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Unveiling the pandemic's impact: Did COVID-19 drive business failures? A Cutting-Edge Analysis with Spatial Autoregressive Modelling

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Abstract:

The objective of this study is to estimate the impact of Covid-19 on business behavior and its spatial effect among companies. Four specifications have been developed to analyze the pandemic's influence on key variables determining business behavior: liquidity, indebtedness, profitability, and efficiency. This study has focused on the province of Barcelona, Spain, from which a database of failed and non-failed companies has been compiled, both before and after the pandemic. The models have been estimated using the spatial Seemingly Unrelated Regressions (SUR) methodology, and each equation was estimated following a spatial Differences-in-Differences model. The results confirm that the emergence of Covid-19 has had a significant impact on companies' financial ratios, worsening their positions in terms of liquidity, indebtedness, and efficiency, with the existence of a spatial contagion pattern.

Keywords: Business failure; covid; Differences-in-Differences; current ratio; debt ratio; profitability; efficiency; spatial dependence.
JEL Classification: C01; C14.

Revelando el impacto de la pandemia: ¿La COVID-19 provocó fracasos empresariales? Un análisis de vanguardia con modelado autorregresivo espacial

Resumen:

El objetivo de este estudio es estimar el impacto de la Covid-19 en el comportamiento de las empresas y su efecto espacial entre empresas. Se han desarrollado cuatro especificaciones con el fin de analizar la influencia de la pandemia en las variables clave que determinan el comportamiento de las empresas: liquidez, endeudamiento, rentabilidad y eficiencia. Este estudio se ha centrado en la provincia de Barcelona, España, de la cual se ha compilado una base de datos de empresas fracasadas y no fracasadas, antes y después de la pandemia. Los modelos se han estimado utilizando la metodología multi-ecuacional SUR espacial y cada una de las ecuaciones fue estimada siguiendo un modelo espacial de diferencias en diferencias. Los resultados obtenidos confirman que la aparición de la Covid-19 ha tenido un impacto significativo en las ratios financieras de las empresas empeorando sus posiciones en relación a la liquidez, endeudamiento y eficiencia de las empresas con la existencia de un patrón de contagio espacial.

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Palabras clave: Fracaso empresarial; Covid; Diferencias en Diferencias; liquidez; endeudamiento; rentabilidad; eficiencia; dependencia espacial.
Clasificación JEL: C01; C14.

1. Introduction

The Covid-19 pandemic has profoundly impacted global societal and economic structures, posing a significant threat to the viability of numerous businesses worldwide, especially in service-oriented economies and nations heavily reliant on international trade (Fernandes, 2020; Wenzel et al., 2021). Policymakers' measures to curb the virus's spread have led to widespread economic contractions, increases in unemployment rates, and a decline in consumer demand, creating a complex web of challenges for businesses (He & Wang, 2022; Melnyk et al., 2021). While some companies have demonstrated resilience, others have faced significant setbacks, particularly in sectors such as hospitality, retail, and entertainment (Bartik et al., 2020; Coad et al., 2023).

Nevertheless, the existing body of research examining the impact of Covid-19 on corporate financial behavior is relatively limited, leaving a significant gap in our understanding of this topic. Most studies to date have predominantly focused on internal factors, such as operational efficiency, liquidity management, and cost structures, that influence business performance during the pandemic. While these internal dynamics are undoubtedly crucial, they offer an incomplete picture of the multifaceted challenges businesses face in the current environment. Conversely, there has been a relative scarcity of research that explores the role of external factors, including market conditions, regulatory changes, supply chain disruptions, and shifts in consumer behavior, in shaping corporate financial outcomes during the pandemic. Notable exceptions to this trend include the study by Ruiz-Marín et al. (2023), which highlights the importance of examining changes in firms' external environments in relation to business failure during the pandemic.

