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Original Article

Impact of the COVID-19 outbreak on credit ratings: Application of the through-the-cycle approach

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ABSTRACT

The objective of this study was to analyze how the COVID-19 crisis has affected the determinants and predictability of the domestic credit rating issued by Fitch Ratings in Argentina. Additionally, it aims to evaluate the effects of credit rating agencies using the through-the-cycle method. Given the subjective nature of credit rating categorization, researchers have developed models for explaining and predicting credit ratings. This subjectivity is significant during economic events. Therefore, it is important to investigate whether the factors that determine and predict credit ratings remained consistent before and during the COVID-19 crisis. This paper contributes significantly to understanding how the application of the through-the-cycle method affects the determinants and predictability of credit ratings in economic crises. The application of the through-the-cycle method by credit rating agencies as a criterion during the COVID-19 crisis resulted in a breakdown of the usual correlation between determinants and credit rating. Understanding whether variables are permanent or transitory components is crucial for investors and borrowers to anticipate credit rating changes during economic downturns. The dependent variables are the long-term domestic credit rating categories. The independent variables are derived from the Fitch Ratings credit rating methodology and the literature, which includes quantitative and qualitative variables. The statistical methods used are ordinal logistic regression, generalized ordinal logistic regression, and support vector machines. The COVID-19 crisis was considered a transitory event due to the application of the through-the-cycle approach by rating agencies. During the pandemic, specific determinants of credit ratings are not considered due to their transitory nature. The study identifies interest coverage ratio and competitive position as transitory components. This approach led to less predictability but a more stable credit rating.

Keywords: credit rating, through-the-cycle approach, COVID-19, financial information.

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Impacto do surto de COVID-19 nos ratings de crédito: aplicação da abordagem through-the-cycle

RESUMO

O objetivo deste estudo foi analisar como a crise da COVID-19 afetou os determinantes e a previsibilidade do rating de crédito doméstico emitida pela Fitch Ratings na Argentina. Além disso, pretende-se avaliar os efeitos das agências de classificação de risco de crédito usando o método through-the-cycle (ao longo do ciclo). Dada a natureza subjetiva da categorização dos ratings de crédito, os pesquisadores desenvolveram modelos para explicar e prever esses ratings. Essa subjetividade é significativa durante eventos econômicos. Portanto, é importante investigar se os fatores que determinam e preveem os ratings de crédito permaneceram consistentes antes e durante a crise da COVID-19. Este artigo contribui significativamente para a compreensão de como a aplicação do método through-the-cycle afeta os determinantes e a previsibilidade dos ratings de crédito em crises econômicas. A aplicação do método through-the-cycle pelas agências de classificação de risco de crédito como um critério durante a crise da COVID-19 resultou em uma quebra da correlação usual entre os determinantes e os ratings de crédito. Entender se as variáveis são componentes permanentes ou transitórios é fundamental para que os investidores e tomadores de empréstimos antecipem as mudanças nos ratings de crédito durante as recessões econômicas. As variáveis dependentes são as categorias de rating de crédito doméstico de longo prazo. As variáveis independentes são derivadas da metodologia de rating de crédito da Fitch Ratings e da literatura, que inclui variáveis quantitativas e qualitativas. Os métodos estatísticos utilizados são a regressão logística ordinal, a regressão logística ordinal generalizada e as máquinas de vetores de suporte. A crise da COVID-19 foi considerada um evento transitório devido à aplicação da abordagem through-the-cycle pelas agências de classificação de risco de crédito. Durante a pandemia, os determinantes específicos dos ratings de crédito não são considerados devido à sua natureza transitória. O estudo identifica o índice de cobertura de juros e a posição competitiva como componentes transitórios. Essa abordagem levou a uma menor previsibilidade, mas a um rating de crédito mais estável.

Palavras-chave: *rating de crédito, abordagem through-the-cycle, COVID-19, informações financeiras.*

1. INTRODUCTION

Rating agencies play a crucial role in the financial markets. They provide an independent opinion about an issuer's fundamental creditworthiness and ability to meet its debt obligations in full and on time. The opinion is expressed in the form of a credit rating. According to Kang and Liu (2007), financial markets have widely adopted credit ratings because they can predict the likelihood of defaults by reflecting changes in credit quality levels.

Credit rating agencies issue global and domestic credit ratings. Local credit ratings exclude sovereign effects, transfer risk, and the possibility that investors may be unable to repatriate interest and principal payments (FixScr, 2014). These ratings reflect the perceived level of risk and ability to fulfill obligations within a specific country. Countries with middle-income economies have more domestic credit rating agencies and more developed domestic bond markets.

