit model, but it shows the impact not only of the hotel characteristics but also of the variables related to the tourist destination on the probability of failure in 2015 (destination-level model).

In general, estimates confirm a negative relationship with the probability of failure of size, distance to transport nodes such as airports and train stations, efficiency, and market share in the Spanish hotel sector. The relationship is positive considering the indebtedness variable. In relation to the tourist destination, the level of competitive concentration, the occupancy rate, and the seasonality reduce the probability of failure. However, the average size of the hotels in the tourist destination considering the number of rooms increases. These results at the hotel and tourist destination levels confirm the evidence obtained in previous studies by Lado-Sestayo et al. (2016b) and Vivel-Búa et al. (2016, 2018) in the Spanish hotel sector, although they evaluated the period 2005–2011, prior to the economic crisis of 2008, and included large companies in their empirical study.

Table 3. Probit model estimations

Variables	FIRM-LEVEL MODEL (only hotel characteristics)	DESTINATION-LEVEL MODEL (hotel & tourist destination characteristics)
	Coef. (Std. error)	Coef. (Std. error)
(Intercept)	0.1715 (0.1400)	0.8085*** (0.2158)
Size	-0.1991*** (0.0188)	-0.2069*** (0.0203)
Leverage	-0.0192 (0.0265)	0.0199 (0.0274)
Liquidity	0.0005 (0.0014)	0.0006 (0.0014)
Near_dist_air_km	-0.0009* (0.0005)	-0.0016** (0.0006)
Near_dist_train_station_km	-0.0004*** (0.0001)	-0.0004** (0.0001)
Asset_efficiency	-0.0721*** (0.0159)	-0.0669*** (0.0162)
Market_share	-0.0082 (0.0104)	-0.016 (0.0113)
Concentration	-	-0.0918* (0.0392)
Rooms	-	0.0008* (0.0003)
Occupancy_rate	-	-0.0119** (0.0037)
Seasonality	-	-0.0266*** (0.0067)
Observations (no. of failed hotels)	3948 (507)	3948 (507)
Log-likelihood	1348.19	-1329.68
AIC	2712.380	2683.400
BIC	2762.628	2758.729
AUC % (95% interval)	72.86 (70.49–75.22)	74.46 (72.20–76.72)
AUC test (only firm/firm & spatial)	-	3.558***
Moran.test	5.296***	4.404***
NRI+ (only firm / firm & spatial)	-	2.96***
NRI- (only firm / firm & spatial)	-	1.86***
NRI G (only firm / firm & spatial)	-	4.82***

Notes: Coef. is the coefficient of independent variables, and Std. error is the heteroscedasticity-robust asymptotic standard error. Log-likelihood is the value of the maximum likelihood function. AIC (Akaike information criterion) and BIC (Bayesian information criterion) are model selection criteria based on the log-likelihood function values. Models with lower values are preferred. AUC is the area under the receiver operating characteristic (ROC) curve. Its confidence interval is computed following DeLong, DeLong, and Clarke-Pearson (1988) and using the algorithm proposed by Sun and Xu (2014). The Moran test is a test of spatial autocorrelation under the null hypothesis of random spatial distribution of residuals. NRI is the net reclassification improvement, which measures the percentage of firms reclassified according to the model in each group (+ failure, -healthy firm, and G global) and where the confidence intervals are computed by means of the percentile bootstrap method.

Supplement Figure 2 evaluates the residues of the destination-level model to verify if location patterns persist once the variables related to the characteristics of the hotel and the tourist destination have been jointly considered in the probit estimate. The results confirm that the residues present first-order spatial autocorrelation and that the effect of second-order neighbors (neighbors of neighbors) and higher orders is not statistically significant. Therefore, it is possible that there is a contagion effect on hotel failure that is not captured by the previous probit estimates (Table 3). In addition, a first-order spatial matrix would be sufficient to analyze this contagion effect as is expected (LeSage & Pace, 2014). A first-order spatial matrix is commonly used in previous empirical studies, such as those by Rodríguez-Fuentes et al. (2016) and Calabrese et al. (2017).

