CADERNOS EBAPE.BR FGV EBAPE

ARTICLE

Impact of COVID-19 on SMEs in Brazil and managerial perception drivers: a novel neural model based on entropy-weighted utility functions

Luiz Gustavo Medeiros Barbosa [1]
Peter Fernandes Wanke [2]
Jorge Junio Moreira Antunes [2]
Saulo Barroso Rocha [3]

[1] Fundação Getulio Vargas (FGV EBAPE) / Escola Brasileira de Administração Pública e de Empresas, Rio de Janeiro – RJ, Brazil
[2] Universidade Federal do Rio de Janeiro (COPPEAD UFRJ) / Instituto de Pós-Graduação e Pesquisa, Rio de Janeiro – RJ, Brazil
[3] Universidade Federal Fluminense (UFF) / Departamento de Empreendedorismo e Gestão, Niterói – RJ, Brazil

Abstract

Departing from the inconclusive results of the scant literature on the COVID-19 impact on Small and Medium Enterprises (SMEs), this paper proposes a novel evaluation model for addressing this issue through managerial perceptions. Over 6000 SMEs responded to twelve rounds of surveys from 2020 to 2021 during the pandemic, allowing to track the evolution over time of the perceived impact of the pandemic on small businesses. A novel entropy-weighted utility function approach is proposed here, followed by artificial neural network regression to map the variables related to the SME's businesses that most foster the perceived utility of each business criterion during the pandemic. First, weights of business-related criteria were computed using Stepwise Weight Assessment Ratio Analysis (SWARA), sorting their relative importance – or perceptions- based on information entropy ranks derived from questionnaires collected. Transfer entropy measurements also helped in unveiling the hidden cause-effect relationships among criteria. Second, business utility functions for each criterion were computed using Complex Proportional Assessment based on SWARA weights. Third, neural network regressions were used to explain the managerial perceptions on each business criterion during the pandemic, considering each business variable. Our expected and unexpected results suggest that more resilient SMEs in Brazil are 5-10 years old and operating in the services and construction sectors. Moreover, loan success is the second most impactful criterion, deeply impacting the continuity of economic activity levels, and it is not impacted by any other business criteria. Implications for policymakers and governmental actions are highlighted.
Keywords: SME. Business-related variables. Utility functions. Information entropy. COVID-19 impact

Impacto da COVID-19 nas PMEs no Brasil e drivers de percepção gerencial: um novo modelo neural baseado em funções de utilidade ponderadas pela entropia

Resumo

Partindo dos resultados inconclusivos da escassa literatura sobre o impacto do COVID-19 nas pequenas e médias empresas (PMEs), este artigo propõe um novo modelo de avaliação para abordar esse problema por meio de percepções gerenciais. Para atingir esse objetivo, mais de 6.000 PMEs responderam doze rodadas de pesquisas de 2020 a 2021, durante a pandemia, permitindo assim acompanhar a evolução do impacto percebido da pandemia nas pequenas e médias empresas. Uma nova abordagem de função de utilidade ponderada pela entropia é proposta aqui, seguida por regressão de rede neural para mapear quais variáveis relacionadas aos negócios das PMEs impulsionam mais a utilidade percebida de cada critério de negócios durante a pandemia. Primeiro, os pesos dos critérios relacionados aos negócios foram calculados usando a análise de proporção de avaliação de peso passo a passo (SWARA), classificando sua importância relativa- ou percepções- com base nas classificações de entropia de informações derivadas de dados coletados. As medições de entropia de transferência também ajudaram a revelar as relações de causa e efeito entre os critérios. Em segundo lugar, as funções de utilidade comercial para cada critério foram calculadas usando a Avaliação Proporcional Complexa com base nos pesos SWARA. Terceiro, regressões de redes neurais foram usadas para explicar as percepções gerenciais sobre cada critério de negócios durante a pandemia à luz de cada variável de negócios. Nossos resultados, esperados e inesperados, sugerem que as PMEs mais resilientes no Brasil são aquelas com 5 a 10 anos de idade operando nos setores de serviços e construção. Além disso, o sucesso do empréstimo é o segundo critério de maior impacto, impactando profundamente a continuidade dos níveis de atividade econômica; e não é afetado por nenhum outro critério de negócio. Implicações para formuladores de políticas e ações governamentais são destacadas.
Palavras-chave: PME. Variáveis relacionadas ao negócio. Funções utilitárias. Entropia da informação. Impacto da COVID-19.

Impacto de la COVID-19 en las pymes en Brasil y factores impulsores de la percepción gerencial: un nuevo modelo neuronal basado en funciones de utilidad ponderadas por entropía

Resumen

Con base en los resultados no concluyentes de la escasa literatura sobre el impacto de la COVID-19 en las pequeñas y medianas empresas (pymes), este artículo propone un nuevo modelo de evaluación para abordar este problema a través de las percepciones gerenciales. Para lograr este objetivo, más de 6.000 pymes respondieron a doce rondas de encuestas de 2020 a 2021, durante la pandemia, lo que permitió monitorear la evolución del impacto percibido de la pandemia en las pequeñas y medianas empresas. Aquí se propone un nuevo enfoque de función de utilidad ponderada por entropía, seguido de una regresión de red neuronal para mapear qué variables relacionadas con el negocio de las pymes impulsan más la utilidad percibida de cada criterio comercial durante la pandemia. Primero, los pesos de los criterios relacionados con el negocio se calcularon utilizando un análisis de relación de evaluación de peso paso a paso (SWARA), clasificando su importancia relativa –o percepciones– en función de las calificaciones de entropía de la información derivada de los datos recopilados. Las mediciones de entropía de transferencia también ayudaron a revelar las relaciones de causa y efecto entre los criterios. En segundo lugar, las funciones de utilidad comercial para cada criterio se calcularon mediante una evaluación proporcional compleja basada en los pesos SWARA. En tercer lugar, se utilizaron regresiones de redes neuronales para explicar las percepciones gerenciales de cada criterio comercial durante la pandemia a la luz de cada variable comercial. Nuestros resultados, esperados e inesperados, sugieren que las pymes más resilientes en Brasil son aquellas que tienen de 5 a 10 años, que operan en los sectores de servicios y construcción. Además, el éxito del préstamo es el segundo criterio de mayor impacto, que afecta profundamente la continuidad de los niveles de actividad económica; y no se ve afectado por ningún otro criterio comercial. Se destacan las implicaciones para los formuladores de políticas y las acciones gubernamentales.
Palabras clave: Pymes. Variables relacionadas con el negocio. Funciones de utilidad. Entropía de la información. Impacto de la COVID-19.

Article received on December 01, 2022, and accepted on August 18, 2023.
[Original version]

DOI: https://doi.org/10.1590/1679-395120220273x

INTRODUCTION

Evidence shows that elsewhere in most developed and developing economies, SMEs employ the largest proportion of the workforce. In Brazil, these businesses account for approximately eighteen million formal companies, employing most of the workforce, from agricultural products to the cultural sector (Barbosa et al., 2022). Besides, Brazil had 8,863 exporting SMEs in 2017, which represented 40.8% of the country's exporting companies in the year, with 17.8% referring to micro-enterprises and 23.1% to small businesses (Serviço de Apoio às Micro e Pequenas Empresas Brasileiras [SEBRAE], 2022).

Some studies evaluating the impacts of COVID-19 for SMEs were carried out for the Brazilian context (Bretas & Alon, 2020; Dweck, 2020; Pereira & Patel, 2022; Rediske et al., 2022; Reis et al., 2021), that operate in different sectors; with a focus on commerce and services (Marques et al., 2021), on educational institutions (A. D. S. M. Costa et al., 2020; B. G. S. Costa et al., 2022; Dias & Ramos, 2022), on the strategies used (Wecker et al., 2020). Thus far, however, it has not been made clear how SME business-related variables impact on the perceived utility of business-criteria, particularly during the COVID-19 pandemic. Precisely, this research focused on five major **business-criteria** to capture the managerial perceptions of the pandemic impact to SME performance: *business impact* (whether it remained without operational changes or was affect either by temporary or permanently closure) (Bartik et al., 2020; Latham, 2009); *business operation* (whether its economic activity level increased, decreased or remained stable) (Dess & Robinson, 1984; S. Singh et al., 2016) ; *employee dismissal* (whether its jobs were spared during the pandemic or not); *loan success* (whether it could borrow working capital from banks to sustain their operation or not); and *crisis duration* (how long pandemic impacts were perceived to last, despite lockdowns, governmental support etc.) (Brown et al., 2020; Deyoung et al., 2015). On the other hand, a comprehensive number of **business-related variables**, encompassing socio-demographic issues both related to the SMEs and the respondents themselves were targeted as possible perception drivers. As regards the respondents, their *academic level,* and their respective *age*; as regards the SMEs, their relative *size*, *time* in business, business *type*, economic *sector*, and the respective Brazilian *State* where they are located (Lim et al., 2020; Schepers et al., 2021).

The distinctive methodological approach offered by this research is twofold. First, by unveiling, through the transfer entropy approach, the cause-effect and feedback relationships among major **business-criteria**, based on the distributional profile of the respondents' perceptions. Information entropy is a well-stablished concept related to the reliability of a dataset (Núñez et al., 1996). The maximal entropy principle states that the probability distribution which best represents the current state of knowledge for a given **business-criteria** is the one with largest entropy (Peter et al., 2010) . Second, and differently from previous research, this paper aims at answering how socio-demographic, **business-related**, variables impact on the perceived utility of distinct **business-criteria** in Brazilian SME. By computing the information entropy of the distribution of perceptions for each criterion, it becomes possible to focus on the most meaningful criteria for policy making, and their socio-demographic drivers, for which it is not possible to be ascertained *a priori*.