However, rating agencies do not disclose the methodology used for determining credit ratings, which remains opaque and subjective. As such, it is difficult to independently reproduce credit ratings with 100% accuracy (Shin & Han, 2001). Given this subjectivity, research has sought to identify the variables that underpin credit ratings in order to anticipate those ratings or detect situations where credit rating agencies apply lax criteria.

According to certain investors, rating agencies should update their ratings more quickly (Chodnicka-Jaworska, 2022; Altman & Rijken, 2004). One widely accepted reason for this is the agencies' through-the-cycle methodology and rating migration policy (Altman & Rijken, 2004). In contrast to one-year default prediction models, rating agencies using the through-the-cycle approach focus on the probability of default in a stress scenario, with the reference point being the permanent credit quality of a borrower. Therefore, this method requires the separation of permanent and transitory components (Löffler, 2004). The time horizon considered by agencies for credit ratings can be viewed as a period ranging from five to ten years (Gonzales et al., 2004). The purpose is to provide greater stability to credit ratings (Altman & Rijken, 2004).

The COVID-19 outbreak resulted in an unprecedented decline in global economic activity and increased global financial risks, which adversely affected global financial markets (Gormsen & Koijen, 2020; Phan & Narayan, 2020). The pandemic has led to extensive research on its effects, assessing its impact on the economy and financial market (Fernandes, 2020; Sharif et al., 2020), firm bankruptcy (Bernardi et al., 2021), corporate performance (Hu & Zhang, 2021), and credit risk downgrades (Altman et al., 2022).

In a recent study by Dubinova et al. (2021), it was found that there was a shift in the correlation between macro fundamentals and credit risk at the beginning of the pandemic. However, no research has been conducted to determine the factors that influenced credit ratings during the COVID-19 crisis. The question remains whether the determinants and predictability of credit rating categories in economic stability remained consistent during the COVID-19 crisis. Rating agencies typically use the through-the-cycle approach to assess the probability of default in a stress scenario. It is important to assess how this approach affected the determinants and predictability during the COVID-19 crisis. This study aims to address this research gap by investigating these questions.

This study aims to examine the impact of the COVID-19 crisis on the determinants and predictability of the domestic credit rating issued by Fitch Ratings in Argentina, and to assess the consequences of the application of the through-the-cycle method by credit rating agencies. This work compares the results of the proposed models for 2020-2021 (during the COVID-19 outbreak) with the period 2018-2019 (before the COVID-19 outbreak). Fix Scr is the affiliate of Fitch Ratings in Argentina and is responsible for issuing most domestic credit ratings. Fix Scr (2020) documented that during the COVID-19 pandemic, ratings were based on the expected credit profile by the end of 2021, rather than the worst moment of the crisis.

The research takes place in Argentina, which is the third-largest economy in Latin America, following Brazil and Mexico. The country has abundant natural resources, which has made it one of the region's leading food producers and exporters. However, over the past decade, the economy has experienced macroeconomic uncertainty, including inflation, exchange rate fluctuations, and a decline in production levels (Aromí et al.. 2022; Cepal, 2020). In this situation, the pandemic had a severe impact on Argentina, with its gross domestic product (GDP) falling by 10% in 2020 (IMF, 2021). As a result, the COVID-19 crisis had a significant impact on Argentine businesses, making it an interesting case study to evaluate the effects of the pandemic.

This study contributes to a better understanding of the rating methodology used by credit rating agencies and, consequently, to the predictability of credit ratings during economic crises. The results of this study can help investors decide whether to trust the credit ratings assigned by credit rating agencies, anticipate any potential downgrades in domestic credit ratings, and enable debt issuers to determine their borrowing costs. The academic significance of this research lies in the refinement of credit risk assessment studies by distinguishing between the cycle and point-in-time methods. Furthermore, the implications of this research may be helpful to policymakers by helping them maintain an ideal balance between rating stability and rating timeliness.

This paper is divided into five sections. The second section provides the theoretical framework; the third section presents the data and empirical methodology; the fourth section presents the results, which include model estimation and forecasting; and the fifth section concludes the study with concluding remarks and suggestions for future research.