In this context, the aim of our study is twofold: first, to investigate whether the Covid-19 pandemic has affected on the probability of business failure by quantifying the causal effect, comparing the financial behavior of distressed and non-distressed companies, and observing their interactions with variables that are considered to condition their behavior in terms of business performance; and second, verify if firms environmental characteristics impact on the spread of this crisis. To get this purpose, we develop an empirical application on a sample of companies located in Barcelona (Spain) due to its economic diversity and significance as a major business center in Spain. Based on this dataset, we apply a multi-equational spatial SUR model where each equation follows a spatial Differences-in-Differences (DiD) specification. This methodology allows us to determine whether the COVID pandemic has caused further financial differences when healthy and unhealthy companies are examined (Puhani, 2012). In addition, this methodology contrasts the impact of environmental characteristics on the financial conditions of each company. We consider whether the financial characteristics of neighbor companies impact on the financial distress of each company in the sample.

This study is structured as follows: first, we present a review of the previous literature, second, we show a detailed description of the applied methodology and describe the datasets and variables. The third section introduces the results and finally, we expose the discussion and conclusions of this study.

2. Business failure: The effects of Covid-19 on business behavior and spatial considerations

2.1. Effects of Covid-19 on business behavior

From a global perspective, the Covid-19 pandemic has exerted profound and far-reaching effects, reshaping both societal structures and the economic frameworks. The crisis poses a severe threat to the viability of countless businesses across the globe (Wenzel et al., 2021). Particularly vulnerable are business situated in service-oriented economies or nations heavily reliant on international trade, where disruptions in supply chains and decrease consumer demand have shaken their economic stability (Fernandes, 2020). Additionally, the pandemic's impact has disproportionately affected in countries with underdeveloped healthcare systems, fragile financial structures, and institutional deficiencies, exacerbating pre-existing vulnerabilities and widening economic disparities among nations (Hu & Zhang, 2021).

At the macroeconomic level, the repercussions of the Covid-19 pandemic have been substantial and multifaceted, reshaping the global economic landscape in profound ways. This impact can largely be attributed to the stringent measures imposed by policymakers to curb the spread of the virus. While these measures have been essential for safeguarding public health, they have led to a widespread contraction in GDP (Melnyk et al., 2021). The pandemic has triggered a cascade of economic challenges, including elevated levels of unemployment as businesses grapple with reduced operations and closures. The labor market has been significantly impacted, with many sectors experiencing layoffs and job losses due to decreased consumer demand and operational constraints (He & Wang, 2022). Additionally, the pandemic has fueled inflationary pressures, driven by supply chain disruptions, increased production costs, and heightened consumer demand for essential goods and services. These inflationary pressures have further strained household budgets and diminished purchasing power, contributing to a broader economic downturn. Moreover, the pandemic-induced economic downturn has led to a substantial decline in consumer demand across various sectors, as consumers prioritized essential spending and adopt more cautious consumption patterns. This diminished demand has placed additional financial strain on businesses, particularly those operating in non-essential sectors, further exacerbating their weakness, and increasing the likelihood of business closures (Melnyk et al., 2021).

At the microeconomic level, the impact of Covid-19 on firms has manifested in diverse and often contrasting ways, reflecting the inherent vulnerabilities and strengths within different business sectors. Companies that were already experiencing declining growth prior to the pandemic have found themselves particularly vulnerable to the economic shocks induced by Covid-19, struggling to maintain operations and financial stability amidst reduced demand and operational constraints (Coad et al., 2023). Conversely, firms in a phase of expansion prior to the pandemic have exhibited greater resilience, leveraging their growth situation and adaptive capabilities to face the challenges posed by the crisis more effectively. These firms have demonstrated agility in adjusting their business models, reallocating resources, and tapping into new market opportunities to sustain growth and mitigate the adverse impacts of the pandemic (Coad et al., 2023).

Furthermore, certain sectors have been disproportionately affected by the pandemic, with firms operating in the hospitality, retail, personal services, entertainment, and arts sectors bearing the brunt of the economic downturn (Bartik et al., 2020). These sectors have experimented significant disruptions due to lockdown measures, social distancing protocols, and reduced consumer spending, leading to widespread closures, layoffs, and financial distress among businesses within these industries. In fact, empirical evidence from a study conducted by Fairlie (2020) has highlighted a marked increase in the number of businesses succumbing to the pandemic's impact during its early stages. This observation aligns with the concept proposed by Caballero & Hammour (1991), suggesting a cleansing effect on the business landscape in the aftermath of recessions, where weaker and less resilient firms are more likely to exit the market, making way for more adaptive and robust businesses to emerge and thrive.