Table 4 shows the third estimated model, a spatial probit model, which considers the contagion effect (i.e., how the failure of a hotel in 2015 influences the probability of failure of another one, considering a spatial data structure with 30 neighbors [contagion model]). The fourth, fifth, and sixth models estimate this contagion effect with one year, two years, and three years of delay, respectively. Therefore, these models estimate how the failure of a hotel in 2014, 2013, and 2012 influences the probability of failure in 2015. To do so, the spatial weight matrix (W) was changed to incorporate failed hotels in the previous years (2014, 2013, and 2012), removing the impact of failed hotels in 2015.

According to the AUC, NRI, AIC, and BIC, the destination-level model and the contagion model are preferable to the firm-level model. However, there are no statistically significant differences between the destination-level model and the contagion model. The predictive capacity of both models is very similar, although the contagion model contributes to clarify the causes of failure (i.e., to identify to what extent the hotel's probability of failing is related to the failure of its closest competitors geographically). Thus, the contagion model has a better explanatory capacity for the phenomenon of hotel failure. Moreover, according to AIC and BIC, this model that considers 30 neighbors is the best fitting model. None of the W definitions changes the sign of the estimated coefficients, so the results are robust. This result is in accordance with LeSage and Pace's (2014) statements about selection of a distance-based matrix.

Focusing on the temporal evolution of the contagion effect, the results show that this effect decreases over time and is even negative when considering a time horizon of three years. Hotels that fail in 2015 and 2014 have a positive and significant contagion effect on the probability of failure in 2015, but hotels that fail in 2012 have a negative contagion effect; that is, they reduce the probability of failure in 2015. This evidence can relate to

the effects of failure on the competitors identified by Lang and Stulz (1992). These authors identify a negative effect related to the reduction of their market value because the bankrupt company generates a negative image of the sector. This paper confirms this effect considering the infection with a delay of one and two years compared to the current moment. On the other hand, Lang and Stulz (1992) also propose the existence of a positive effect, because competitors can increase their market share as a company disappears from the sector. This would be in line with the evidence obtained considering three years of delay in the contagion effect.

Table 4. Spatial probit model estimations

Variables	CONTAGION MODEL (hotel & tourist destination characteristics & contagion effect)			
	Instantaneous 2015	One-year delay (2014)	Two-year delay (2013)	Three-year delay (2012)
	Coef. (Std. error)	Coef. (Std. error)	Coef. (Std. error)	Coef. (Std. error)
(Intercept)	0.860*** (0.218)	0.818*** (0.142)	2.085*** (0.173)	1.987*** (0.141)
Size	-0.202*** (0.023)	-0.171*** (0.019)	-0.245*** (0.014)	-0.251*** (0.013)
Leverage	-0.040 (0.026)	-0.014 (0.012)	-0.144** (0.062)	-0.018** (0.009)
Liquidity	0.000 (0.002)	0.001 (0.001)	-0.001 (0.002)	0.000 (0.002)
Near_dist_air_km	-0.001*** (0.000)	-0.002*** (0.000)	-0.003*** (0.000)	-0.003*** (0.000)
Near_dist_train_station_km	0.000*** (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Asset_efficiency	0.069*** (0.017)	0.080*** (0.015)	0.000 (0.000)	0.001* (0.000)
Market_share	0.015 (0.011)	0.013 (0.011)	0.013 (0.012)	0.031*** (0.008)
Concentration	-0.080** (0.038)	-0.225*** (0.035)	-0.329*** (0.032)	-0.413*** (0.038)
Rooms	0.001*** (0.000)	0.001*** (0.000)	0.002*** (0.000)	0.002*** (0.000)
Occupancy_rate	-0.010*** (0.003)	-0.024*** (0.003)	-0.040*** (0.003)	-0.046*** (0.004)
Seasonality	-0.024*** (0.006)	-0.006 (0.005)	-0.016*** (0.006)	-0.016*** (0.005)
Rho (contagion effect)	0.166*** (0.060)	0.157*** (0.041)	0.023 (0.044)	-0.063** (0.029)
Observations (no. of failed hotels)	3948 (507)	4061 (761)	4159 (1010)	4232 (1140)
Log-likelihood	-1330.35	-1732.21	-1945.67	-2033.68
AIC	2686.705	3490.414	3917.345	4093.36
BIC	2768.358	3572.433	3999.674	4175.915
AUC % (95% interval)	74.48 (72.23–76.73)	72.83 (70.80–74.87)	76.19 (74.56–77.91)	77.23 (75.58–78.88)
AUC test (only firm/firm & spatial)	3.458*** /0.1807			
Moran.test	-			
NRI+ (only firm / firm & spatial)	3.75*** / 0.79			
NRI- (only firm / firm & spatial)	1.89*** / 0.03			
NRI G (only firm / firm & spatial)	5.65*** / 0.81			