2. THEORETICAL FRAMEWORK

Several studies have found that the market-based model is more effective in explaining credit ratings than the accounting-based model (Figlioli et al., 2019; Novotná, 2013; Tanthanongsakkun & Treepongkaruna, 2008). However, Du and Suo (2007) suggest that Merton's theoretical default measure is not a sufficient statistic of stock market information on credit quality.

Financial ratios have a pronounced effect on credit ratings, mainly interest coverage with earnings before interest, taxes, depreciation, and amortization (EBITDA) and leverage (Gray et al., 2006; Feki & Khoufi, 2015; Hung et al., 2013). Other studies have also shown the relevance of firm size, as measured by total assets, and liquidity (Feki & Khoufi, 2015). Damasceno et al. (2008) found that return on assets, total debt to total assets, and presence in the capital market are essential factors in determining a corporate credit rating. Access to external financing is also an essential factor (Murcia et al., 2014). Additionally, Drobetz and Heller (2014) suggested that profitability does not significantly affect the rating assessment.

The literature suggests that incorporating both quantitative and qualitative factors can improve the predictability of credit rating models. Lehmann (2003) confirmed that including qualitative information significantly improves model performance for different classification measures. More recently, Drobetz and Heller

(2014) suggested that strategic objectives and future liquidity risks are the most important business risk factors affecting credit ratings and that qualitative information is relevant in explaining credit ratings. Soares et al. (2012) found that corporate governance is the main determinant of credit ratings, along with accounting data.

According to the literature, the effects of variables on credit ratings are not direct and linear across all categories. For instance, Gray et al. (2006) found that financial ratios affect credit rating categories differently. In particular, financial ratios help distinguish between A- and BBB-rated firms, but are less precise in separating AA- from A-rated firms. Krichene and Khoufi (2016) noted that the interest coverage ratio loses all significance when it falls below zero or exceeds 20. Likewise, the debt coverage ratio loses all significance when it falls below negative one or exceeds one. Blume et al. (1998), motivated by the strong skewness in the distribution of interest coverage, support the hypothesis that there is a non-linear effect for the interest coverage ratio.

The studies on credit ratings in Argentina found more interest in the sovereign credit market than in the corporate debt market. Freitas and Minardi (2013) found that the announcement of rating downgrades significantly impacts Latin American stock prices.

Other papers have examined the impacts of COVID-19 on corporate credit ratings. In one such study, Altman et al. (2022) estimated the impact of the COVID-19 pandemic on credit risk changes. They applied the Altman Z”-score model to analyze several possible crisis scenarios. The analysis showed that the subsequent downgrades from the base case (in 2019) are non-linear for the initial rating category or the economic sector. The severity of the downgrades in different scenarios depends on the characteristics of individual firms and cannot be determined at a general or sectoral level.

Dubinova et al. (2021) showed that credit risk models based on observable covariates typically suffer from instability problems from the pre-COVID-19 period to the early pandemic months. In contrast, models based on unobserved components and frailty dynamics appear to capture credit dynamics better, even in extreme periods such as the COVID-19 pandemic. Chodnicka-Jaworska (2022) carried out a study of European banks during the COVID-19 pandemic (2000–2021). This study confirms the strong impact of the macroeconomic environment on default risk and the direct influence on the methodology used by agencies. It also confirms the notion of a delayed reaction of agencies to changes in the situation during the pandemic. Furthermore, the study reveals a more substantial impact on banks from developing countries and outside the Eurozone.

3. DATA AND EMPIRICAL METHODOLOGY

3.1 Dependent Variable

The dependent variables are the domestic long-term rating categories. The scale of Fix Scr for Argentina is divided into four ordinal rating categories, as shown in Table 1.

Table 1
Ordinal rating categories

Rating	Number of firm-years	Combined rating	Ordinal rating
AAA	7	AAA/AA	4
AA	22		
A	52	A	3
BBB	49	BBB	2
BB	5	BB/C	1
B	4		
CCC	3		
CC	5		
C	3		
Total	150		

Source: *Elaborated by the authors.*

The rating categories are combined based on the following criteria:

- AAA/AA: The rating categories AAA and AA are combined in the same group; both imply very solid credit quality and the lowest relative expectation of default risk.
- A: This category implies very solid credit quality, but changes in economic conditions may affect the ability to meet obligations.
- BBB: This rating category indicates adequate credit quality, but changes in economic conditions have the highest probability of affecting the ability to meet obligations.
- BB/C: The rating category BB denotes a high risk of default, and the firm is more vulnerable to changes in economic conditions. Rating category B indicates higher vulnerability than BB and is dependent on sustained and favorable development of economic conditions. Categories CCC to C denote a high risk of default, with C indicating a high risk of default if economic and business conditions do not change. Rating categories BB to C are grouped together because there are few observations in each category. However, this group includes ratings with different levels of financial distress. It is difficult for firms with financial problems to be removed from the rating.
- D: Rating category D denotes an issuer that has entered bankruptcy, which does not need to be included in a model because it can be objectively known.