The impact of the COVID-19 pandemic on SMEs has led to reflection and attention on the SME ecosystem and has attracted the awareness of academics and practitioners (Bretas & Alon, 2020; Cepel et al., 2020; A. D. S. M. Costa et al., 2020; B. G. S. Costa et al., 2022; Habachi & Haddad, 2021; Kamaldeep, 2021; Pereira & Patel, 2022; Reis et al., 2021;). Most of this literature on COVID-19 and SMEs reveals an understanding of how companies have responded to or been impacted by the effects of COVID-19 (Bretas & Alon, 2020; A. D. S. M. Costa et al., 2020; Dejardin et al., 2023; Dweck, 2020; Habachi & Haddad, 2021; Kamaldeep, 2021; Ma et al., 2021; Pereira & Patel, 2022; Rediske et al., 2022; Reis et al., 2021). In other words, these studies tend to describe the dynamics of COVID-19 and its effects on SMEs, mostly based on descriptive studies. Although the body of research has generated relevant results on the subject, the success, or difficulties of SMEs during the pandemic has not yet been understood, with undeveloped aspects regarding the effect of the pandemic on SMEs from emerging countries.

Spurred on by the research gaps, this original study reports on a series of survey data collected in Brazilian SME by means of a novel neural-MCDM (multi-criteria decision making) model structured in three stages (Sheng-Hshiung et al., 1997; T. C. Wang & Lee, 2009). This model is proven capable of deriving unbiased utility functions for distinct **business-criteria** based on information entropy levels captured from the respective respondent´s perceptions. In fact, information entropy is the cornerstone method used in this research to assess the perceived importance of each **business-criteria**, based on weights computed using the recent SWARA model. Compared with other methods, information entropy provides the benefits of lower bias and higher robustness to unconsidered assumptions, which can lead to a more comprehensive interpretation of the results as regards how the utility of distinct attributes, as derived by COPRAS (Zavadskas & Kaklauskas, 1996), are perceived by distinct demographic groups. Results indicate that analyzing each criterion in an isolated fashion, *crisis duration, business operation and* employee dismissal appears as the most relevant criterions, as expected due to the economic moment caused by the pandemic. The two least relevant criteria, *loan success* and *business impact*, relate to actions that could be taken to keep SMEs running even despite lockdown interruptions. Most SMEs suffered from business interruptions that may have caused operational changes, thus yielding lower economic activity. Besides, while most of them did not find financial support in banking loans for working capital, they are so diminished in size (self-entrepreneurs) that employee dismissal presented a limited impact on explaining the lower utility function levels. In general, our paper contributes to our understanding of the impact of COVID-19 on the small business ecosystem in Brazil. This survey on the impact of the COVID-19 pandemic on the operations of small and medium-sized enterprises (SMEs) in Brazil is, to date, the most comprehensive and representative in the sector. The study involved 7,000 companies from different segments and regions. The rest of this paper includes four sections. Literature review is presented in Section 2, while methodology is presented in Section 3. Section 4 focuses on the analysis and discussion of results, and conclusions are elaborated in Section 5.

IMPACT OF COVID-19 ON SMES

In March 2020, along with the rest of the world, Brazil was in the agony of the COVID-19 pandemic. Organizations have responded to the shutdown of the global economy in multiple ways, having to make decisions in a context of uncertainty about the duration of the crisis and potential public policies to support business. It is clear, exemplified and documented that the crisis caused by COVID-19 has led to the disruption of business operations, supply chain and management models. And COVID-19 pandemic demonstrated that small and medium-sized enterprises (SMEs) are mostly susceptible to crises and shocks (Fasth et al., 2022; Kurland et al., 2022; Miklian & Hoelscher, 2022; Organization for Economic Co-operation and Development [OECD], 2021; Puthusserry et al., 2022). Demand and supply-side interruption, business contraction and restricted access to loan and trade credit are just some of the consequences SMEs face from exogenous shocks (Miklian & Hoelscher, 2022). Decisions made during a crisis are described as complex since they have a propensity to contain paradoxes, such as having to be made carefully but quickly (Vargo & Seville, 2011), affecting operations, performance, and survival (Ozanne et al., 2022; Puthusserry et al., 2022). Still, as more evidence is gathered and reported about the experience of COVID-19 among SMEs, we gradually develop our understanding of the policies, preparatory steps and procedures that are best suited in a global type of crisis such as COVID-19 (Fasth et al., 2022).

The pandemic's length also affects smaller firms more strongly as they lack adequate resources to tolerate extended periods of disturbance with many closings once they drain their operating finances (Brown et al., 2020; Cowling et al., 2020). The diverse collection of small and medium-sized enterprises is often more vulnerable than large firms under diverse shock settings (Deyoung et al., 2015). While all exogenous shocks bring a degree of economic effect, their scale and magnitude can differ, for example, in the range of the time needed to 'return to normal' (Miklian & Hoelscher, 2022). Time is money even for SMEs, and unlike large firms, SMEs do not have satisfactory access to the capital markets and thus have a much more restricted menu of diverse sources of external finance. There are only two economically important alternatives for SMEs: bank loans and trade credit (Carbó-Valverde et al., 2016). Credit rationing is a common phenomenon faced by firms in Brazil (Maffioli et al., 2017; Maia et al., 2019; Zambaldi et al., 2011), one that has negative consequences for long-term investments. In Brazil, public credit plays a vital role in supporting firms: state-owned banks account for half of the outstanding credit (Maffioli et al., 2017). The relation of past budgetary crisis to SMEs (Carbó-Valverde et al., 2016) indicates that the financial crisis was associated with a credit crunch that affected the SME sector by increasing the number of credit constrained firms. Thus, a well-developed local financial system increases the availability of bank loans and reduces the need of SMEs to hold cash as a precautionary buffer against adverse shocks (Fasano & Deloof, 2021).

More specifically, the COVID-19 pandemic had a significant impact on small and medium-sized enterprises (SMEs), leading to a decrease in sales, an increase in costs, and uncertainty, resulting in rising unemployment rates, amplifying the consequences of the tragedy caused by the pandemic (Dweck, 2020; Klein & Todesco, 2021; Puthusserry et al., 2022). The COVID-19 pandemic led to a decrease in sales for SMEs in several sectors, including tourism, retail, and hospitality. This was due to business closures and travel restrictions. Fasano and Deloof (2021) found that Italian SMEs that were most affected by the pandemic had an average decrease of 50% in sales. Machado et al. (2022) found that Brazilian food exports to the United Kingdom fell by an average of 40% during the pandemic. The pandemic also led to an increase in costs for SMEs, as a result of mobility restrictions, store closures, and a decline in productivity. Wecker et al. (2020) found that Brazilian SMEs faced an average increase of 20% in costs during the pandemic. In addition to these impacts, the pandemic period brought uncertainty to business in general, making it difficult to make decisions and plan. This was due to uncertainty about the duration of the pandemic, the impact of the pandemic on the economy, and consumer behavior. Nicolletti et al. (2020) found that European SMEs were more likely to report uncertainty about the future of their business during the pandemic.

Governments can take measures to support SMEs, in order to prevent them from closing down and losing jobs. Cowling et al. (2020) argued that governments need to take measures to support SMEs to prevent them from closing and losing jobs. Providing lines of credit and other types of financing to help SMEs cover their expenses and keep their businesses running. Providing tax breaks and other types of financial relief to help SMEs reduce their costs. Offering training and technical support to help SMEs adapt to the new realities of the market and become more resilient, and helping SMEs connect with customers and suppliers to help them maintain their sales and operations (Cowling et al., 2020; Habachi & Haddad, 2021; Klein & Todesco, 2021; Maia et al., 2019). SMEs are responsible for a large part of the economy and employment, and their success is essential for the post-COVID-19 economic recovery.

In addition to studies on the direct impact of COVID-19 on the operational performance of small and medium-sized enterprises (SMEs), some researchers have addressed different perspectives of organizations during the pandemic. SMEs that adopted new innovations with external support were more likely to survive the pandemic (Adam & Alarifi, 2021). This is in line with the research where it was found that the pandemic accelerated the digitalization of companies, as SMEs were forced to adopt new technologies to remain competitive (Klein & Todesco, 2021). SMEs that adopted digital transformation were more likely to survive the pandemic and emerge stronger. According to Doerr et al. (2021), companies with a stronger technological capacity were more likely to recover from the pandemic than companies with a weaker technological capacity. Technological capacity as defined in Bernades et al. (2019).

Clampit (2021), Dejardin et al. (2023), and Wecker et al. (2020) presented studies on the impact of dynamic capabilities on SME performance during the COVID-19 crisis. SMEs with stronger dynamic capabilities had a better performance during the pandemic, therefore, SMEs that invest in dynamic capabilities are better prepared to face challenges and take advantage of opportunities in times of crisis (Dejardin et al., 2023). This is also in line with Wecker et al. (2020): "crisis management strategies can help companies to develop and improve their dynamic capabilities", and Clampit (2021) where "SMEs with stronger dynamic capabilities were more likely to maintain their performance during the COVID-19 pandemic." The three main dynamic capabilities that were found to be important for SME performance stability were sensing, seizing, and reconfiguring (Clampit et al., 2021). The studies converge to the conclusion that dynamic capabilities and crisis management strategies are essential for the success of companies in the post-COVID-19 era.

New research on the impact of COVID-19 on organizations is likely to emerge in the coming years, covering both the supply and demand sides. This research focused on studies that analyzed the operational impact dimension and its underlying variables. We will discuss the methodology in the following section.

METHODOLOGY

Research sample and data collection procedures]

Brazilian Support Service for Micro and Small Enterprises (SEBRAE) and Fundação Getulio Vargas (FGV) conducted surveys between March 2020 and September 2021. SEBRAE and FGV conducted twelve waves of web surveys, interviewing approximately 7,000 SMEs in each one, corresponding to 85.857 observations. Table 1 presents the number of SMEs interviewed in each wave of the survey. The list of variables used are available in (Serviço de Apoio às Micro e Pequenas Empresas Brasileiras [SEBRAE], 2022).

