Did Covid-19 modify the spatial concentration of business failure?

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The existing literature has examined the impact of the coronavirus disease (Covid-19) pandemic on business failure, highlighting firms' internal characteristics. However, information on changes in firms' external environments remains scarce. This study examines whether Covid-19 has also influenced the spatial co-locational patterns of business failure processes. Therefore, the authors apply symbolisation techniques to identify different business failure processes during pre- and post-covid periods. In addition, the authors compute the Q(m) spatial dependence test for categorical variables to identify differences in the co-location patterns before and after covid. The studie find significant differences in the spatial association of business failure processes, which are further understood when the authors examine sectoral differences.

Introduction

The Covid-19 health crisis has caused financial disruptions to productive activities. Commercial transactions of companies have sharply decreased owing to government restrictions on social interaction to control contagion (Baqaee–Farhi 2020). This has motivated many recent studies to determine the effects of covid on companies' productive systems (Ramelli–Wagner 2020). These studies examined the impact of Covid-19 based on firms' internal characteristics and, specifically, their financial variables. Ramelli–Wagner (2020) found a negative relationship between returns and debt and a positive link between cash holdings and stock returns during the covid crisis. De Vito–Gomez (2020) analysed the time when firms with limited operating flexibility are operative before they use cash reserves. Pagano et al. (2020) indicated that firms whose productive activities do not require social distancing experienced smaller decreases in stock prices. Furthermore, Fahlenbrach et al. (2021) showed that the pandemic had less impact on firms with more financial capacity. Previous studies have considered the effects of Covid-19 from an internal business perspective, but

studies including external geographical factors are practically non-existent in this context.

Geography is a key element in various areas of business research. In the case of business failure models, some authors stated that failure is also caused by external variables (Everett–Watson 1998). Location characteristics that consider firms' proximity to one another have rarely been examined. Fernandes–Artes (2016) proposed a credit scoring model with spatial dependence among companies. Their proposal provides better adjusted results than the score without spatial interactions. Calabrese et al. (2017) showed that spatial interaction effects are significant in score models and improve their capacity to predict business failure. Mate-Sanchez-Val et al. (2018) determined the presence of significant spatial interaction effects and geographical proximities to evaluate the probability of business failure.

Following the literature, this spatial interaction effect could be motivated by the presence of knowledge spillovers among companies (Zdanowska et al. 2020). Physical proximity among companies facilitates intercompany information exchanges. Thus, geographical proximity eases the diffusion of social capital, increasing firms' capacity to share knowledge and learn from external information (Karlsson et al. 2015). CEOs in common locations tend to build face-to-face relationships, share experiences, and learn from each other's management practices. Thus, positive spillover effects exist in these environments that provide direct information to geographically close companies. They can use this external knowledge to pursue managerial success (Maskell 2001). The literature on imitation also states that companies tend to follow the management practices of neighbouring companies with better market positions (Leary–Roberts 2005). Informational asymmetries provide more incentives to companies to create relationships with geographically-close firms to overcome their information deficits and adopt better-informed decisions (Carreira–Silva 2010).

The present study aims to evaluate the geographical effects of spatial distribution on business failure processes by comparing pre- and post-covid periods. Particularly, we apply a symbolisation process to identify business failure processes and use the Q(m) spatial dependence test to evaluate whether the spatial distribution of business failures has changed over this period. We apply symbolisation techniques to a sample of companies located in Madrid (Spain). Our study answers the following research questions: Are there significant geographical co-localised trends in the territorial distribution of business failure? If so, are there differences in this spatial behaviour when we compare pre- and post-covid periods? The answers to these research questions provide further insight into the role geography plays in business behaviour. Policymakers can use this information to design regional policies focused on mitigating the negative effects of the covid pandemic or any other unexpected crisis in specific areas.

In addition, identifying the spatial behaviour of specific types of business failures will allow local governments to implement financial policies to reduce their incidence.