3.2 Independent Variables

The independent variables were obtained from the Fitch Ratings credit rating methodology and variables used in previous research (Jiang & Packer, 2017; Drobetz & Heller, 2014). Later, the selection of variables was based on the significance of the coefficients and their ability to reflect the character of the credit rating category.

The variables can be divided into quantitative and qualitative factors.

3.2.1 Quantitative factors

3.2.1.1 Firm size

Studies of bankruptcy have identified firm size as an important explanatory variable. Larger firms generally have access to a wider range of financing sources and more flexibility to redeploy assets than smaller firms. Until recently, the probability of bankruptcy was very low for large firms (Wahlen et al., 2014). The larger the firm, the greater the potential to diversify non-systematic risks, which reduces the risk of the company's bonds (Elton & Gruber, 1995). Domestic rating agencies weigh size more heavily as a positive credit risk factor than global agencies (Jiang & Packer, 2017). Most studies measure size using total assets, which are calculated as follows:

$$Firm\,size = \log(assets) \tag{1}$$

The asset value was adjusted using the IPC (Consumer Price Index) from the fiscal year-end to the last month of the study period (October 2021) to achieve homogeneity in the values.

3.2.1.2 Leverage

The leverage ratio measures how much a firm is financed with debt. The greater the firm's leverage ratio, the greater its risk of failure. Conversely, a lower leverage ratio leads to a better rating for the firm. This ratio can be calculated as follows:

$$Leverage = \frac{Total\,liabilities}{Assets} \tag{2}$$

3.2.1.3 Interest coverage ratio

The interest coverage ratio with EBITDA is part of Fitch Ratings' methodology, and there is a more frequently cited determinant variable in the literature (Feki & Khoufi, 2015). The interest coverage ratio indicates the number of times a firm's earnings or cash flow could cover its interest expenses. This ratio can be calculated as follows:

$$Interest\,coverage\,ratio = \frac{EBITDA}{Interest\,expenses} \tag{3}$$

EBITDA: Earnings before interest, taxes, depreciation, and amortization.

Nominal interest includes inflation coverage as Argentina is an inflationary economy. Interest expenses are calculated using the average of the last three years. Intermediate periods are annualized.

3.2.1.4 Financial flexibility

Graham and Harvey (2001) report that corporate managers consider financial flexibility and maintaining a good credit rating as the two most important determinants of their debt financing policy. An analysis of Fitch's reported ratings reveals that the main characteristic of firms rated between BB and CCC is limited financial flexibility. These firms face difficulties in rolling over their obligations due to insufficient cash flow. Financial flexibility (FF) can be measured at a different level based on the number of times net earnings are negative over the analysis periods. This is presented as a categorical variable, as shown in Table 2:

Table 2
Financial flexibility

Variable name	Financial flexibility level	FF[a]	Dummy variable
FF1	High	0	0 or 1
FF2	Medium	1	0 or 1
FF3	Moderate	2	0 or 1
FF4	Limited	3	0 or 1

[a] $FF = \sum_1^3 NITWO$; *NITWO = One if net income was negative, zero otherwise.*
Source: *Elaborated by the authors.*

3.2.2 Qualitative factors

Qualitative factors are information that is not measured by a number, but can represent either negative or positive forces affecting the firm. The interpretation of qualitative data implies a certain degree of subjectivity and depends on the context (Liberti & Petersen, 2019). However, qualitative data can be summarized in numerical information.

3.2.2.1 Sector risk

One of the first steps in analyzing a firm is to determine the characteristics of the economic sector or industry in which it participates (FixScr, 2014). The main factors considered are industry characteristics, competitiveness, growth prospects, entry and exit barriers, regulations, cyclical factors, price volatility, and counterparty risk. This variable is defined as an ordinal variable based on the level of risk in the firm's sector, as shown in Table 3:

Table 3
Sector risk

Sector level risk	Ordinal variable
Low	1
Medium	2
High	3

Source: *Elaborated by the authors.*

3.2.2.2 Competitive position

Competitive position seeks to determine how the firm is positioned within its specific sector and its performance within it (FixScr, 2014). The main factors considered are market share, geographic and product diversification, business integration, supplier and buyer power, and economies of scale. This variable is classified as follows in Table 4:

Table 4
Competitive position

Competitive position	Ordinal variable
High	1
Medium	2
Low	3

Source: *Elaborated by the authors.*

Finally, Table 5 summarizes the independent variables used in the analysis.