Table 1
Number of SMEs

Ed.	1	2	3	4	5	6	7	8	9	10	11	12	Total
n	9,105	6,080	10,384	7,403	6,470	6,506	7,586	6,033	6,138	6,228	7,820	6,104	85,857
When	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Mar	May	Jun	

Source: Elaborated by the authors.

The variables analyzed were grouped into **Business-criteria** and **business-related variables**. Business-criteria consisted of the following sub-unit of analysis: business-impact, business-operation, crisis duration, employee-dismissal, and loan success. Business-related variables comprised the following socio-demographic aspects: state, sector, business-size, business-time, business-type, years (age), academic level.

Business-impact. Economic recessions represent a period that threatens the survival of all firms. This is particularly the case for SMEs and start-up firms, which have been shown to fail at a much higher rate compared with their larger, more established peers (Latham, 2009). SMEs have experienced from a shortage of production inputs because of distortions that affected supply chains, which negatively impacted their sales. Thus, in this research, business-impact is a variable with a 4-point scale, taking a value of one if SME permanently closed business, two for temporary closed business, three for business with operational changes, and four for business without operational changes.

Business-operation. Organizational performance (OP) lies at the heart of an organization's survival. it must be reiterated that measuring OP is a complex task, as literature and real-life experience of scores of researchers shows, given the accessibility to reliable financial data and other performance measures (S. Singh et al., 2016). To face this problem, the value of performance measures, obtained from top management teams, is an alternative way to capture firms' performance (Dess & Robinson, 1984). To capture performance of SMEs in pandemic context, we employed growth in sales variation, with the following attributes: Lesser, Equal, or Greater.

Loan success. Small and medium enterprises face strong asymmetric information problems when trying to access credit. In previous economic crises, the supply of credit via loan to small and medium-sized companies was drastically reduced due to the increase in lender risk aversion (Deyoung et al., 2015). A reduction in SME credit supply could exacerbate the economic downturn by denying SMEs the short-term credit necessary to finance supplies and retain employees.

Crisis duration. Crisis duration is entrepreneurs' perception of how long it will take for the economy to return to normal.

Employee dismissal. Employee dismissal refers to information about employees who had their employment contracts terminated during the pandemic.

Business-related variables are the sociodemographic variables of the SMEs interviewed, namely: state, sector, business-size, business-time, business-type, years, and academic level. The proposed model used these variables, specifically in Neural Network Regression, as presented in the next section.

Proposed model

Multiple Attribute Decision Making (MADM) is a research field focused on the assessment of different alternatives when considering multiple attributes (Sheng-Hshiung et al., 1997; T. C. Wang & Lee, 2009). The most common models applied to compute the weightings of these attributes include the Entropy Method (Sheng-Hshiung et al., 1997; R. K. Singh & Benyoucef, 2011), Information Entropy Weight (IEW) (Zhang et al., 2011), Analytic Hierarchy Process (AHP) (Dağdeviren et al., 2009; Sheng-Hshiung et al., 1997; Yu et al., 2011), Fuzzy AHP (Gumus, 2009; Sun, 2010; J. W. Wang et al., 2009) and Rough AHP (Aydogan, 2011). More recently, SWARA emerges a general tool that is used for calculating attribute weights within the ambit of performance measurement, as well as the respective resulting importance levels (Keršuliene et al., 2010).

Liang and Ding (2003) focus specifically on respondents to determine the weightings of attributes, based on perceptual Likert scales. However, the inherent uncertainty and subjectivity of such scales can result in weighting errors, yielding biased conclusions as regards the relative importance of each attribute. In this sense, information entropy can be conceptualized as a probabilistic measure of uncertainty. Depending on the socio-demographic group, the randomness level at given attribute may vary, and this variation can be captured by calculating the information entropy for each sub-unit of analysis. The greater the information entropy value, the greater the randomness within the range of respondents and, therefore, the greater the inherent discriminatory power of a given attribute (Núñez et al., 1996).

In this paper, information entropy is used to set the initial importance order of **business-criteria** in SWARA, through which unbiased weights are computed. These weights serve subsequently as inputs to COPRAS, which differently from other MADM methods, helps in establishing a partial utility degree for each **business-criteria** in Brazilian SMEs (Kaklauskas et al., 2006; Zavadskas et al., 2007). Readers should recall that utility functions are a well-known economic concept applied in MADM (Dyer et al., 1992). Precisely, utility is an important concept that measures perceptions or preferences over a set of **business-criteria** (Kassem & Hakim, 2016; Rezaeisaray et al., 2016). The COPRAS utility function approach is the most simply and easily understood by academics and practitioners since it does not require any stronger restrictions on the preference structures than the aggregation formula, straightforwardly establishing the relation between **business-criteria** and partial value function amounts (Gandhi et al., 2015, 2016; Janssen et al., 2017). The simplicity of the additive aggregation makes the utility function approach particularly appealing for serving as inputs of subsequent multivariate analysis (de Almeida et al., 2016). The following sub-sections dig further into the novel neural-MADM methods utilized in this paper to apprehend the socio-demographic impacts on the perceived utility of distinct SMEs attributes.

SWARA

The SWARA steps used in this research are duly described next (Stanujkic et al., 2015).

Step 1: Sort **business-criteria** from the highest to the lowest based on the information entropy ranking for each criterion.

Step 2: Assign the null value for the preference of the first **business-criteria**. Allocate preferences to the second most important **business-criteria**; repeat this step until the least important **business-criteria** is reached. These preferences are computed by comparing a given **business-criteria** with the first one with highest entropy. Compute their pairwise relative importance, denoted by , which shows the ratio of this comparison.

Step 3: Set-up pairwise efficiency criteria by:

$$K_j = \begin{cases} 1, j = 1 \\ S_j + 1, j > 1 \end{cases} \quad \textbf{(8)}$$

Step 4: Compute relative weights (q_j) (based on sorted pairwise efficiency with respect to the importance criterion rank:

$$q_j = \begin{cases} 1 & j = 1 \\ \frac{K_{j-1}}{K_j} & j > 1 \end{cases} \quad \textbf{(9)}$$

Step 5: Compute final weights as $W_j = \frac{q_j}{\sum_{k=1}^{n} q_k}$, where denotes the weight of each criterion *j.*

COPRAS

COPRAS was first introduced more than two decades ago by Zavadskas and Kaklauskas (1996). Since then, several different researches have been published on possible alternative ways for combining SWARA and COPRAS (Zolfani & Bahrami, 2014; Nakhaei et al., 2016; Valipour et al., 2017); SWARA and Fuzzy COPRAS (Bekar et al., 2016; Yazdani et al., 2011); and COPRAS and other MCDMs (Aghdaie et al., 2012; Ecer, 2014; Fouladgar et al., 2012; Rezaeiniya et al., 2012; Zolfani et al., 2012). The next lines briefly present the major steps of the COPRAS method applied in this research for deriving utility functions based on different **business-criteria** importance weights (cf. previous section):

Step 1: Create a decision-making matrix **X**, containing m respondents and n **business-criteria**:

$$X = \begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{pmatrix} i = 1,2,\ldots n; j = 1,2,\ldots,m \quad \textbf{(10)}$$

Step 2: Normalize the decision matrix **X** by computing:

$$\overline{x_{ij}} = \frac{x_{ij}}{\sum_{j=1}^{n} x_{ij}} \quad \textbf{(11)}$$

Then the decision matrix will be:

$$\overline{X} = \begin{pmatrix} \overline{x}_{11} & \cdots & \overline{x}_{1n} \\ \vdots & \ddots & \vdots \\ \overline{x}_{m1} & \cdots & \overline{x}_{mn} \end{pmatrix} \quad \textbf{(12)}$$

Step 3: Compute the weighted normalized decision matrix by means of:

$$\widehat{x_{ij}} = \overline{x}_{ij} \times w_{ij}; i = 1,2,\ldots,n; j = 1,2,\ldots,m \quad \textbf{(13)}$$

Therefore,

$$\hat{X} = \begin{pmatrix} \hat{x}_{11} & \cdots & \hat{x}_{1n} \\ \vdots & \ddots & \vdots \\ \hat{x}_{m1} & \cdots & \hat{x}_{mn} \end{pmatrix}; i = 1,2,\ldots,n; j = 1,2,\ldots,m \quad \textbf{(14)}$$

Step 4: Sum-up the larger values that are more preferable, named as P_i:

$$P_i = \sum_{j=1}^{k} \overline{x_{ij}} \quad \textbf{(15)}$$

Step 5: Sum-up the smaller values that are more preferable, named as R_i:

$$R_i = \sum_{j=k+1}^{k} \overline{x_{ij}} \quad \textbf{(16)}$$

Then the number of **business-criteria** that should be minimized is given by the difference *m-k*.

Step 6: Minimize R_i observing eq. (8):

$$R_{\min} = \min_i R_i; i = 1,2,\ldots,n \quad \textbf{(17)}$$

Step 7: Compute the relative significance of each **business-criterion** Q_i as given:

$$Q_i = P_i + \frac{R_{\min} \sum_{i=1}^{n} R_i}{R_i \sum_{i=1}^{n} \frac{R_{\min}}{R_i}} \quad \textbf{(18)}$$

Step 8: Identify the optimal **business-criterion** i, given by K, as is illustrated:

$$K = \max_{i} Q_i ; i = 1, 2, \ldots, n \quad \textbf{(19)}$$

Step 9: Prioritize **business-criteria** in a descending order.