Notes: Coef. is the coefficient of independent variables, and Std. error is the heteroscedasticity-robust asymptotic standard error. Log-likelihood is the value of the maximum likelihood function. AIC (Akaike information criterion) and BIC (Bayesian information criterion) are model selection criteria based on the log-likelihood function values. Models with lower values are preferred. AUC is the area under the receiver operating characteristic (ROC) curve. Its confidence interval is computed following DeLong et al. (1988) and using the algorithm proposed by Sun and Xu (2014). The Moran test is a test of spatial autocorrelation under the null hypothesis of random spatial distribution of residuals. NRI is the net reclassification improvement, which measures the percentage of firms reclassified according to the model in each group (+

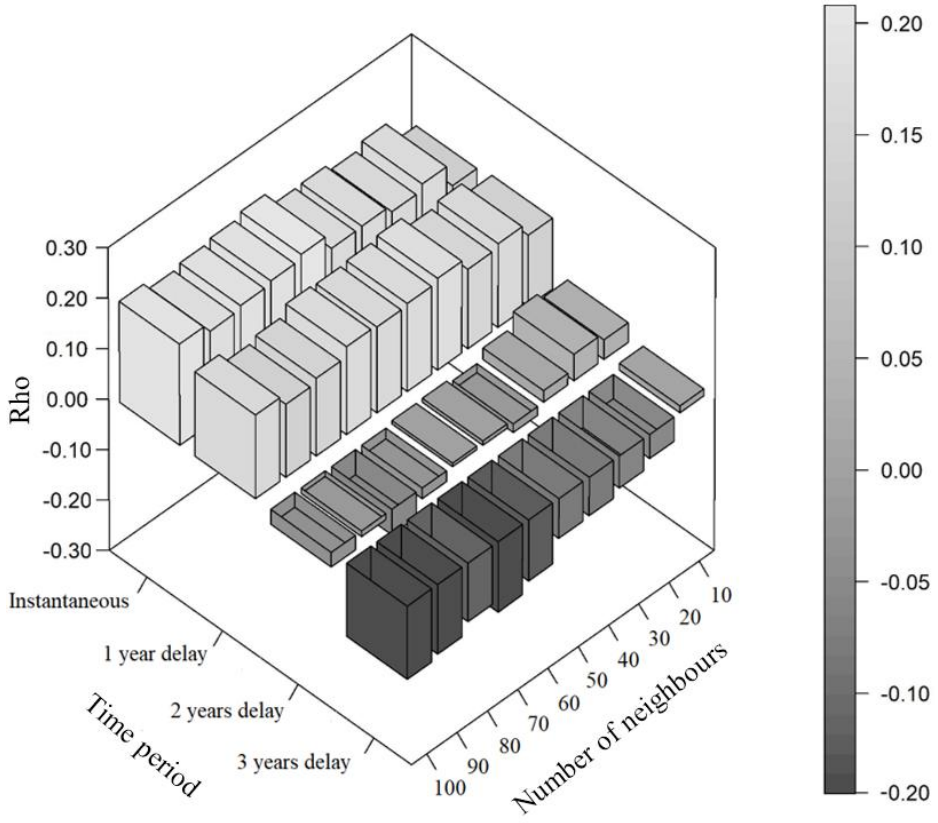
failure, -healthy firm, and G global) and where the confidence intervals are computed by means of the percentile bootstrap method.

Supplement Figure 3 shows the Rho parameter obtained by estimating the contagion model considering a spatial weight matrix from 10 to 100 neighbors in intervals of 10. This parameter shows the intensity of the contagion effect with data relative to 2015. The evidence obtained shows that the Rho effect increases when the number of neighbors also increases, but the differences between the parameters are not statistically significant. Therefore, the results are robust to the choice of one or another distance matrix and indicate that the effect of geographically farther neighbors is marginal and insignificant to explain the failure.