Table 5
Financial and qualitative variables

Name	Description	Type
FrmSz	Firm size	Numeric
Lev	Leverage	Numeric
EA	Interest coverage ratio	Numeric
FF1	Financial flexibility-High	Categorical
FF2	Financial flexibility-Medium	Categorical
FF3	Financial flexibility-Moderate	Categorical
FF4	Financial flexibility-Limited	Categorical
SR	Sector risk	Ordinal
CP	Competitive position	Ordinal

Source: *Elaborated by the authors.*

3.3 Statistical Methods

3.3.1 Ordinal logistic regression

The most common statistical methodologies in credit rating prediction are ordinal logistic or probit models because rating categories can be represented as ordinal variables (Amato & Furfine, 2004; Drobetz & Heller, 2014). Ordinal logistic regression (OLR) is a statistical method that models the relationship between an ordinal multilevel dependent variable and independent variables. The values of the dependent variable have a natural order or ranking. The OLR model compares the probability of a response less than or equal to a given category (j=1,…J-1) to the probability of a response in a higher category. The model can be expressed as follows (Liu, 2009):

$$Logit\left(Y \leq j|x_1, x_2 \ldots x_n\right)$$

$$= ln\left[\frac{\pi\left(Y \leq j|x_1, x_2 \ldots x_n\right)}{\pi\left(Y > j|x_1, x_2 \ldots x_n\right)}\right] = \alpha_j + \left(-\beta_1 X_1 - \beta_2 X_2 \ldots - \beta_n X_n\right) \quad \boxed{4}$$

where $x = [x_1, x_2, \ldots, x_n]^T$ is a vector of n explanatory variables, $\beta = [\beta_1, \beta_2, \ldots, \beta_n]^T$ is the corresponding coefficient vector, and α is the cut-off point for rating category *y*. Thus, this model predicts cumulative logits across J−1 response categories. The cumulative logits can then be used to calculate the estimated cumulative odds and the cumulative probabilities at or below the j category.

One of the key points of OLR is the proportional odds assumption, which assumes that the effect of the explanatory variables on the independent variable is constant across all categories. This assumption implies that the coefficients of the independent variable are consistent across the categories, resulting in parallel slopes at all response levels. This requirement is essential for interpreting model coefficients and the validity of predictions.

The proportional odds assumption holds when the regression x' β is independent of j, such that β has the same effect for each of the j-1 cumulative logits. It is noteworthy that x' β does not contain an intercept, since the α_j (threshold) acts as an intercept. Another assumption is the absence of multicollinearity, which occurs when the independent variables are too highly correlated. The models are estimated using the maximum likelihood method, and the observed information matrix calculates variance estimates.

3.3.2 Generalized ordinal logistic regression

The generalized ordinal logistic regression (GOLR) model extends the OLR model by relaxing the proportional odds assumption. When a particular predictor violates the assumption, its effect will be estimated freely across different categories of the dependent variable. The GOLR model is expressed as follows (Williams, 2006):

$$Logit\left(Y > j|x_1, x_2 \ldots x_n\right)$$

$$= ln\left[\frac{\pi\left(Y \leq j|x_1, x_2 \ldots x_n\right)}{\pi\left(Y > j|x_1, x_2 \ldots x_n\right)}\right] = \alpha_j + \left(-\beta_{1j} X_1 - \beta_{2j} X_2 \ldots - \beta_{nj} X_n\right) \quad \boxed{5}$$

In this expression, all the effects of the independent variables vary at each cut-off point. If some of these effects are stable, they will be constrained to be equal, as in the proportional odds assumption. Thus, the GOLR model refers to the case in which at least one of the coefficients for a predictor varies across categories.

3.3.3 Support vector machines

The bibliographic review of Louzada et al. (2016) on classification methods applied to credit scoring finds that the support vector machine method has better predictive performance than other methods.