Step 10: Determine the utility degree N of each subsequent **business-criterion** i, given as:

$$N_i = \frac{Q_i}{Q_{\max}} \times 100\% \quad \textbf{(20)}$$

Transfer entropy

The information flow between two **business-criteria** i and j can be measured combining both Shannon Entropy (Shannon, 1948a, 1948b) with Kullback-Leibler divergence (Kullback & Leibler, 1951) considering a Markov process with k and l levels or factors, respectively (Schreiber, 2000). Assuming the probabilities distributions $p(i)$ and $p(j)$ for **business-criteria** i and j respectively and the joint probability $p(i,j)$, the information flow from **business-criteria** j to i is given by (Dimpfl & Peter, 2013):

$$T_{J\to I}(k,l) = \sum_{i,j} p\left(i_{t+1}, i_t^{(k)}, j_t^{(l)}\right) . \log\left(\frac{p\left(i_{t+1} | i_t^{(k)}, j_t^{(l)}\right)}{p\left(i_{t+1} | i_t^{(k)}\right)}\right) \quad \textbf{(21)}$$

which measure the deviation from generalized Markov process $p\left(i_{t+1} | i_t^{(k)}\right) = p\left(i_{t+1} | i_t^{(k)}, j_t^{(l)}\right)$ at the marginal conditional distribution odds-ratio $\log\left(\frac{p\left(i_{t+1} | i_t^{(k)}, j_t^{(l)}\right)}{p\left(i_{t+1} | i_t^{(k)}\right)}\right)$.

Since the information flow from i to j is measured analogously, it is possible to define the causation direction between two given **business-criteria** based on the net information flow computed as the difference between flows from i to j and j to i. By bootstrapping the inherent probability distributions for each factor/level in each criterion, it is possible to run this Markov process n times and compute the statistical significance for the net information flow from one business criteria to another (Peter et al., 2010).

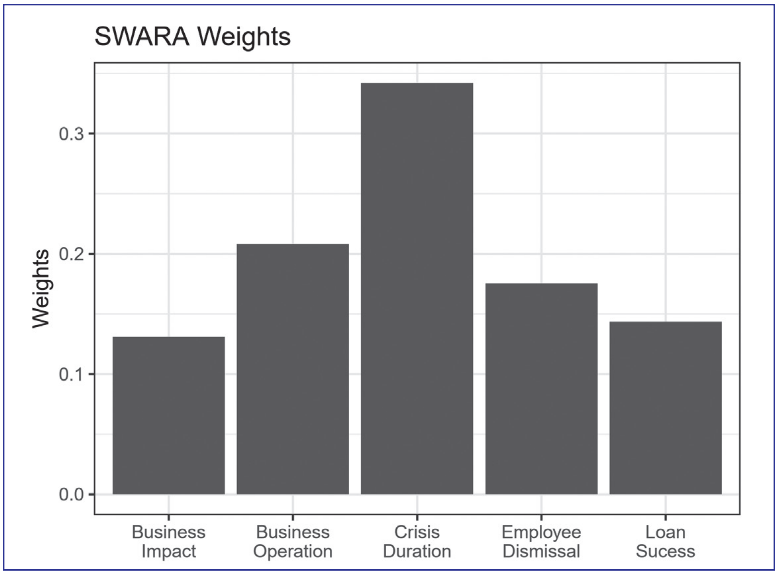
Neural network regression

ANNs (Artificial Neural Networks) are used to analyze the responses for each **business-criterion** as a resultant of a series of socio-demographic, **business-related**, variables while controlling for the respective utility function. Precisely, an ANN regression is computed to unveil the non-linear impact of each socio-demographic, **business-related**, variable on the response factors or levels asked in each **business-criterion**. When controlling these relationships between criteria and demographic variables, higher (lower) values of perceived utility not only denote that a given **business-criterion** is regarded – as a whole – as more (less) relevant by respondents, but also that the distribution of the responses of this **business-criterion** is more (less) scattered or dispersed, thus making it more difficult to make *a priori* inferences based on socio-demographic variables without using more sophisticated inference techniques. In this research, we particularly look at the MLP (Multi-Layer Perceptron) network which has been the most used of ANNs architectures for forecasting (Mubiru & Banda, 2008). We also observed the Connection Weight Approach (CWA) (Olden et al., 2004; Olden & Jackson, 2002) for accurately quantifying the relative importance of each socio-demographic variable on the response levels or factors for each **business-criterion**.

ANALYSIS AND DISCUSSION OF RESULTS

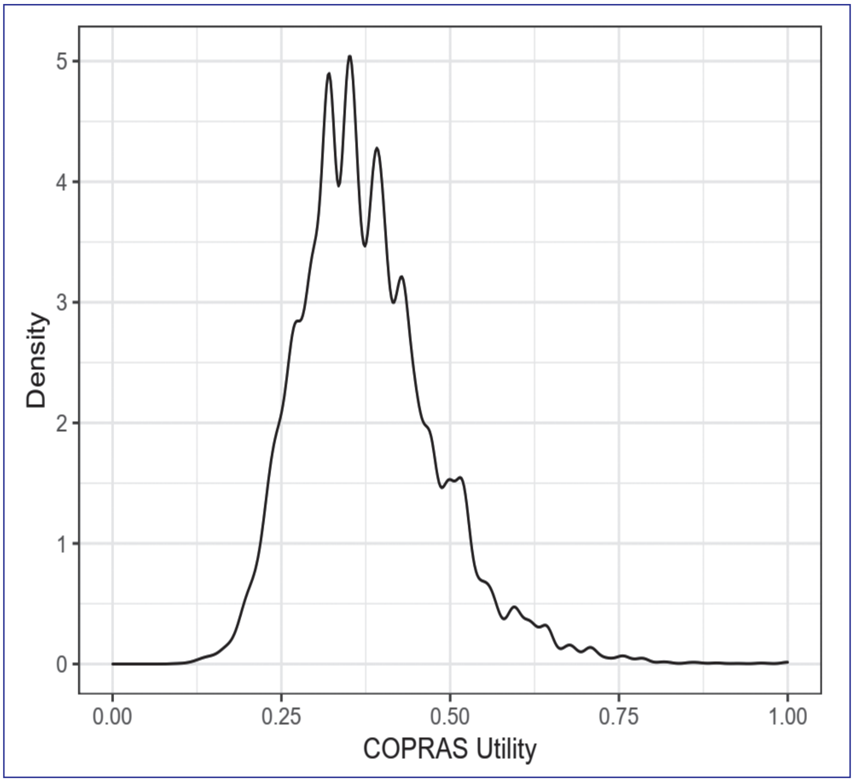
Density plots for the **business-criteria** weights computed using SWARA are depicted in Figure 1, based on the information entropy distributions provided by respondents for each criterion. Analyzing each criterion in an isolated fashion, *crisis duration* appears as the most relevant criterion, followed by *business operation* and *employee dismissal* as expected due to the singular economic moment caused by the pandemic. These three most relevant criteria indicate that SME concerns are mostly related to lockdown decisions and the consequent impact on economic activity and employment level. The two least relevant criteria, *loan success* and *business impact*, relate to actions that could be taken to keep SMEs running even despite lockdown interruptions. Besides, this importance imbalance among **business-criteria** is also reflected on the overall utility function distribution: SMEs tend perceive such utility as low – most utility function values are below 0.50 – what in some sort anticipates the nature of problem faced during the pandemic in light of the response levels/factors for each **business-criteria** as depicted in Table 2. Most SMEs suffered from business interruptions that may have caused operational changes, thus yielding lower economic activity. Besides, while most of them did not find financial support in banking loans for working capital, they are so diminished in size (self-entrepreneurs) that employee dismissal presented a limited impact on explaining the lower utility function levels.

Figure 1
Barplot for the business-criteria information entropy weights computed using SWARA



Source: Elaborated by the authors.

Figure 2
COPRAS utility function results



Source: Elaborated by the authors.

Table 2
Descriptive statistics for the business-criteria and their respective response levels

Business criteria*	Frequency distribution for each response/ factor level (number in brackets denote the response level)							
Business Impact (+)	Permanently Closed Business (1)	0.32%	Temporary Closed Business (2)	30.22%	Business with Operational changes (3)	56.93%	Business without Operational changes (4)	12.53%
Business Operation (+)	Lesser (1)	85.63%	Equal (2)	7.90%	Greater (3)	6.47%		
Employee Dismissal (-)	Without Dismissal (1)	39.85%	Business without employees (2)	48.48%	With Dismissal (3)	11.67%		
Loan Sucess (+)	Loan Denied (1)	79.03%	Waiting Response (2)	9.89%	Loan Approved (3)	11.08%		
Crisis Duration(-)	**Descriptives**							
	Min	0	Max	365	Mean	11.89	SD	11.64

* Signs are related to the positive or negative impact of a given criteria on overall utility. They reflect the factor/response levels for each criterion, observing intrinsic relations such as "the higher the better," "the higher the worse" w.r.t. utility function values.

Source: Elaborated by the authors.

Transfer entropy and neural network results for cause-effect relationships among **business-criteria** and **business-related** variables in Brazilian SME are depicted in Figure 3. Table 3 also reports on the best ANN architecture found for each regression, after cross-validating the originally trained models with a randomly selected 20% of the sample. One may easily note that *business operation* is the most critical criteria: it impacts three other criteria (*crisis duration*, *employee dismissal* and *business impact*), and it is only impacted by one (*loan success*). Greater economic activity not only impacts on the respondent´s perceptions about the duration of lockdowns and the persistence of pandemic effects but can also revert decisions with respect to reduction in workforce or even shutting down the business. *Loan success* is the second most impact criterion, deeply impacting the continuity of economic activity levels; it could be considered a pure exogenous criterion since it is not impacted by any other **business-criteria**. Consistent with Deyoung et al. (2015) and Maffioli et al. (2017), the availability of credit resources for SMEs directly impacts the business operation.