2.2. Geographical proximity and business performance

The business environment is intricately shaped by a combination of inherent traits that define its operational reality and the dynamic interplay among the various agents engaged in the economic process. This interconnectedness often leads to contagion effects among firms, where decisions made by one company can have significant effects, influencing the decisions and outcomes of other companies within the business ecosystem (Vivel-Búa & Lado-Sestayo, 2023). These contagion effects can be conceptualized as the phenomenon through which a change in one company is transmitted and impacts another firm, reflecting the complex web of relationships and dependencies that exist within the business environment. The extent and nature of these contagion effects are closely linked to the physical spatial proximity between firms (Calabrese, 2023). Geographical closeness has long been recognized as a catalyst for knowledge creation and exchange in the business context, facilitating information flows and collaborative interactions (Maskell, 2001). This proximity-driven knowledge exchange is particularly evident in the formation and dynamics of business clusters, where firms within the same sector tend to cluster together to leverage shared resources, expertise, and market opportunities (Audretsch, 2003; Kronenberg, 2013). Thus, companies located in close proximity to one another are more likely to benefit from knowledge spillovers, as they can easily access and share valuable insights, best practices, and innovative ideas with their neighboring firms. This collaborative environment fosters creativity, drives innovation, and enhances the overall competitiveness of the cluster, creating a synergistic effect that amplifies the growth potential and resilience of the businesses operating within it.

The physical proximity to suppliers and clients has also been proven to be important in terms of productivity and performance, both at inter and intraregional level. This underscores the importance of not just clustering but also the closeness of relationships between business. Oerlemans & Meeus (2005) delve into the significance of proximity among firms in fostering innovation. This perspective is echoed by Di Minin & Rossi (2016), who argue that firm clustering facilitates a continuous flow of information. Given the ease of exchanging human capital between clustered firms, these businesses are more likely to thrive.

While clustering can indeed bolster the prospects of success by facilitating collaboration and knowledge exchange among firms, it simultaneously poses an elevated risk of failure. Maté-Sánchez-Val et al. (2017) provide empirical evidence supporting this notion, revealing a significant correlation between the likelihood of business failure and the proximity of firms. This idea is further reinforced by Ruiz-Marín et al. (2023), who observe a pattern wherein financially constrained companies tend to cluster together, especially in the aftermath of disruptive events like the Covid-19 pandemic. Such clustering may inadvertently intensify vulnerabilities within these firms, potentially leading to cascading failures. Thus, in the context of the Covid-19 pandemic, the concept of contagion extends beyond the realm of public health to economic sectors. Contagion effects have been a focal point of research across various domains, with studies even exploring their impact on stock markets (Gunay & Can, 2022). Intriguingly, these effects have been disproportionately felt in developed nations compared to their emerging counterparts. Moreover, Western countries have exhibited a more pronounced susceptibility to these contagion effects than Eastern nations, suggesting varied resilience and response mechanisms across global regions (Iwanicz-Drozdowska et al., 2021).

3. Methodology

3.1. Differences in differences model

In this study, we apply a quasi-experimental analysis using the Differences in Differences (DiD) estimator to determine if there is a causal effect between the onset of the Covid-19 pandemic and the probability of business failure. Our analysis deeply delves into characterizing the financial situation of companies experiencing business failure both before and after the pandemic. The DiD methodology serves as the cornerstone of our analytical framework, which involves comparing four distinct groups: the treatment group after the event (post-pandemic), the treatment group before the event (pre-pandemic), the control group before the event, and the control group after the event (Lechner, 2010).