Our study contributes to the business literature by providing further evidence on the kinds of business failure processes related to the Covid-19 pandemic. The spatial dimension is crucial in this context. It adds further understanding of the economic consequences of the covid crisis in an urban context, determining whether it has had a disproportionate impact in specific environments. Unlike the previous economic crises, the Covid crisis had unpredictable and uncontrolled characteristics. Therefore, with the aim of overcoming these unexpected market conditions in the case of a pandemic in the future, it is important to analyse business failure processes during the Covid crisis as well as its geographic dimension (Nyikos et al. 2021). In this study, in addition to characterising different business failure processes, we analyse their spatial clustering patterns and compare them with the pre-Covid period. Our findings show the different co-location patterns of business failures.

The remainder of this paper is organised as follows. The each sections presents the symbolisation methods applied to identify the business failure processes and spatial co-location patterns, the database and the variables, the results, and the discussion and conclusions of this study.

Methods

Identifying business failure processes

To identify business failure processes, we used qualitative techniques. Our proposal was derived from a fuzzy qualitative comparative analysis (fsQCA) (Ragin, 1987, 2000) to determine the set of financial conditions that cause failure. Unlike fsQCA, we built a true table by assigning values of 0 or 1 to each explanatory variable according to a previously estimated threshold. These thresholds were computed through an algorithm using the classical Chow test (Chow 1960). These values were applied to identify structural changes in each financial ratio distribution when failed and non-failed companies were examined. Based on these thresholds, we applied symbols to each examined financial ratio (R1, R2, R3, R4, R5) using a set of 32 symbols. Symbolising financial ratios provided a general perspective on firms' financial patterns. We analysed these patterns before and after the covid pandemic.

Specifically, we considered a collection $\Gamma = \{(0,0,0,0,0); (1,0,0,0,0); \ldots; (1,1,1,1,1)\}$ of all the 5-tuples, with values $\{0,1\}$ in each entry. The cardinality of Γ is 32, and each tuple is called a symbol. In our case, for each financial ratio R_i ($i = 1, 2, \ldots, 5$), we took D_l^i, ($l = 1, 2, \ldots, 9$) as the l-th decile that splits each financial ratio distribution R_i into ten equal frequency intervals. Taking these decile values, we split the sample of companies into two parts, one composed of companies verifying that $R_i \leq D_l^i$ and the other group is made up of the remaining companies. For these groups, we computed a Chow test where the dependent variable is the dichotomous variable representing firm failure (0 non-failed and 1 failed), and we included five financial ratios (R_1, R_2, R_3, R_4, R_5) as explanatory variables. We chose the deciles that provide the maximum

Chow test value, termed $\mathfrak{D}^i$. This process improves on the previous fsQCA method because it objectively identifies the thresholds at which each financial ratio impacts the condition of business failure.

Based on this process, we proposed a symbolization map $S\colon \mathbb{R}^5 \to \Gamma$ determined by

$$S(x_1, x_2, x_3, x_4, x_5) = (\mathfrak{T}^1(x_1), \mathfrak{T}^2(x_2), \mathfrak{T}^3(x_3), \mathfrak{T}^4(x_4), \mathfrak{T}^5(x_5)) \qquad (1)$$

with

$$\mathfrak{T}^i(a) = \begin{cases} 1 & \text{if } a > \mathfrak{D}^i \\ 0 & \text{otherwise} \end{cases} \qquad (2)$$

an indicator function that takes a value of 1 when its argument is larger than the corresponding decile $\mathfrak{D}^i$. The symbolisation procedure S transforms a vector defined by the five financial ratios into a 5-tuple symbol for each firm:

Finally, to identify business failure processes, we performed clustering on the S map of symbols using the k-means algorithm based on the Hamming distance. From this process, we obtained a set of failed companies with similar financial characteristics, identified by symbolisation.

Spatial dependence Q(m) test of qualitative data

The Q(m) test applies symbolic dynamics to analyse discrete processes (Ruiz et al. 2010). Thus, this test is proposed to contrast the spatial dependence in spatially discrete events. To undertake the symbolisation process, the researcher defines a space in which different states of a system are considered. Each state has only one representative point in space. This space is then split into a finite number of parts, each of which can be identified using a different letter. Apart from the capacity to determine spatial associations, this statistic allows us to identify specific patterns of spatial associations that can be tested with different interpretations of the spatial behaviour of business failure processes.