On the other hand, *business impact* is purely endogenous, its perception is the resultant of the countervailing forces represented by economic activity level; reduction of labor force; and successful working capital loans for sustaining business during the pandemic. These pure exogenous and endogenous business criteria may explain why their perceived utility is high (COPRAS function present a positive impact highlighted in green). Hence, more resilient SMEs – without operational changes – are those with 5-10 years’ operating in the services and construction sectors. On the other hand, SMEs that suffered the most with lockdowns are those related to food and technology industries. As regards banking support, food services SMEs were more successful in borrowing working capital from banks than novel SMEs that operate in the gym, pet shop, and educational services in general. It is important to note that, regardless of the **business-criteria**, the educational respondent profile, and the state of location of the SME were also found to be pretty heterogeneous, results that suggest that perceptions and the utility functions on the distinct **business-criteria** still depends on whether the SME is located in poorer or richer Brazilian states or on whether the self-entrepreneurs are illiterate or not. This is crucial evidence of the impact of formal education on the survival of SMEs during the COVID-19 pandemic crisis. The absence of adequate education to run a business can make it difficult to deploy dynamic capabilities, or technological capabilities. This is an underlying and relevant variable in any business model, in any sector. Education is important for small and medium-sized enterprises (SMEs) because it can help to improve productivity, increase competitiveness, and create new jobs. Differences in local financial development particularly affect corporate finance decisions of small and medium-sized firms (Fasano & Deloof, 2021). The full set of ANN results are depicted in the Appendix.

Table 3
Best Neural Network architecture validation

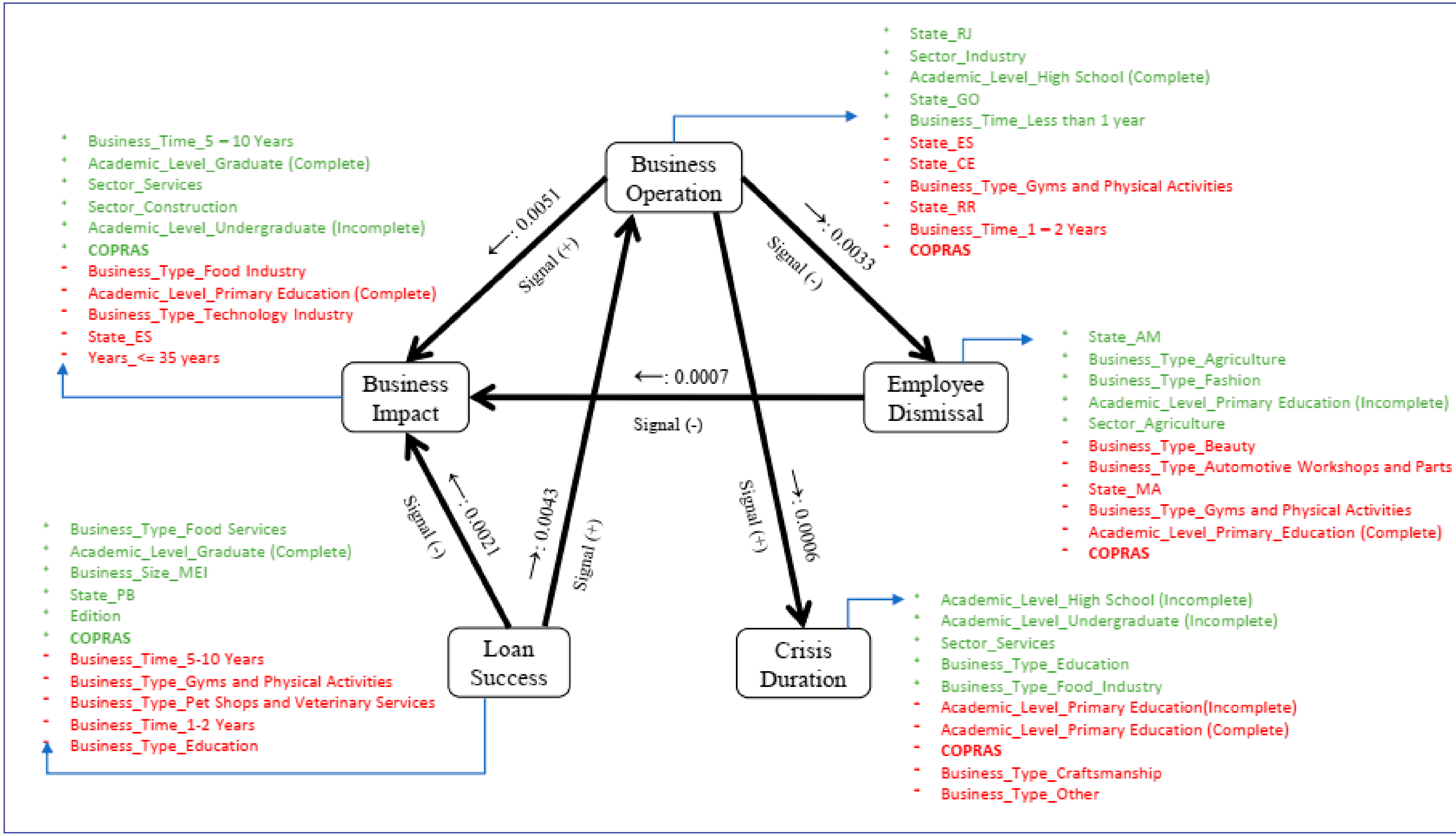
Business-Criteria	Layers	Neurons per Layer	L1 Regularization	L2 Regularization	Error Measure	Validation Error
Business Impact	1	35	1.00E-07	1.00E-07	ACC	71.22%
Business Operation	2	5	1.00E-05	1.00E-07	ACC	76.37%
Employee Dismissal	4	30	1.00E-05	1.00E-05	ACC	70.08%
Loan Sucess	3	35	1.00E-06	1.00E-05	ACC	53.91%
Crisis Duration	3	5	1.00E-06	1.00E-05	MAE	0.53

Validation with 20% of total dataset observations. MAE stands for mean absolute error, while ACC stands for accuracy, that is, the fraction of correct predictions. Readers should note that for the first four business-criteria, a classification neural network model was performed to regress socio-demographic variables onto a respective response level.

Source: Elaborated by the authors.

Figure 3

Results for the transfer entropy analysis (arrows among business-criteria) and for the ANN regressions (business-related variables) for each criterion



Key: List of the five most relevant positive in green and negative in red.

Note: All results were controlled by COPRAS utility function scores.

Source: Elaborated by the authors.

CONCLUSIONS

The study aimed to propose a novel evaluation model for addressing the impact of COVID-19 on SMES through managerial perceptions. A novel entropy-weighted utility function approach is proposed here, followed by artificial neural network regression to map which SME business-related variables drivers the most the perceived utility of each SME business-criteria during the pandemic. Neural network regressions were used to explain the managerial perceptions on each business criterion during the pandemic considering each business variable, while controlling for the respective criterion utility.

The entropy-weighted utility function approach and the ANN regression were impactful in figuring out the SMEs business-related variables that most drive the perceived utility of each SME business criterion during the pandemic for some reasons: 1) it considers the uncertainty and variability of data by incorporating entropy calculations. This helps in managing the complexity of business-related variables and their impact on perceived utility. This type of approach could be used to any unpredictable and rapidly changing situations; 2) by considering the weights (Olden & Jackson, 2002; Olden et al., 2004), decision-makers can prioritize and focus on the variables that have the greatest impact on business outcomes; 3) By using ANN regression, the business-related variables and their influence on the perceived utility can be mapped in a non-linear manner. But while the proposed model offers valuable insights, there are certain limitations, such as: it requires a precise specification of the utility function and the probability distribution of the outcomes, which may not be easy to elicit in real-world problems.

Forthcoming studies might conduct more research on these managerial perceptions issues to improve the proposed model, additional granular examinations of isolated business type, or focus on the smallest SMEs (e.g., less than 5 employees). Fasano and Deloof (2021) identified that the distribution of financial credit, with the purpose of lengthening payment terms, to the supply chain of a given SME can be more effective than the resource directly allocated in the company, depending on the context and SME's operating sector. This was not investigated in this study and, if studied, this aspect might contribute to the design of policies for SMEs. SMEs' financial performance could be investigated considering business impact and operational functions, including SME structure and owner capability. The role of education in building dynamic strategies and technological capacity is critical for SMEs, especially in times of crisis. There is a gap on this subject in the literature on strategy and business resilience for SMEs.

Finally, the model proposed in this article enables capturing intricate relationships that may not be easily identifiable through traditional statistical methods. By understanding the described transformations in steps for SWARA and COPRAS, and how the ANN was applied, researchers can assess whether this method is suitable for their research problem.

REFERENCES

Adam, N. A., & Alarifi, G. (2021). Innovation practices for survival of small and medium enterprises (SMEs) in the COVID-19 times: the role of external support. *Journal of Innovation and Entrepreneurship*, *10*(1), 15. https://doi.org/10.1186/s13731-021-00156-6

Aghdaie, M. H., Zolfani, S. H., & Zavadskas, E. K. (2012). Prioritizing constructing projects of municipalities based on AHP and COPRAS-G: a case study about footbridges in Iran. *The Baltic Journal of Road and Bridge Engineering*, *7*(2), 145-153. https://doi.org/10.3846/bjrbe.2012.20

Almeida, A. T. de, Almeida, J. A. de, Costa, A. P. C. S., & Almeida-Filho, A. T. de. (2016). A new method for elicitation of criteria weights in additive models: flexible and interactive tradeoff. *European Journal of Operational Research*, *250*(1), 179-191. https://doi.org/10.1016/j.ejor.2015.08.058

Aydogan, E. K. (2011). Performance measurement model for Turkish aviation firms using the rough-AHP and TOPSIS methods under fuzzy environment. *Expert Systems with Applications*, *38*(4), 3992-3998. https://doi.org/10.1016/j.eswa.2010.09.060

Barbosa, L. G. M., Rocha, S. B., & Guimarães, I. L. B. (2022). The economic impact of Brazil's cultural incentive policy. *Revista Pensamento Contemporâneo Em Administração*, *16*(1), 1-14. https://doi.org/10.12712/rpca.v16i1.52479