To operationalize this methodology, we formulate the following equation (1):

$$Y_{it} = \alpha_0 + \alpha_1 Time_t + \alpha_2 Treatment_i + \delta(Time_t * Treatment_i) + \beta X_{ikt} + \varepsilon_{it} \tag{1}$$

where Y_{it} represents the dependent variables of the observation i, $i = 1, 2, 3, \dots, M$ in the period t, with $t = \{0,1\}$, depending on whether the observation is pre-covid ($t = 0$) or post-covid ($t = 1$). $Time_t$ is a dummy variable that shows if the observation is allocated before ($Time = 0$) or after the event ($Time = 1$). $Treatment_i$ is a dummy variable that shows if the observation belongs to the treatment group ($Treatment_i = 1$) or to the control group ($Treatment_i = 0$). In this study, we consider the treatment group represents failed companies. $Time_t * Treatment_i$ is the interaction between event and groups and shows the differential effect of the event (onset of Covid-19) on the dependent variables between the treatment and control groups. X_{ikt} is a matrix of k variables that are known to influence those that may indicate business failure and i observations. α_0, α_1, α_2, δ, β are the parameters of the model to be estimated. ε_{it} is the error term.

The coefficient δ captures the causal effect of the onset of Covid-19 on the dependent variable. This coefficient will indicate the effect of being a failed company after the treatment period (Covid-19) in each of the dimensions that can be indicative of failure.

The assumptions of this model are based on a correct specification of the model, the absence of heterogeneity, and the assumption that, in the absence of the event, the trend between the treatment group and the control group would be similar[1].

3.2. Spatial Seemingly Unrelated Regression (SUR)

Due to the nature of the financial ratios and the interrelationships among them, a cross-sectional influence is assumed (Lev & Sunder, 1979). In this particular case, also financial information from different periods in time has been considered, as the existence of a casual effect in the financial behavior between failed and non-failed companies due to the onset of the Covid-19 pandemic is being examined. Thus, the residuals of the model will also be assumed to contain a time-inertia element amongst the financial ratios (Ioannidis et al., 2003), so we propose a Seemingly Unrelated Regression.

Additionally, we apply spatial econometric tools to reflect the territorial interaction between the observations by assuming that the observed value of i affects j. The proposed model in equation (2) shows the SUR model adapted to a Spatial Lag Model (SUR-SLM) (Mínguez et al., 2022):

$$Y_{it} = \alpha + \rho W^* Y_{it} + \beta X_{ikt} + \varepsilon_{it}; \;\; \varepsilon \sim N(0, \Omega) \tag{2}$$

where Y_{it} represents a $NM \times 1$ column matrix, for N representing each model and M representing the total number of observations. X_{ikt} is a $NM \times NQ$ diagonal matrix, for N representing each model, M representing the total number of observations, and Q representing the number of variables. β is a $NQ \times 1$ column matrix of coefficients to be estimated in the model. $W^* Y_{it}$ represents the dependent variable spatially lagged by the weighted neighboring matrix W^*, being $W^* = I_M \otimes W$, where I_M is the identity matrix, $\otimes$ is the Kronecker product, and W is the matrix of spatial weights. ρ represents the spatial interaction coefficients, where a positive coefficient indicates spatial concentration of observations by values. α is a vector of intercepts.

As we assume the residuals are correlated amongst the models, then $\Omega = \Sigma \otimes I_M$, where $\Sigma = \sigma_{ij}$ is a $N \times N$ variance covariance matrix, $\otimes$ denotes the Kronecker product and I_M is the identity matrix. The SUR-SLM estimation has been estimated using R package "spsur".

4. Dataset and variables

4.1. Dataset

The financial and accounting data, as well as the geographical information of every firm, used in this study were collected from the Iberian Balance Analysis System (SABI) database, which encompasses various financial metrics such as the number of employees, company size, age, balance sheet, and profit and loss statements of Spanish and Portuguese firms. To narrow down the scope of our study, we filtered the dataset to exclusively include companies located in the province of Barcelona, Spain, and industrial firms, based on the National Classification of Economic Activities (Eurostat). This region was selected due to its unique characteristics related to business fabric, infrastructure, demography, geographic location, and institutional framework. Additionally, we identified the legal status of each company, distinguishing between active

[1] Graphical tests have been carried out on the residuals, and a similar trend between both groups before the event has been confirmed.

firms and those that had ceased operations, with the latter being classified as business failures. Given the study's focus on examining changes before and after the Covid-19 event, an issue arose concerning observations that transitioned from active to failed status over time. To address this, we divided the primary dataset into two distinct databases: one containing pre-event data and the other post-event data. For this data we collect information for the period 2015-2022.