Dataset and variables

We used the Iberian Balance Sheet Analysis System (SABI) database to obtain a sample of companies, taking financial information from their financial statements from 2017–2020. This sample comprised 30,101 firms with available information. From this sample, we defined failed companies as those in legal bankruptcy processes (Zorn et al. 2017). Our sample consists of 1,421 failed companies (498 in 2018, 463 in 2019, and 460 in 2020) whose bankruptcy processes were filed at the end of 2018, 2019, and 2020. We considered firms' financial ratios as applied in Altman's (1968) Z-score model. Table 1 lists the definitions and average values.

Table 1

Variables and descriptive statistics

	Definition	Interpretation	Average values (sd)	
			Failed	Non-Failed
BF	Business failure	Companies that have filed for bankruptcy in the corresponding year and have available information	1,421 companies	28,680 companies
R1	Working capital to total assets	Firms' working capital represents their financial situation in the short term. A positive ratio indicates that the company can face its short-term financial obligations.	0.0268 (0.992)	0.0450 (0.855)
R2	Retained earnings to total assets	A high ratio of retained earnings to total assets shows that the company applies retained earnings to finance capital expenditures.	0.0320 (0.821)	0.0375 (0.801)
R3	Earnings before interest and taxes (EBIT) to total assets	This evaluates a firm's capacity to generate profits only from its own activity	0.0495 (0.723)	0.0425 (1.0476)
R4	Total assets to total liabilities	A high R4 is interpreted as a high level of investor confidence in the financial stability of the firm	2.9187 (1.751)	3.8299 (1.551)
R5	Sales to total assets	A high R5 means that management needs little investment to generate sales, which increases the overall profitability of the company	1.2973 (1.739)	2.5751 (2.060)

Descriptive statistics per year. Average values and standard deviations in brackets

	2018	2019	2020
R1	0.0819 (0.872)	0.1063 (0.866)	0.1248 (0.894)
R2	0.0215 (0.854)	0.0214 (0.798)	0.0260 (0.955)
R3	0.0160 (0.913)	0.0415 (0.837)	0.0443 (0.853)
R4	0.5697 (0.992)	0.7505 (0.991)	0.8037 (0.981)
R5	1.4583 (0.945)	1.5000 (0.961)	1.5152 (0.943)

Results

Business failure processes

We applied the proposed algorithm based on Chow tests to identify the thresholds indicating the signs for each company in the sample. Based on this result, we employed a clustering k-means process with Hamming distance to classify companies into different business failure processes. We applied this procedure to pre- and post-covid samples. Table 2 presents the financial characteristics of each group.

Table 2

Clustering processes

Panel A. Cluster characterization		
Cluster	Centroid[a]	Interpretation
Cluster 1	1 0 1 0 1	Firms that are highly dependent on external financial resources and are undercapitalized
Cluster 2	0 1 1 0 1	Firms with financial rigidities and scarce capitalization
Cluster 3	0 0 0 0 1	Firms with financial rigidities, great dependence on external financial resources, and scarce capacity to create profit from their productive activity.

a) We found similar centroids for each year of the analysed period, 2018–2020.