Bartik, A. W., Bertrand, M., Cullen, Z., Glaeser, E. L., Luca, M., & Stanton, C. (2020). The impact of COVID-19 on small business outcomes and expectations. *Proceedings of the National Academy of Sciences of the United States of America*, *117*(30), 17656-17666. https://doi.org/10.1073/pnas.2006991117

Bekar, E., Cakmakci, M., & Kahraman, C. (2016). Fuzzy COPRAS method for performance measurement in total productive maintenance: a comparative analysis. *Journal of Business Economics and Management*, *17*(5), 663-684. https://doi.org/10.3846/16111699.2016.1202314

Bernardes, R., Borini, F., & Figueiredo, P. N. (2019). Inovação em organizações de economias emergentes. *Cadernos EBAPE.BR*, *17*(4), 886-894. https://doi.org/10.1590/1679-395120190184

Bretas, V. P. G., & Alon, I. (2020). The impact of COVID-19 on franchising in emerging markets: an example from Brazil. *Global Business and Organizational Excellence*, *39*(6), 6-16. https://doi.org/10.1002/joe.22053

Brown, R., Rocha, A., & Cowling, M. (2020). Financing entrepreneurship in times of crisis: exploring the impact of COVID-19 on the market for entrepreneurial finance in the United Kingdom. *International Small Business Journal: Researching Entrepreneurship*, *38*(5), 380-390. https://doi.org/10.1177/0266242620937464

Carbó-Valverde, S., Rodríguez-Fernández, F., & Udell, G. F. (2016). Trade credit the financial crisis and SME access to finance. *Journal of Money, Credit and Banking*, *48*(1), 113-143. https://doi.org/10.1111/jmcb.12292

Cepel, M., Gavurová, B., Dvorský, J., & Bélas, J. (2020). The impact of the COVID-19 crisis on the perception of business risk in the SME segment. *The Journal of International Studies*, *13*(3), 248-263. https://doi.org/10.14254/2071-8330.2020/13-3/16

Clampit, J. A., Lorenz, M. P., Gamble, J. E., & Lee, J. (2021). Performance stability among small and medium-sized enterprises during COVID-19: a test of the efficacy of dynamic capabilities. *International Small Business Journal: Researching Entrepreneurship*, *40*(3), 403-419. https://doi.org/10.1177/02662426211033270

Costa, A. D. S. M., Paiva, E. L., Gomes, M. V. P., & Brei, V. A. (2020). Impactos da COVID-19 nas organizações. *Revista de Administração de Empresas*, *60*(6), 385-387. https://doi.org/10.1590/S0034-759020200602

Costa, B. G. dos S., Espigão, H. S., & Pinto, M. de R. (2022). Professor ou youtuber? A crise da COVID-19, as mudanças de práticas sociais e a adoção de tecnologias para o ensino remoto. *Cadernos EBAPE.BR*, *20*(3), 387-400. https://doi.org/10.1590/1679-395120210044

Cowling, M., Brown, R., & Rocha, A. (2020). Did you save some cash for a rainy COVID-19 day? The crisis and SMEs. *International Small Business Journal: Researching Entrepreneurship*, *38*(7), 593-604. https://doi.org/10.1177/0266242620945102

Dağdeviren, M., Yavuz, S., & Kılınç, N. (2009). Weapon selection using the AHP and TOPSIS methods under fuzzy environment. *Expert Systems with Applications*, *36*(4), 8143-8151. https://doi.org/https://doi.org/10.1016/j.eswa.2008.10.016

Dejardin, M., Raposo, M. L., Ferreira, J. J., Fernandes, C. I., Veiga, P. M., & Farinha, L. (2023). The impact of dynamic capabilities on SME performance during COVID-19. *Review of Managerial Science*, *17*(5), 1703-1729. https://doi.org/10.1007/s11846-022-00569-x

Dess, G. G., & Robinson, R. B., Jr. (1984). Measuring organizational performance in the absence of objective measures: the case of the privately-held firm and conglomerate business unit. *Strategic Management Journal*, *5*(3), 265-273. https://doi.org/https://doi.org/10.1002/smj.4250050306

Deyoung, R., Gron, A., Torna, G., & Winton, A. (2015). Risk overhang and loan portfolio decisions: small business loan supply before and during the financial crisis. *Journal of Finance*, *70*(6), 2451-2488. https://doi.org/10.1111/jofi.12356

Dias, É., & Ramos, M. N. (2022). A educação e os impactos da COVID-19 nas aprendizagens escolares. *Ensaio*, *30*(117), 859-870. https://doi.org/10.1590/S0104-40362022004000001

Dimpfl, T., & Peter, F. J. (2013). Using transfer entropy to measure information flows between financial markets. *Studies in Nonlinear Dynamics and Econometrics*, *17*(1), 85-102. https://doi.org/10.1515/SNDE-2012-0044/DOWNLOADASSET/SNDE_PROGS.ZIP

Dweck, E. (Coord.). (2020, maio). *Impactos macroeconômicos e setoriais da COVID-19 no Brasil* (Nota Técnica). Rio de Janeiro, RJ, Instituto de Economia, Universidade Federal do Rio de Janeiro. https://www.ie.ufrj.br/images/IE/grupos/GIC/GIC_IE_NT_ImpactosMacroSetoriaisdaC19noBrasilvfinal22-05-2020.pdf

Dyer, J. S., Fishburn, P. C., Steuer, R. E., Wallenius, J., & Zionts, S. (1992). Multiple criteria decision making, multiattribute utility theory: the next ten years. *Management Science*, *38*(5), 645-654. https://www.jstor.org/stable/2632682

Ecer, F. (2014). A hybrid banking websites quality evaluation model using AHP and COPRAS-G: a Turkey case. *Technological and Economic Development of Economy*, *20*(4), 758-782. https://doi.org/10.3846/20294913.2014.915596

Fasano, F., & Deloof, M. (2021). Local financial development and cash holdings in Italian SMEs. *International Small Business Journal: Researching Entrepreneurship*, *39*(8), 781-799. https://doi.org/10.1177/02662426211011554

Fasth, J., Elliot, V., & Styhre, A. (2022). Crisis management as practice in small- and medium-sized enterprises during the first period of COVID-19. *Journal of Contingencies and Crisis Management*, *30*(2), 161-170. https://doi.org/10.1111/1468-5973.12371

Fouladgar, M. M., Yazdani-Chamzini, A., Lashgari, A., Zavadskas, E. K., & Turskis, Z. (2012). Maintenance strategy selection using AHP and COPRAS under fuzzy environment. *International Journal of Strategic Property Management*, *16*(1), 85-104.

Gandhi, S., Mangla, S. K., Kumar, P., & Kumar, D. (2015). Evaluating factors in implementation of successful green supply chain management using DEMATEL: a case study. *International Strategic Management Review*, *3*(1-2), 96-109. https://doi.org/10.1016/j.ism.2015.05.001

Gandhi, S., Mangla, S. K., Kumar, P., & Kumar, D. (2016). A combined approach using AHP and DEMATEL for evaluating success factors in implementation of green supply chain management in Indian manufacturing industries. *International Journal of Logistics Research and Applications*, *19*(6), 537-561. https://doi.org/10.1080/13675567.2016.1164126

Gumus, A. T. (2009). Evaluation of hazardous waste transportation firms by using a two step fuzzy-AHP and TOPSIS methodology. *Expert Systems with Applications*, *36*(2), 4067-4074. https://doi.org/10.1016/j.eswa.2008.03.013

Habachi, M., & Haddad, S. E. (2021). Impact of COVID-19 on SME portfolios in morocco: evaluation of banking risk costs and the effectiveness of state support measures. *Investment Management and Financial Innovations*, *18*(3), 260-276. https://doi.org/10.21511/imfi.18(3).2021.23

Janssen, M., van der Voort, H., & Wahyudi, A. (2017). Factors influencing big data decision-making quality. *Journal of Business Research*, *70*, 338-345. https://doi.org/10.1016/j.jbusres.2016.08.007

Kaklauskas, A., Zavadskas, E. K., Raslanas, S., Ginevicius, R., Komka, A., & Malinauskas, P. (2006). Selection of low-e windows in retrofit of public buildings by applying multiple criteria method COPRAS: a Lithuanian case. *Energy and Buildings*, *38*(5), 454-462. https://doi.org/10.1016/j.enbuild.2005.08.005

Kamaldeep, S. (2021). Impact of Covid-19 on SMEs Globally. *SHS Web of Conferences*, *129*, 01012. https://doi.org/10.1051/shsconf/202112901012

Kassem, A., & Hakim, L. J. (2016). *Assessing critical success factors (CSFs) for a supplier in a relationship-driven B2B-market* [Master Thesis]. KTH Industrial Engineering and Management, Stockholm, Sweden. https://www.diva-portal.org/smash/get/diva2:1060844/FULLTEXT01.pdf

Keršuliene, V., Zavadskas, E. K., & Turskis, Z. (2010). Selection of rational dispute resolution method by applying new step-wise weight assessment ratio analysis (SWARA). *Journal of Business Economics and Management*, *11*(2), 243-258.