4.2. Variables

4.2.1. Dependent variables

To comprehensively characterize the financial health of the examined companies, we selected various financial ratios representing key dimensions of a business. These ratios have been widely recognized in the literature for their predictive power in identifying financial distress. Specifically, we focused on the following key ratios representing the different financial dimensions of the company: Current Ratio, Long-Term Debt to Total Assets, and EBIT (Earnings Before Interest and Taxes) to Total Assets (Altman, 1968; Beaver, 1966; Liou & Yang, 2008; Xu et al., 2014; Zavgren, 1985).

The Current Ratio, expressed as current assets divided by current liabilities, serves as a barometer of short-term liquidity. This ratio assesses a firm's capacity to meet its short-term financial obligations using its readily available assets. The Long-Term Debt to Total Assets ratio provides a measure of a company's leverage and financial risk. It calculates the proportion of a firm's assets that are financed through debt, as opposed to equity, by dividing total debt by total assets. The EBIT to Total Assets ratio offers insights into a company's profitability and operational efficiency. It indicates the amount of profit generated for each euro of assets employed in the business. Additionally, we included the Assets Turnover ratio to assess operational efficiency (Altman, 1984; Serrano-Cinca et al., 2019). This ratio measures how effectively a company utilizes its assets to generate sales, offering valuable insights into operational productivity.

4.2.2. Explanatory variables

We consider the firm size, measured as the natural logarithm of total assets. Previous research has identified firm size as a key determinant influencing the likelihood of business failure, with larger firms generally exhibiting greater resilience (Altman, 1968; Altman et al., 1995; Back, 2005; Honjo, 2000; Maté-Sánchez-Val et al., 2018). Next, we incorporated the degree of internationalization, represented by a variable labeled "Inter." Existing literature has highlighted the significance of international engagement in determining the probability of business distress (Lee et al., 2012). To capture this dimension, we created a dummy variable distinguishing between firms engaged in any form of international relationships and those operating solely at a national level.

We also introduce the level of technological intensity within firms. This factor has been shown to be a crucial predictor of business distress (Mata & Portugal, 1999; Pittiglio & Reganati, 2015). Previous studies suggest that firms with higher technological intensity are more likely to survive (Esteve et al., 2004). We categorized firms into four levels of technological intensity: low, medium-low, medium-high, and high. Each observation was classified based on its NACE code and the classification provided by the Spanish National Institute of Statistics (INE). For the purposes of our model, we included the low, medium-low, and medium-high intensity categories, excluding high intensity to avoid the dummy variable trap.

Table 1.
Description of variables for DiD regression models

Variable	Description	Mean (σ)
Dependent Variables		
$Liquidity_0$	Current ratio for years 2015 and 2018, measured as the ratio of Current Assets to Current Liabilities	2.20 (1.75) 2.22 (1.71)
$Debt_0$	Long-term debt ratio for years 2015 and 2018, measured as the ratio of Total Debt to Total Assets	0.62 (0.28) 0.59 (0.26)
$Prof_0$	Profitability ratio for years 2015 and 2018, measured as the ratio of EBIT to Total Assets	0.09 (0.09) 0.09 (0.09)
$Turn_0$	Efficiency ratio for years 2015 and 2018, measured as the ratio of Sales to Total Assets	1.37 (0.82) 1.46 (0.87)
Independent Variables		
	Differences in Differences variables	n (%)
Treatment	1 if it belongs to treatment group, 0 otherwise	279 (4.69)
Time	1 if it belongs to after event group, 0 otherwise	2957 (49.77)
Treatment * Time	1 if it belongs to treatment group after the event, 0 otherwise	142 (2.39)
Control variables		
	Continuous variables	Mean (σ)
$Liquidity_1$	Current ratio for years 2017/2018/2019 and 2020/2021/2022, measured as the ratio of Current Assets to Current Liabilities	2.35 (1.83) 2.56 (1.93)
$Debt_1$	Long-term debt ratio for years 2017/2018/2019 and 2020/2021/2022, measured as the ratio of Total Debt to Total Assets	0.57 (0.27) 0.59 (0.27)
$Prof_1$	Profitability ratio for years 2017/2018/2019 and 2020/2021/2022, measured as the ratio of EBIT to Total Assets	0.09 (0.08) 0.07 (0.09)
$Turn_1$	Efficiency ratio for years 2017/2018/2019 and 2020/2021/2022, measured as the ratio of Sales to Total Assets	1.29 (0.68) 1.38 (0.79)
Size	Log of number of Total Assets	7.22 (1.76)
	Categoric variables	n (%)
Inter	1 if international, 0 otherwise	2639 (44.42)
Low	1 if low technology intensity, 0 otherwise	2353 (39.61)
Medium -Low	1 if medium-low technology intensity, 0 otherwise	2172 (36.56)
Medium - High	1 if medium-high technology intensity, 0 otherwise	1197 (20.15)