Geographical distribution of business failure processes

Figure 1 shows the spatial distribution of previously detected business failure processes during the pre- and post-covid periods.
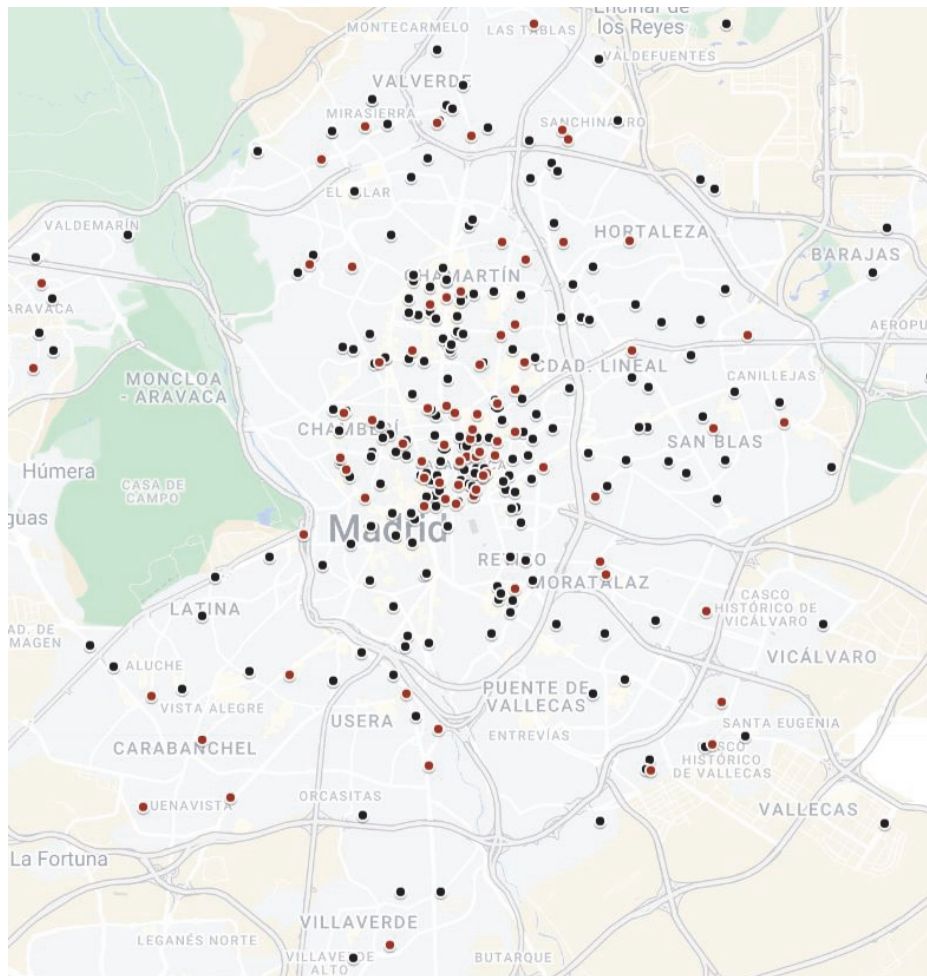
The figure above shows a change in the geographical distribution of business failures in clusters 1 (Figure 1. Panel A) and 2 (Figure 1. Panel B), and 3 (Figure 1. Panel C) pre- and post-covid. We found a spatial concentration of companies with business failure processes in cluster 3 during the pre-covid period, whereas this behaviour disappears in the post-covid period. In contrast, the business failure processes of cluster 1 do not show a spatial concentration during the pre-covid period, but this behaviour becomes evident after the crisis. This result coincides with previous studies that demonstrated the existence of spatial concentration among companies in bankruptcy (Mate-Sanchez-Val et al. 2018). In addition, we identify different types of business failure processes. We found that during the pre-covid period, spatially concentrated failed companies are characterised by financial rigidities, are highly dependent on external financial resources, and have little capacity to create profits from their productive activities. During the post-covid period, spatial concentration appears for companies that present the business failure processes of cluster 1. These companies are highly dependent on external financial resources and have low capitalisation values. Thus, Figure 1 shows co-localised trends in the

territorial distribution of business failure processes geographically, with differences between pre- and post-covid periods. In the next section, we examine the significance of the co-location effects.