Klein, V. B., & Todesco, J. L. (2021). COVID-19 crisis and SMEs responses: the role of digital transformation. *Knowledge and Process Management*, *28*(2), 117-133. https://doi.org/10.1002/kpm.1660

Kullback, S., & Leibler, R. A. (1951). On information and sufficiency. *The Annals of Mathematical Statistics*, *22*(1), 79-86. https://doi.org/10.1214/aoms/1177729694

Kurland, N. B., Baucus, M., & Steckler, E. (2022). Business and society in the age of COVID-19: introduction to the special issue. *Business and Society Review*, *127*(S1), 147-157. https://doi.org/10.1111/basr.12265

Latham, S. (2009). Contrasting strategic response to economic recession in start-up versus established software firms. *Journal of Small Business Management*, *47*(2), 180-201. https://doi.org/10.1111/j.1540-627X.2009.00267.x

Lim, D. S. K., Morse, E. A., & Yu, N. (2020). The impact of the global crisis on the growth of SMEs: a resource system perspective. *In International Small Business Journal: Researching Entrepreneurship*, *38*(6), 492-503. https://doi.org/10.1177/0266242620950159

Ma, Z., Liu, Y., & Gao, Y. (2021). Research on the impact of COVID-19 on Chinese small and medium-sized enterprises: evidence from Beijing. *PLOS ONE*, *16*(12), e0257036. https://doi.org/10.1371/journal.pone.0257036

Maffioli, A., Negri, J. A. de, Rodriguez, C. M., & Vazquez-Bare, G. (2017). Public credit programmes and firm performance in Brazil. *Development Policy Review*, *35*(5), 675-702. https://doi.org/10.1111/dpr.12250

Maia, A. G., Eusébio, G. dos S., & Silveira, R. L. F. da. (2019). Can credit help small family farming? Evidence from Brazil. *Agricultural Finance Review*, *80*(2), 212-230. https://doi.org/10.1108/AFR-10-2018-0087

Marques, L., Chimenti, P. C. P. de S., & Mendes-da-Silva, W. (2021). Aprendizados Sobre o impacto do COVID-19 nas organizações. *Revista de Administração Contemporânea*, *25*(spe), 1-5. https://doi.org/10.1590/1982-7849rac2021210064.por

Miklian, J., & Hoelscher, K. (2022). SMEs and exogenous shocks: a conceptual literature review and forward research agenda. *In International Small Business Journal: Researching Entrepreneurship*, *40*(2), 178-204. https://doi.org/10.1177/02662426211050796

Mubiru, J., & Banda, E. J. K. B. (2008). Estimation of monthly average daily global solar irradiation using artificial neural networks. *Solar Energy*, *82*(2), 181-187. https://doi.org/https://doi.org/10.1016/j.solener.2007.06.003

Nakhaei, J., Lale Arefi, S., Bitarafan, M., & Kildienė, S. (2016). Evaluation of light supply in the public underground safe spaces by using of COPRAS-SWARA methods. *International Journal of Strategic Property Management*, *20*(2), 198-206.

Nicolletti, M., Alem, G., Blazek, M., Fillippi, P., & Bismarchi, L. F. (2020). Business action on sustainability and resilience in the context of COVID-19. *Revista de Administracao de Empresas*, *60*(6), 413-425. https://doi.org/10.1590/S0034-759020200605

Núñez, J. A., Cincotta, P. M., & Wachlin, F. C. (1996). Information entropy. *Celestial Mechanics and Dynamical Astronomy*, *64*(1), 43-53. https://doi.org/10.1007/BF00051604

Organization for Economic Co-operation and Development. (2021). *One year of SME and entrepreneurship policy responses to COVID-19: lessons learned to "build back better"*. https://www.oecd.org/coronavirus/policy-responses/one-year-of-sme-and-entrepreneurship-policy-responses-to-covid-19-lessons-learned-to-build-back-better-9a230220/

Olden, J. D., & Jackson, D. A. (2002). Illuminating the "black box": a randomization approach for understanding variable contributions in artificial neural networks. *Ecological Modelling*, *154*(1-2), 135-150. https://doi.org/10.1016/S0304-3800(02)00064-9

Olden, J. D., Joy, M. K., & Death, R. G. (2004). An accurate comparison of methods for quantifying variable importance in artificial neural networks using simulated data. *Ecological Modelling*, *178*(3-4), 389-397. https://doi.org/10.1016/J.ECOLMODEL.2004.03.013

Ozanne, L. K., Chowdhury, M., Prayag, G., & Mollenkopf, D. A. (2022). SMEs navigating COVID-19: The influence of social capital and dynamic capabilities on organizational resilience. *Industrial Marketing Management*, *104*, 116-135. https://doi.org/10.1016/j.indmarman.2022.04.009

Pereira, I., & Patel, P. C. (2022). Impact of the COVID-19 pandemic on the hours lost by self-employed racial minorities: evidence from Brazil. *Small Business Economics*, *58*(2), 769-805. https://doi.org/10.1007/s11187-021-00529-x

Peter, F. J., Dimpfl, T., & Huergo, L. (2010, September 28). Using transfer entropy to measure information flows between financial markets. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1683948

Puthusserry, P., King, T., Miller, K., & Khan, Z. (2022). A typology of emerging market smes' covid-19 response strategies: the role of tmts and organizational design. *British Journal of Management*, *33*(2), 603-633. https://doi.org/10.1111/1467-8551.12591

Rediske, G., Lorenzoni, L., Rigo, P., Siluk, J., Michels, L., & Marchesan, T. (2022). The impact of the COVID-19 pandemic on the economic viability of distributed photovoltaic systems in Brazil. *Environmental Progress & Sustainable Energy*, *41*(5), e13841. https://doi.org/10.1002/ep.13841

Reis, J. G. M. dos, Machado, S. T., & Aktas, E. (2021). Food exports from Brazil to the United Kingdom: an exploratory analysis of COVID-19 impact on trade. In A. Dolgui, A. Bernard, D. Lemoine, G. von Cieminski, & D. Romero (Eds.), *Advances in Production Management Systems* (Vol. 631, pp. 577-584). Springer. https://doi.org/10.1007/978-3-030-85902-2_61

Rezaeiniya, N., Zolfani, S. H., & Zavadskas, E. K. (2012). Greenhouse locating based on ANP-COPRAS-G methods – an empirical study based on Iran. *International Journal of Strategic Property Management*, *16*(2), 188-200. https://doi.org/10.3846/1648715X.2012.686459

Rezaeisaray, M., Ebrahimnejad, S., & Khalili-Damghani, K. (2016). A novel hybrid MCDM approach for outsourcing supplier selection: a case study in pipe and fittings manufacturing. *Journal of Modelling in Management*, *11*(2), 536-559. https://doi.org/10.1108/JM2-06-2014-0045

Schepers, J., Vandekerkhof, P., & Dillen, Y. (2021). The impact of the COVID-19 crisis on growth-oriented smes: Building entrepreneurial resilience. *Sustainability*, *13*(16), 9296. https://doi.org/10.3390/su13169296

Schreiber, T. (2000). Measuring information transfer. *Physical Review Letters*, *85*(2), 461. https://doi.org/10.1103/PhysRevLett.85.461

Serviço de Apoio às Micro e Pequenas Empresas Brasileiras. (2022). *O impacto do Coronavírus nos pequenos negócios*. https://datasebrae.com.br/covid/

Shannon, C. E. (1948a). A note on the concept of entropy. *The Bell System Technical Journal*, *27*(3), 379-423.

Shannon, C. E. (1948b). The Shannon information entropy of protein sequences. *The Bell System Technical Journal*, *27*(3), 623-656.

Sheng-Hshiung, T., Gwo-Hshiung, T., & Kuo-Ching, W. (1997). Evaluating tourist risks from fuzzy perspectives. *Annals of Tourism Research*, *24*(4), 796-812. https://doi.org/https://doi.org/10.1016/S0160-7383(97)00059-5

Singh, R. K., & Benyoucef, L. (2011). A fuzzy TOPSIS based approach for e-sourcing. *Engineering Applications of Artificial Intelligence*, *24*(3), 437-448. https://doi.org/10.1016/j.engappai.2010.09.006

Singh, S., Darwish, T. K., & Potočnik, K. (2016). Measuring Organizational Performance: A Case for Subjective Measures. *British Journal of Management*, *27*(1), 214-224. https://doi.org/10.1111/1467-8551.12126

Stanujkic, D., Karabasevic, D., & Zavadskas, E. K. (2015). A framework for the selection of a packaging design based on the SWARA method. *Inzinerine Ekonomika-Engineering Economics*, *26*(2), 181-187. https://doi.org/10.5755/j01.ee.26.2.8820

Sun, C. C. (2010). A performance evaluation model by integrating fuzzy AHP and fuzzy TOPSIS methods. Expert Systems with Applications, *37*(12), 7745-7754. https://doi.org/https://doi.org/10.1016/j.eswa.2010.04.066

Valipour, A., Yahaya, N., Noor, N. M., Antuchevičienė, J., & Tamošaitienė, J. (2017). Hybrid SWARA-COPRAS method for risk assessment in deep foundation excavation project: An Iranian case study. *Journal of Civil Engineering and Management*, *23*(4), 524-532. https://doi.org/10.3846/13923730.2017.1281842

Vargo, J., & Seville, E. (2011). Crisis strategic planning for SMEs: finding the silver lining. *International Journal of Production Research*, *49*(18), 5619-5635. https://doi.org/10.1080/00207543.2011.563902

Wang, J. W., Cheng, C. H., & Huang, K. C. (2009). Fuzzy Hierarchical TOPSIS for Supplier Selection. *Applied Soft Computing*, *9*(1), 377-386. https://doi.org/10.1016/j.asoc.2008.04.014

Wang, T. C., & Lee, H. Da. (2009). Developing a fuzzy TOPSIS approach based on subjective weights and objective weights. *Expert Systems with Applications*, *36*(5), 8980-8985. https://doi.org/10.1016/J.ESWA.2008.11.035

Wecker, A. C., Froehlich, C., & Gonçalves, M. A. (2020). Capacidades dinâmicas e estratégias para enfrentamento da crise diante da pandemia da COVID-19. *Revista Gestão Organizacional*, *14*(1), 10-32. https://doi.org/10.22277/rgo.v14i1.5711

Yazdani, M., Alidoosti, A., & Zavadskas, E. K. (2011). Risk analysis of critical infrastructures using fuzzy COPRAS. *Economic Research-Ekonomska Istraživanja*, *24*(4), 27-40. https://doi.org/10.1080/1331677X.2011.11517478

Yu, X., Guo, S., Guo, J., & Huang, X. (2011). Rank B2C e-commerce websites in e-alliance based on AHP and fuzzy TOPSIS. *Expert Systems with Applications*, *38(*4), 3550-3557. https://doi.org/10.1016/J.ESWA.2010.08.143