5. Results and discussion

We begin with the estimation of a Seemingly Unrelated Regression (SUR) model, where each equation represents a different financial dimension. The specification of each equation follows a Difference-in-Differences (DID) model, where the treatment group consists of failed companies and the control group consists of non-failed companies. The distinguishing event is the Covid-19 pandemic. The following table (Table 2) displays the results of the spatial dependency tests for this model[2].

The Lagrange Multiplier (or Rao's Score) tests for spatial dependence in the model. The probability values shown in Table 2 are significant in both LM Error test and LM Lag test. However, as in all the cases the probability value is smaller in LM Lag test, Florax & Folmer (1992) suggest that the best methodology to be applied is a spatially lagged dependent variable regression.

We have developed four models to test for a casual effect on the probability of business failure considering spatial dependence and a correlation of the residuals. Thus, a SUR-SLM model is applied. The specification of our SUR-DiD model is shown in equation (3):

$$Y_{it} = \alpha_0 + \alpha_1 Time_t + \alpha_2 Treatment_i + \delta(Time_t * Treatment_i) + \rho W^* Y_{it} + \beta X_{ikt} + \varepsilon_{it};\ \ \varepsilon \sim N(0, \Omega) \tag{3}$$

Equation (3) can be developed in four different models, one for each dimension observed, as shown in equations (4), (5), (6), and (7):

$$\begin{aligned}\text{Liquidity}_0 = {} & \alpha_0 + \alpha_1 Time_t + \alpha_2 Treatment_i + \delta(Time_t * Treatment_i) + \rho W^* \text{Liquidity}_0 \\ & + \beta_1 \text{Debt}_1 + \beta_2 \text{Prof}_1 + \beta_3 \text{Turn}_1 + \beta_4 \text{Size} + \beta_5 \text{Inter} + \beta_6 \text{Low} \\ & + \beta_7 (\text{Medium} - \text{Low}) + \beta_8 (\text{Medium} - \text{High}) + \varepsilon_{it}\end{aligned} \tag{4}$$

$$\begin{aligned}\text{Debt}_0 = {} & \alpha_0 + \alpha_1 Time_t + \alpha_2 Treatment_i + \delta(Time_t * Treatment_i) + \rho W^* \text{Debt}_0 \\ & + \beta_1 \text{Liquidity}_1 + \beta_2 \text{Prof}_1 + \beta_3 \text{Turn}_1 + \beta_4 \text{Size} + \beta_5 \text{Inter} + \beta_6 \text{Low} \\ & + \beta_7 (\text{Medium} - \text{Low}) + \beta_8 (\text{Medium} - \text{High}) + \varepsilon_{it}\end{aligned} \tag{5}$$

$$\begin{aligned}\text{Prof}_0 = {} & \alpha_0 + \alpha_1 Time_t + \alpha_2 Treatment_i + \delta(Time_t * Treatment_i) + \rho W^* \text{Prof}_0 + \beta_1 \text{Liquidity}_1 \\ & + \beta_2 \text{Debt}_1 + \beta_3 \text{Turn}_1 + \beta_4 \text{Size} + \beta_5 \text{Inter} + \beta_6 \text{Low} + \beta_7 (\text{Medium} - \text{Low}) \\ & + \beta_8 (\text{Medium} - \text{High}) + \varepsilon_{it}\end{aligned} \tag{6}$$