Support vector machines (SVMs) seek to find an optimal hyperplane with a maximum margin that acts as the decision boundary to separate two different categories. Given a training set of labeled instance pairs (x〗i,y_i), where i is the number of instances i = 1,2,3, …, m, x〗_i ∈R and y_i ∈ {−1, +1}, the decision boundary to separate two different categories in the SVM is generally expressed as:

$$w * x + b = 0 \quad \boxed{6}$$

The optimal separating hyperplane is the only one with maximum margin, and all training instances are assumed to satisfy the constraint:

$$y_i\left(w * x_i + b\right) \geq 1 \quad \boxed{7}$$

The convex optimization problem is defined as follows:

$$min\ \emptyset\ (w,b) = \frac{1}{2}\ \|w\|^2 + C\sum_{i=1}^{m} \epsilon_i \tag{8}$$

$$\text{s.t.}\, y_i\ (w\ *\ x_i + b) \geq 1 \tag{9}$$

The optimal hyperplane is equivalent to the optimization problem of a quadratic function, where the Lagrange function is utilized to find the global maximum. The slack variable ϵ_i is introduced to account for misclassification, accompanied by C as the penalty cost. The kernel trick is used to modify the SVM formulation. Linear and radial basis function (RBF) kernels are used:

$$\text{(i)Linear: } x_i * y_i \tag{10}$$

$$\text{(ii)Radial basis function (RBF): } \exp\left\{-\gamma\left\|x_i - x_j\right\|^2\right\} \tag{11}$$

This explanation can be extended to more than two variables using the same reasoning.

3.4 Model Estimation

The dependent variable in this study is the credit rating category, represented as an ordinal variable, as shown in Table 1. The independent variables are size, leverage, interest coverage ratio, financial flexibility, sector risk, and competitive position, as shown in Table 5. To model this relationship, the following expression is used:

$$R_{j=1..4} = f\left(FrmSz, Lev, EA, FF, SR, CP\right) \tag{12}$$

Rj represents the credit rating category (j = 1...4) and FF is a categorical variable that captures financial flexibility. Specifically, it tests the effects of three levels of financial flexibility (medium, moderate, and limited) relative to a high level captured by the intercept FF1. RLO and RLOG will be applied to obtain the magnitudes and significance levels of the regression coefficients.

This study will also evaluate the predictive accuracy of the model. Overfitting is one of the biggest issues when building an effective predictive model. This occurs when a statistical model is too closely aligned with a limited set of data points. Therefore, it is crucial to measure the predictive accuracy with out-of-sample data. The most commonly used method for this purpose is cross-validation, which involves randomly partitioning the original sample into k equal-sized subsamples. A single subsample is retained as the validation data for testing the model, and the remaining k−1 subsamples are used as training data. Then, the cross-validation process is repeated k times, with each of the k subsamples used exactly once as the validation data. The k results can then be averaged to produce a single estimation.

3.5 Data and Summary Statistics

The data were obtained from the FixScr national rating reports of the company issuers of long-term financial obligations in Argentina (FixScr, 2021). The sample includes large and medium-sized firms rated in 2018-2019 (before the COVID-19 crisis) and 2020-2021 (during the COVID-19 crisis). The financial data cover the interim financial statements prior to the issuance of the rating and two subsequent fiscal years. The dataset contains 150 firm-year observations, 75 firm-years per period. The qualitative factors were obtained from the Fix Scr rating reports, firms' annual reports, and other publicly available information.

The rule for identifying outliers is based on considering any data point that is more than 2.5 standard deviations ($\bar{x} \pm 2.5\ \sigma$) away from the mean in a sample. According to this criterion, the variable interest coverage ratio was winsorized at the 4th and 96th percentiles; the other variables are not winsorized. The interest coverage ratio has a significant dispersion due to interest rate volatility caused by inflation.

Table 6 presents the number of firm-years for each rating category. The A and BBB categories have the highest number of firm-year observations, while the remaining categories have relatively fewer observations; therefore, they were combined.

Table 6
Firm-years for rating categories

Rating	Number of firm-years	Combined rating	Number of firm-years	Number of firms during COVID-19	Number of firms before COVID-19
AAA	7	AAA/AA	29	16	13
AA	22				
A	52	A	52	26	26
BBB	49	BBB	49	21	28

Table 6
Cont.

Rating	Number of firm-years	Combined rating	Number of firm-years	Number of firms during COVID-19	Number of firms before COVID-19
BB	5	BB/C	20	12	8
B	4				
CCC	3				
CC	5				
C	3				
Total	150		150	75	75

Source: *Elaborated by the authors.*

Table 7 shows the changes in credit rating categories during the COVID-19 crisis relative to the pre-COVID-19 period. The data reveal that 32% of firms experienced a change in their credit rating category, with a higher proportion of low-rated firms being affected.