Figure 1

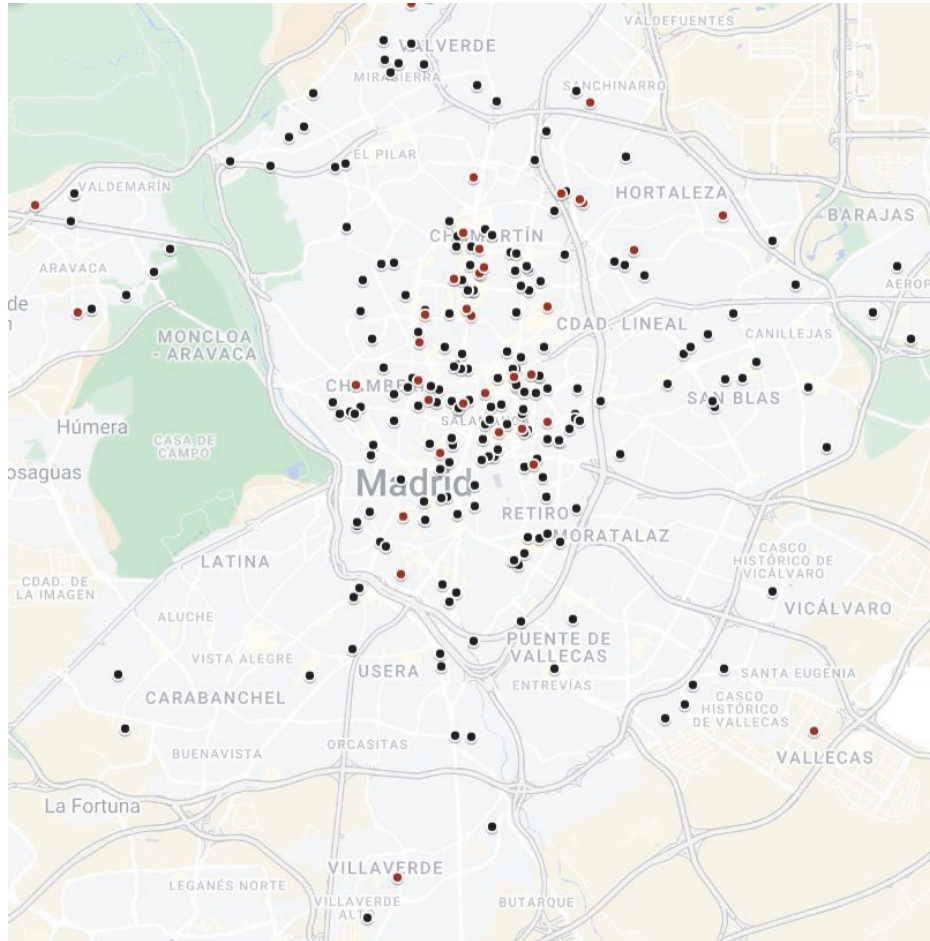## Geographical distribution of business failure processes pre- and post-covid