Supplement Figure 4 shows the Rho parameter and its confidence interval, corresponding to the 5th and 95th percentiles, in the four spatial probit estimates of the contagion model (2015; one-year delay, 2014; two-year delay, 2013; three-year delay, 2012). The objective is to evaluate if there are differences between the parameters obtained for each model. The results indicate that the contagion effect is reduced as the time period increases, being negative and statistically significant when the model considers the impact three years later. This result is a novelty in the literature, since there are no studies that analyze the temporal evolution of the contagion effect.

Finally, Figure 1 shows the Rho parameter in the contagion model estimates considering each of the distance matrixes (from 10 to 100 neighbors, at intervals of 10 neighbors and their temporal variations). This helps to identify to what extent temporal or spatial variations influence the intensity of the contagion effect. The results show that the variations observed in the Rho parameter are more influenced by variations of a temporal rather than a spatial nature. Therefore, when analyzing the contagion effect on hotel failure, it is more important to consider temporary delays than different alternatives in the spatial weight matrix. This is very relevant because previous literature has emphasized the inclusion of different spatial weight matrixes, not assessing the importance of time delay (Calabrese et al., 2017).

Figure 1. Temporal and spatial variation of the contagion effect (Rho values)



4. CONCLUSIONS

This paper evaluated the contagion effect on business failure by focusing on MSME hotels in the Spanish market. Thus, this research analyzed the spatial interaction related to geographical proximity, considering a time horizon of four years. In general, the results show that there is a significant contagion effect on hotel failure, contributing to identify a new relevant variable in the explanation of this business phenomenon.

RESEARCH IMPLICATIONS

This investigation concludes that it is important not only to include variables related to the characteristics of the hotel and the tourist destination to explain the failure, as has been usual in the previous literature, but also to consider the contagion effect at the spatial level. Therefore, this paper helps to show that neither the absolute location nor the relative location of a company can be ignored when analyzing its probability of failure. This is especially relevant in a sector like the hotel sector, where location is a strategic factor.

In addition, this paper found that the contagion effect should not only be considered at a time, but it is also relevant to include its temporal evolution, since its impact on the probability of failure is different. In particular, this research identified that the impact of

the contagion effect on the probability of failure is positive when a four-year time horizon is analyzed in the hotel sector. This is relevant because the previous literature is focused on analyzing how the contagion effect can change considering different geographical distances — that is, a greater or lesser number of neighbors — and, in general, avoided considering the temporary effect. In line with LeSage and Pace (2014), this paper helps confirm that the number of neighbors is not relevant in estimating a spatial probit to assess hotel failure. The key factor is to consider how the contagion effect may vary over time.

PRACTICAL IMPLICATIONS

This research has implications for management. Firstly, the failure of a hotel is important for both policymakers and hotel managers because it generates consequences on the company itself, on its nearby competitors geographically, and for several periods of time. From a temporary point of view, and as indicated above, this paper identifies that the impact of a competitor's failure can even reduce the probability of failure of the hotel when three years pass. Consequently, to minimize or neutralize the consequences of a competitor's failure on the company, any strategy must focus on the short term, for example, one or two years, which is when an impact of greater magnitude and with a positive sign is identified. In this way, policymakers could design and apply special financing lines to improve the infrastructure of the hotel, which could generate an increase in the value of their assets without influencing the average size of the hotels in the tourist destination. Another possible strategy could be related to specific measures to increase the occupancy rate that would reduce the probability of failure in hotels that survive the failure of a competitor. Regarding hotel managers, they should focus on improving asset efficiency. A second implication for management relates to investors. This paper helps to underline that the design of any credit scoring to assess the bankruptcy of a company should be adjusted to a sector, including variables related to its location and specifically considering the failure of its competitors in recent years.

LIMITATIONS AND FUTURE RESEARCH

Finally, this research presents some limitations that, at the same time, have contributed to identify future lines of research. Due to the non-availability of information, this paper did not analyze the contagion effect related to companies in other sectors that have commercial, financial, or other relationships with the Spanish hotel sector. Thus, it would be interesting to deepen the study of the contagion effect related to the companies present in the value chain that belong to other sectors (e.g., assessing the impact of bankruptcy of a tour operator on the hotel sector or the impact of hotel failure on nearby restaurants).

The recent bankruptcy of Thomas Cook is an interesting example of how the contagion effect between related sectors is a relevant research focus. In addition, it may also be relevant to expand the focus of research to other sectors where location is a strategic factor, such as the restaurant business in the tourism field.

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