Table 7
Changes in rating categories for firm-years during the COVID-19 crisis relative to the pre-COVID-19 period

Rating	Number of firms changing categories	Number of firms keeping categories	Number of firms pre-COVID-19
AAA/AA	2	11	13
A	7	19	26
BBB	11	17	28
BB/C	4	4	8
Total	24	51	75
%	32.00%	68.00%	100.00%

Source: *Elaborated by the authors.*

Table 8 provides insights into the means of the variables before and during the COVID-19 crisis. The results show that the mean values of FrmSz, Lev, EA, and CP remained similar in both periods. However, the distribution of EA and CP differs across rating categories. The variables FF and SR increase in value in most categories except AAA/AA, which is negatively related to the rating categories.

Table 8
Means for each rating category during and before COVID-19

Panel A: During the COVID-19 crisis						
Rating	**FrmSz**	**Lev**	**EA**	**FF**	**SR**	**CP**
AAA/AA	8.1877	0.6657	4.2150	2.1250	2.0625	2.4375
A	7.5463	0.6614	5.5640	1.5769	2.1538	2.2692
BBB	7.0640	0.7536	3.9216	1.8095	2.3330	1.7619
BB/C	7.3916	0.7684	2.2935	3.3000	2.3000	2.0000
Total	7.5474	0.7123	3.9985	2.2029	2.2123	2.1172
Panel B: Before the COVID-19 crisis						
Rating	**FrmSz**	**Lev**	**EA**	**FF**	**SR**	**CP**
AAA/AA	8.1744	0.6683	6.0026	1.3038	1.5385	2.8452
A	7.4300	0.6693	5.2825	1.6154	1.9231	2.1923
BBB	7.0791	0.7561	3.2703	2.0000	1.9286	1.8214
BB/C	7.0781	0.7936	1.3202	3.0000	2.1000	1.7000
Total	7.4404	0.7218	3.9689	1.9798	1.8725	2.1397

FrmSz = Firm size; Lev = Leverage; EA = Interest coverage ratio; FF = Financial flexibility; SR = Sector risk; CP = Competitive position.
Source: *Elaborated by the authors.*

The pairwise correlations between the variables during and before the COVID-19 crisis are presented in Table 9. The results indicate that FrmSz has a higher correlation with CP, Lev with EA, and EA with FF during and before the COVID-19 period. Moreover, the pre-COVID-19 period shows higher correlations between Lev and FF.

Table 9
Correlation matrix

Panel A: During the COVID-19 crisis						
	FrmSz	**Lev**	**EA**	**FF**	**SR**	**PC**
FrmSz	1.0000					
Lev	-0.1150	1.0000				
EA	-0.0948	-0.4383	1.0000			
FF	0.1841	0.1539	-0.4688	1.0000		
SR	0.2018	0.2221	-0.0968	0.1573	1.0000	
CP	0.3383	-0.2253	0.1468	-0.0482	-0.2921	1.0000
Panel B: Before the COVID-19 crisis						
	FrmSz	**Lev**	**EA**	**FF**	**SR**	**PC**
FrmSz	1.0000					
Lev	-0.0221	1.0000				
EA	0.0981	-0.4247	1.0000			
FF	0.0340	0.5443	-0.3939	1.0000		
SR	0.0091	0.0743	-0.0842	0.0955	1.0000	
CP	0.2426	-0.1983	0.2067	-0.1144	-0.2545	1.0000

FrmSz = Firm size; Lev = Leverage; EA = Interest coverage ratio; FF = Financial flexibility; SR = Sector risk; CP = Competitive position.
Source: *Elaborated by the authors.*

4. EMPIRICAL RESULTS

4.1 Model Estimation

Table 10 presents the results estimated by OLR. Among the quantitative variables, only the FrmSz coefficient is statistically significant during and before the COVID-19 crisis. The positive sign of the FrmSz coefficient indicates a higher value for an increase in the corporate credit rating. These results highlight the importance of firm size in credit rating classification in different situations, suggesting that this variable has a persistent character.

Among the qualitative variables, the FF4 coefficient with FF1 and the SR coefficient are significant in both periods. Conversely, the negative sign of the FF4 and SR coefficients indicates that a higher value decreases the corporate credit rating. Firms facing potential financial problems, as measured by low financial flexibility, continue to be a relevant variable in the pandemic crisis. The inherent risks of the sector also remain significant.