Panel 1: Business failure. Cluster 1

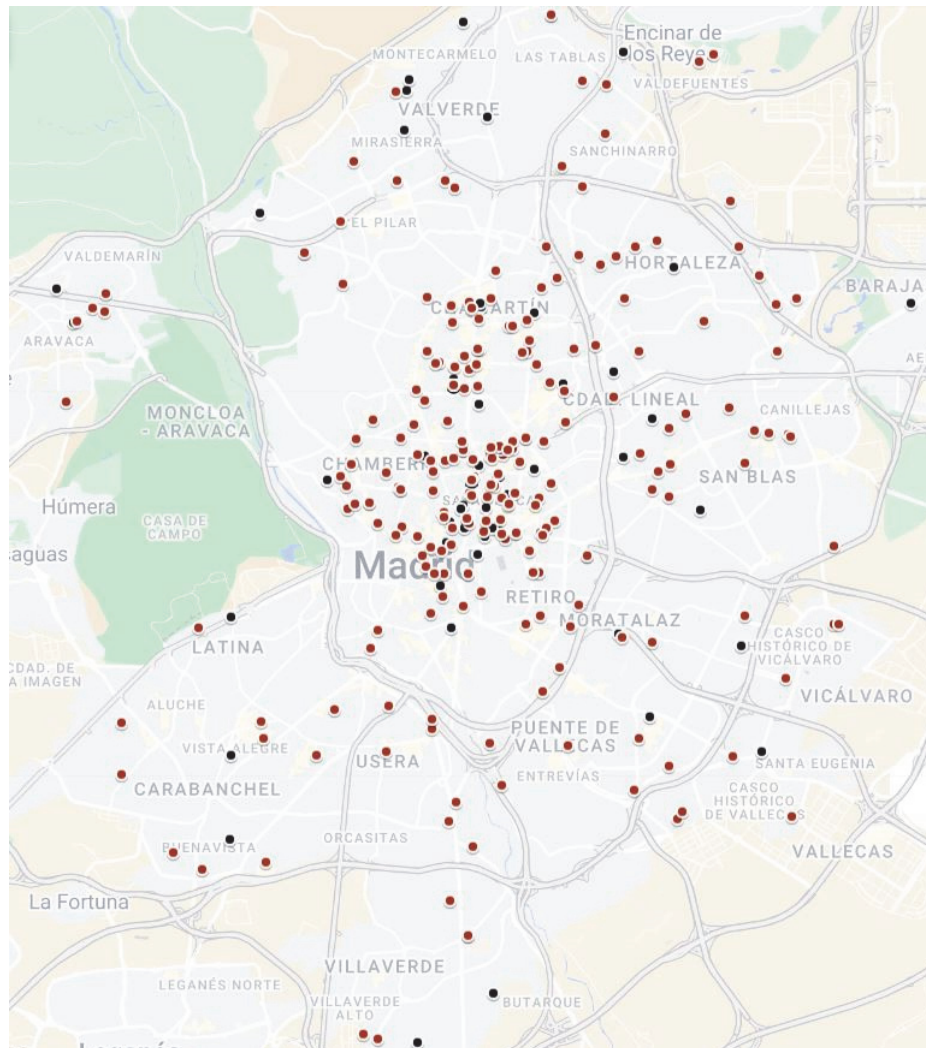*(Figure continues on the next page.)*

(Continued.)

Panel 2: Business failure. Cluster 2

(Figure continues on the next page.)

(Continued.)

Panel 3: Business failure. Cluster 3

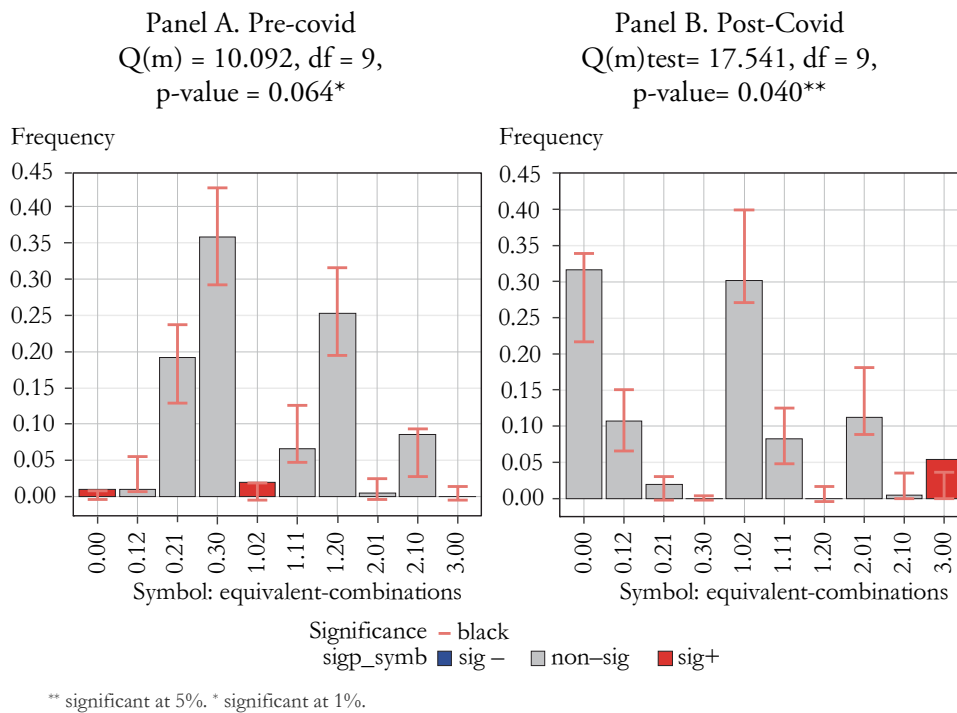*Note:* Black dots represent pre-covid and red dots post-covid period.