Zambaldi, F., Aranha, F., Lopes, H., & Politi, R. (2011). Credit granting to small firms: a Brazilian case. *Journal of Business Research*, *64*(3), 309-315. https://doi.org/10.1016/J.JBUSRES.2009.11.018

Zavadskas, E. K., & Kaklauskas, A. (1996). Determination of an efficient contractor by using the new method of multicriteria assessment. In D. Langford, & A. Retik (Eds.), *The Organization and Management of Construction*. Routledge. https://doi.org/10.4324/9780203477090

Zavadskas, E. K., Kaklauskas, A., Peldschus, F., & Turskis, Z. (2007). Multi-attribute assessment of road design solutions by using the COPRAS method. *The Baltic Journal of Road and Bridge Engineering*, *2*(4), 195-203. https://bjrbe-journals.rtu.lv/article/view/1822-427X.2007.4.195–203

Zhang, H., Gu, C. lin, Gu, L. wen, & Zhang, Y. (2011). The evaluation of tourism destination competitiveness by TOPSIS & information entropy – A case in the Yangtze River Delta of China. *Tourism Management*, *32*(2), 443-451. https://doi.org/10.1016/J.TOURMAN.2010.02.007

Zolfani, S. H., & Bahrami, M. (2014). Investment prioritizing in high tech industries based on SWARA-COPRAS approach. *Technological and Economic Development of Economy*, *20*(3), 534-553. https://doi.org/10.3846/20294913.2014.881435

Zolfani, S. H., Rezaeiniya, N., Aghdaie, M. H., & Zavadskas, E. K. (2012). Quality control manager selection based on AHP-COPRAS-G methods: a case in Iran. *Economic Research-Ekonomska Istraživanja*, *25*(1), 72-86. https://doi.org/10.1080/1331677X.2012.11517495

Luiz Gustavo Medeiros Barbosa
ORCID: https://orcid.org/0000-0002-3172-5878

Professor from the Brazilian School of Public and Business Administration at Getulio Vargas Foundation (FGV EBAPE); Project Coordinator at Getulio Vargas Foundation (FGV Projects). E-mail: luiz.barbosa@fgv.br

Peter Fernandes Wanke
ORCID: http://orcid.org/0000-0003-1395-8907

Full Professor and Coordinator in the Business Analytics and Economics Research Unit (BAE RU) from the COPPEAD Graduate School of Business at the Federal University of Rio de Janeiro (UFRJ). E-mail: peter@coppead.ufrj.br

Jorge Junio Moreira Antunes
ORCID: https://orcid.org/0000-0003-3199-5912

Researcher in the Business Analytics and Economics Research Unit (BAE RU) from the COPPEAD Graduate School of Business at the Federal University of Rio de Janeiro (UFRJ). E-mail: jorge.moreira@coppead.ufrj.br

Saulo Barroso Rocha
ORCID: https://orcid.org/0000-0001-5441-6747

Associate Professor at the Department of Entrepreneurship and Management at Federal Fluminense University (UFF). E-mail: saulorocha@id.uff.br

AUTHORS' CONTRIBUTION

Luiz Gustavo Medeiros Barbosa: Conceptualization (Lead); Investigation (Lead); Project administration (Lead); Supervision (Lead); Validation (Lead); Writing - original draft (Supporting).

Peter Fernandes Wanke: Formal Analysis (Lead); Methodology (Lead); Software (Supporting); Supervision (Lead); Writing- original draft (Supporting); Writing - review & editing (Supporting).

Jorge Junio Moreira Antunes: Formal Analysis (Equal); Methodology (Supporting); Software (Lead); Writing- original draft (Lead); Writing- review & editing (Supporting).

Saulo Barroso Rocha: Conceptualization (Supporting); Investigation (Supporting); Writing- review & editing (Lead).

DATA AVAILABILITY

The dataset supporting the results of this study is not publicly available.

PEER REVIEW REPORT

The peer review report is available at this URL: https://periodicos.fgv.br/cadernosebape/article/view/90536/85321

APPENDIX

Table A
Relative importance of each business-variable on each business-criteria (controlling for the respective utility function – COPRAS value)

Business-variable	Business Impact	Business Operation	Employee Dismissal	Loan Sucesssuccess	Crisis Duration
Academic_Level_Graduate (Complete)	**0.201**	**0.119**	**-0.007**	**0.297**	**1.339**
Academic_Level_High School (Complete)	**0.790**	**0.068**	**0.087**	**-0.274**	**-0.805**
Academic_Level_High School (Incomplete)	**0.219**	**-0.084**	-0.038	-0.150	15.871
Academic_Level_Primary Education (Complete)	0.026	-0.253	-0.242	-0.221	-12.240
Academic_Level_Primary Education (Incomplete)	0.350	0.085	0.235	0.094	-12.435
Academic_Level_Undergraduate (Incomplete)	0.550	0.108	-0.032	-0.134	11.614
Business_Size_EPP	0.165	-0.035	-0.014	-0.016	-2.523
Business_Size_ME	0.375	-0.010	0.005	-0.251	2.478
Business_Size_MEI	0.288	-0.063	-0.193	0.295	-0.934
Business_Time_1- 2 years	-0.238	-0.073	-0.015	-0.282	0.671
Business_Time_2- 5 years	0.605	0.047	-0.010	-0.055	1.377
Business_Time_5- 10 years	-0.033	0.187	0.075	-0.520	0.625
Business_Time_Less than 1 year	0.612	-0.007	0.131	0.170	-2.471
Business_Type_Agriculture	0.237	0.073	0.313	0.124	0.691
Business_Type_Automotive Workshops and Parts	0.115	0.011	-0.322	-0.082	2.149
Business_Type_Beauty	-0.076	-0.080	-0.356	0.079	0.297
Business_Type_Business Services	-0.026	-0.026	-0.143	0.039	0.811
Business_Type_Construction	0.158	-0.019	0.196	0.233	-2.847
Business_Type_Craftsmanship	0.404	-0.059	-0.106	0.066	-6.203
Business_Type_Creative Economy	0.157	-0.056	0.017	-0.005	0.461
Business_Type_Education	0.128	0.041	0.178	-0.281	4.617
Business_Type_Energy	0.143	0.037	-0.029	0.090	2.176
Business_Type_Fashion	0.352	-0.046	0.243	-0.162	-1.260
Business_Type_Food Industry	0.216	-0.336	-0.125	0.001	4.314
Business_Type_Food Services	-0.107	0.078	-0.014	0.314	3.534
Business_Type_Gyms and Physical Activities	-0.322	0.057	-0.252	-0.434	-0.932
Business_Type_Health	0.164	0.055	0.006	0.095	-0.167
Business_Type_Logistics and Transportation	0.074	-0.112	0.117	-0.095	-1.878
Business_Type_Other	0.296	0.000	0.191	-0.075	-5.681
Business_Type_Pet Shops and Veterinary Services	0.360	-0.117	-0.054	-0.359	-2.493

(Continue)

Business-variable	Business Impact	Business Operation	Employee Dismissal	Loan Sucesssuccess	Crisis Duration
Business_Type_Technology Industry	0.038	-0.172	0.003	-0.124	2.268
Business_Type_Tourism	0.572	0.027	-0.110	0.073	-0.839
COPRAS	0.462	-0.094	-0.056	0.060	-6.281
Edition	0.119	-0.056	0.022	0.249	-4.791
Sector_Agriculture	0.125	-0.034	0.234	-0.236	0.191
Sector_Construction	0.214	0.109	0.063	-0.214	1.427
Sector_Industry	0.831	-0.049	-0.141	0.037	1.352
Sector_Services	0.005	0.115	0.170	0.238	4.925
Sex_Female	0.196	0.079	0.199	-0.077	0.590
Years_<= 35 yearsState_AC	0.3730.021	-0.135-0.063	0.231-0.024	0.132-0.155	0.482-0.965
Years_>= 56 yearsState_AL	0.3140.113	0.062-0.009	-0.054-0.021	0.1550.163	-0.705-5.372
State_AM	0.188	0.106	0.346	-0.057	0.019
State_AP	0.207	0.085	0.038	0.101	1.193
State_BA	-0.229	-0.024	-0.145	0.019	-0.197
State_CE	-0.378	0.090	-0.048	0.139	0.596
State_DF	-0.070	0.014	-0.066	0.074	-0.992
State_ES	-0.384	-0.139	0.030	0.061	-0.267
State_GO	0.652	-0.023	-0.065	-0.147	0.927
State_MA	0.486	0.058	-0.296	0.015	-0.606
State_MG	0.146	0.022	-0.095	0.217	0.693
State_MS	0.564	-0.034	0.020	0.063	-0.350
State_MT	0.064	0.061	-0.057	0.219	0.562
State_PA	0.255	0.009	-0.036	0.124	-0.084
State_PB	0.278	0.039	0.210	0.254	0.208
State_PE	0.288	-0.124	0.087	0.006	1.983
State_PI	0.110	0.053	-0.211	0.103	-2.268
State_PR	0.377	-0.016	0.011	-0.086	1.629
State_RJ	0.875	-0.001	0.141	-0.093	-0.549
State_RN	-0.047	0.041	0.014	-0.167	3.192
State_RO	0.060	-0.109	0.123	0.131	-2.513
State_RR	-0.276	0.069	-0.010	-0.007	0.878
State_RS	0.061	0.060	-0.211	0.047	0.697
State_SC	0.045	-0.005	-0.012	0.004	0.479
State_SE	0.023	0.082	-0.094	-0.050	0.129
State_TO	0.015	-0.050	0.158	0.143	3.000
Years_<= 35 years	0.373	-0.135	0.231	0.132	0.482
Years_>= 56 years	0.314	0.062	-0.054	0.155	-0.705

* State information not shown in table.

Source: Elaborated by the authors.