$$\begin{aligned}\text{Turn}_0 = {} & \alpha_0 + \alpha_1 Time_t + \alpha_2 Treatment_i + \delta(Time_t * Treatment_i) + \rho W^* \text{Turn}_0 \\ & + \beta_1 \text{Liquidity}_1 + \beta_2 \text{Debt}_1 + \beta_3 \text{Prof}_1 + \beta_4 \text{Size} + \beta_5 \text{Inter} + \beta_6 \text{Low} \\ & + \beta_7 (\text{Medium} - \text{Low}) + \beta_8 (\text{Medium} - \text{High}) + \varepsilon_{it}\end{aligned} \tag{7}$$

The results of the SUR-SLM test are shown in Table 3. The adequation in carrying out the SUR-SLM model is shown in the table: the Breusch-Pagan test shows strong significance, which means the null hypothesis is rejected. The null hypothesis states that in the variance covariance matrix only the main diagonal has non-null values. The Marginal Lagrange Multipliers (LMM) tests for omitted spatial effects in the specification of the model. In this case, the null hypothesis states that there are not omitted spatial effects in the model. However, as the coefficient is not significant, this means that after incorporating the spatially lagged dependent variable, there is no statistical evidence to confirm that there are omitted spatial values.

[2] We have considered several weight matrixes for the analysis. After a preliminary Moran I Test on the dependent variable for different k neighbors (k=4, 6, 8, 10), the values showing a higher Moran I statistic were k=4 and k=6, with minimal differences. These results are consistent with the Log-Likelihood coefficients that maximize the likelihood of the model. The matrix considered for the model is k=6 neighbors, as this presented a higher R^2 score.

TABLE 2.
Spatial Seemingly Unrelated Regression estimation

	Liquidity	Debt	Profitability	Efficiency
Intercept	5.415***	0.643***	0.078***	-1.076***
Treatment	2.776***	0.578***	-0.027**	-2.035***
Time	-0.033	-0.024***	0.001	-0.004
Treatment * Time	-0.729***	-0.195***	0.003	0.761***
Liquidity		-0.058***	0.002*	0.211***
Debt	-5.348***		-0.067***	3.050***
Prof	-6.275***	-0.031		3.095***
Turn	0.656***	0.154***	0.017***	
Size	-0.038*	-0.016***	0.004***	-0.047***
Inter	-0.073	-0.019*	-0.009**	0.118***
Low	-0.484***	-0.029*	-0.005	0.197**
Medium - Low	-0.449***	-0.045**	0.003	0.218**
Medium - High	-0.353**	-0.037*	-0.004	0.161*
ρ	0.094***	0.091***	0.076***	0.084***
Lagrange Multiplier test for spatial dependence (p-values)				
LM Error	3.625e-06	1.402e-10	9e-3	1.417e-10
LM Lag	2.116e-08	2.689e-12	5e-4	5.749e-12
Residual correlation matrix				
	1.000	0.348	0.012	-0.520
	0.348	1.000	-0.786	-0.667
	0.012	-0.786	1.000	0.121
	-0.520	-0.667	0.121	1.000
R^2 pooled	0.448			
Breusch-Pagan Test	5096***			
Jarque-Bera Test (p-value)	2.2e-16			
LMM Test	7.526			

Significance values: 0 (***), 0.001 (**), 0.01 (*), 0.05 (.)

We detected significant values for the DiD variable (Treatment*Time) across three of the examined models, namely liquidity, debt, and efficiency. This implies that the Covid-19 pandemic instigated shifts in the tendencies of these dependent variables, underscoring a causal impact on these financial dimensions.

In the Liquidity and Debt models, the DiD coefficients presented negative values. This suggests that firms experiencing distress in the aftermath of Covid-19 reported diminished values in both current ratio and long-term debt. Prior studies have consistently shown that distressed firms often display lower current ratios compared to their non-distressed counterparts, emphasizing its linkage with financial distress (Beaver, 1966; Chang et al., 2022). The pandemic appears to have intensified this negative trend, signifying heightened difficulties in accessing liquid assets or a deepening of pre-existing liquidity issues exacerbated by the crisis.