Pre- and post-covid spatial patterns applying the Q(m) spatial dependence test for qualitative data

Figure 2 shows the results of the Q(m) tests during the pre- and post-covid periods. Specifically, the Q(m) tests find spatial co-location patterns for pre- and post-covid periods. However, we found that the significance of this pattern is greater for the post-covid period (Q(m)test= 17.541**). As the Q(m) statistic is based on the

frequency of different symbols being observed, it provides further information on the types of spatial dependence structures in business failure processes during the examined period. This representation is presented in Figure 2. In Panel B, we show the histogram of the frequency of the 10 symbols corresponding to the combinations of business failure processes that could appear in the examined variable. We selected the free parameter m to be 3. Note that, given the sample size and the number of possible co-locations increases as a power of m, the value $m = 3$ is the largest for the probability of a given co-location to be statistically distinguishable from chance. We applied the R package spqdep to compute Q(m) tests and the graphical analysis.

Figure 2

Q(m) test results

Panel A. Pre-covid
Q(m) = 10.092, df = 9,
p-value = 0.064*

Panel B. Post-Covid
Q(m)test= 17.541, df = 9,
p-value= 0.040**

** significant at 5%. * significant at 1%.

During the covid post period, the significant and positive symbol with a spatial dependence structure is (3 0 0), which represents the number of spatially co-located observations of business failure processes in cluster 1 (Symbol=1 0 1 0 1). This cluster comprises companies that are highly dependent on external financial resources and have low capitalisation values. This result adds to the literature. Fahlenbrach et al. (2021) indicate the importance of companies' financial capacity, highlighting that firms with better financial situations are in better positions to overcome crises. We concluded that these companies tend to be geographically concentrated. Thus, we

identified the spatial co-location patterns of business failure processes (Fernandes–Artes 2016, Calabrese et al. 2017, Mate-Sanchez-Val et al. 2018). This is explained by previous literature, which establishes the mechanisms that give companies incentives to follow the financial practices of companies in their geographically close surroundings (Leary–Roberts 2005, Carreira–Silva 2010).

Discussion and conclusions

This study examines the impact of geography on business failure processes in the context of the pandemic. We proposed a procedure to identify different business failure processes based on symbolisation and clustering processes. These were examined from a spatial perspective, resulting in significant spatial co-location patterns. We conclude that there are significant spatial co-location patterns of business failure processes differ when we compare the pre- and post-covid periods. During the pre-covid period, we found geographically close companies with the business failure processes of cluster 3. In the post-covid period, spatially concentrated companies present business failure processes in cluster 1. Cluster 1 corresponds to companies with little financial flexibility and low capitalisation. This coincides with previous financial studies that highlight the relevance of firms' financial flexibility during the pandemic, but also adds to the literature in several ways. First, the symbolisation process indicates that financial flexibility has to be combined with adequate capitalisation to be able to face unexpected crises, such as those caused by covid. Second, geography plays a relevant role in the way companies went bankrupt during the pandemic.

Our study highlights the relevance of local policies that encourage companies to maintain large cash flow positions to survive unexpected demands. Information and dissemination campaigns on the positive results of adequate financial policies could encourage companies to undertake preventive management practices. In addition, spatially concentrated areas of companies with similar business failure processes can guide local policies to increase the probability of business survival in certain areas. Policymakers should provide financial entities with a culture based on financial flexibility. Local investors can be encouraged to participate in companies at specific locations. Despite our results, further studies should focus on other territories to confirm the significance of spatial co-location patterns in business failure processes.

Acknowledgements

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