Concerning long-term debt levels, existing research has associated higher indebtedness with an augmented risk of business distress (Maricica & Georgeta, 2012; Maté-Sánchez-Val et al., 2018). Contrary to this trend, our findings indicate that post-Covid-19, distressed firms reported reduced indebtedness compared to their pre-pandemic levels. This may be attributed to constrained financing avenues post-Covid, coupled with firms' hesitancy to increase their debt burden (Paaso et al., 2023).

In the efficiency model, the DiD variable manifested a positive impact, as evidenced by the asset turnover ratio. This ratio has been inversely linked with business distress probability, suggesting that a higher ratio corresponds to a reduced distress risk (Ong et al., 2011). Remarkably, a significant positive coefficient emerged, suggesting that post-Covid-19, distressed firms demonstrated improved efficiency compared to their pre-pandemic operations. This could be interpreted as companies liquidating underutilized assets to mitigate the financial challenges arising from the pandemic.

The spatial effects, denoted by ρ in Table 3, were found to be statistically significant across all four models analyzed. A robust ρ coefficient serves as an indicator that companies located near each other demonstrate similar financial characteristics. This observation underscores a clustering phenomenon in the geographical distribution of firms, revealing that financial attributes tend to cluster together within certain geographical regions. This spatial clustering of financial traits can be interpreted in several ways. One possibility is that local economic conditions or regional industry trends might influence the financial health of companies operating within the same geographical area. Shared local challenges or opportunities could lead to companies in close proximity adopting similar financial strategies or facing similar financial risks. Moreover, this finding coincides with existing literature that has highlighted the role of physical proximity in shaping business outcomes. Studies by Calabrese (2023), Maté-Sánchez-Val et al. (2018), and Ruiz-Marín et al. (2023) have all suggested that geographic location can significantly impact the likelihood of business distress. For instance, companies operating in the same local market may face similar competitive pressures, regulatory environments, or access to resources, all of which can influence their financial stability.

6. Conclusions

The Covid-19 pandemic has affected the business sector in multiple ways, leading to negative consequences and requiring adaptation to mitigate the adverse effects. The first step in this case has been to determine whether the pandemic has indeed had a significant impact on these negative effects. To do so, we have developed a spatial regression model using the Differences-in-Differences (DiD) methodology applying a SUR method to determine if there was a causal effect between the outbreak of the pandemic and an increased probability of business distress and if there is concentration in the probability of business distress measured by liquidity, debt, profitability, and efficiency levels.

The conclusions obtained indicate that the pandemic has had a significant effect on variations in the overall liquidity, long-term debt, and turnover of assets of firms in the province of Barcelona. The model shows that these variables have suffered a greater variation amongst the group of firms with traits of business failure than those companies taken as control. This is an important key point, as this indicates that these companies presented after the pandemic lower rates of liquidity, which makes it more difficult to face debt short term debt levels; a decrease in long term debt, possibly due to the fact that the access to new credit became more difficult for financially distressed firms; and an increase in efficiency, which shows an interesting phenomenon, since previous literature state that this ratio is positively related to a good financial health. However, this finding suggests that, in some contexts, this ratio could not be a good estimator for business failure.

In addition, the model has shown that spatial proximity of firms seems to significantly affect their financial decisions, which may directly affect their survival. This can be interpreted as that the spatial proximity of firms with traits of poor financial health may increase their probability of business failure.

These results could be considered by policy makers and public institutions at a time at which subsidies and help are granted in those contexts where an exceptional situation like this occurs.

It is important to note that this study that additionally to increased effect of Covid-19 in the probability of business failure in those firms with a poor financial situation, these firms tend to cluster, so this is a key point to early detect financial distress. Perhaps the most significant limitation to consider is the data compilation. The data, as mentioned in section 4.1, have been downloaded from the SABI database, which implies relying on their correct compilation. However, as mentioned earlier, when cleaning the database, a significant number of outliers had to be removed, which may question the suitability of the data for applying the model.

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