The coefficients of the variables EA, FF3 with respect to FF1, and CP are statistically significant only in the pre-COVID-19 period. The positive sign of the EA and CP coefficients indicates that a higher value increases the credit rating. In contrast, the negative sign of FF3 indicates that a higher value decreases the credit rating. The interest coverage ratio is sensitive to economic activity; however, its relevance was bypassed during the pandemic because it was considered a transitory event. Under normal circumstances, prior to the COVID-19 period, the interest coverage ratio served as a crucial financial metric in credit rating assessments. The firm's competitive position was affected by the pandemic. Despite this effect, credit rating agencies tended to downplay its significance by viewing the pandemic as transitory.

Table 10
Ordinal logistic regression model estimates

	Panel A: During the COVID-19 crisis			Panel B: Before the Covid-19 crisis		
	Coefficients			Coefficients		
	Value	t-value		Value	t-value	
FrmSz	2.6218	5.22	***	3.6391	5.22	***
Lev	-2.6136	-1.37		-1.2871	-0.57	
EA	0.1172	1.11		0.2401	2.48	**
FF2	-0.4292	-0.70		-1.2665	-1.72	
FF3	-0.9618	-1.25		-2.2671	-2.48	**
FF4	-3.4886	-3.38	***	-2.8752	-2.76	***
SR	-0.7983	-2.05	**	-0.8645	-2.09	**
CP	-0.3420	-1.12		0.7754	2.39	**
N		75			75	
LR chi2(8)		53.13	***		80.88	***
Pseudo R2		0.2631			0.4220	

FrmSz = Firm size; Lev = Leverage; EA = Interest coverage ratio; FF2 = Medium financial flexibility; FF3 = Moderate financial flexibility; FF4 = Limited financial flexibility; SR = Sector risk; CP = Competitive position.
**** Significant at 1%; ** Significant at 5%.*
Source: *Elaborated by the authors.*

Table 11
Collinearity diagnostics

Variables	Panel A – Period: 2021-2020		Panel B – Period: 2019-2018	
	VIF	Tolerance	VIF	Tolerance
FrmSz	1.2900	0.7752	1.2000	0.8333
Lev	1.4300	0.6993	1.6400	0.6098
EA	1.7000	0.5882	1.3200	0.7576
FF(2)	1.5500	0.6452	1.3600	0.7353
FF(3)	1.6700	0.5988	1.4300	0.6993
FF(4)	1.3400	0.7463	1.5000	0.6667
SR	1.3100	0.7634	1.1000	0.9091
CP	1.3600	0.7353	1.2700	0.7874
Mean	1.4600		1.3500	

VIF =Variance Inflation Factor; Tolerance = (1/VIF)
Source: *Elaborated by the authors.*

The VIF (variance inflation factor) indicates the degree to which the variance of the coefficient estimate is inflated due to multicollinearity. As with tolerance, there is no specific threshold value to definitively determine the presence of multicollinearity. However, VIF values exceeding 2.5 are often considered a potential cause for concern (Johnston et al., 2018). In Table 11, the VIF values of the variables do not exceed the aforementioned threshold, suggesting that multicollinearity may not be a significant issue in the model.

The likelihood ratio test of the proportional odds assumption, shown in the notes to Table 12, indicates the violation of the proportional odds assumption; therefore, it is applied to the GOLR. Panel A presents the results of the GOLR estimates during the COVID-19 crisis. The variables FrmSz, FF3, and SR violate the proportional odds assumption; their coefficients differ across rating categories. FrmSz and SR have a significant coefficient for discriminating the AAA/AA vs. A and A vs. BBB rating categories, with FrmSz having a positive effect and SR hurting the higher rating categories. The FF4 variable has a significant coefficient for all rating categories, and the FF3 variable has a significant coefficient only for discriminating the BBB vs. BB/C rating categories. These variables have a negative effect on credit rating classification.

Table 12
Generalized ordinal logistic model estimation

Panel A: During the COVID-19 crisis									
	From AAA/AA to A			**From A to BBB**			**From BBB to BB/C**		
	Threshold coefficients								
Variables	**Value**	**t value**		**Value**	**t value**		**Value**	**t value**	
FrmSz	7.2188	4.06	***	5.6913	3.55	***	0.4609	0.53	
Lev (+)	-2.0810	-1.14		-2.0810	-1.14		-2.0810	-1.14	
EA (+)	0.2163	1.47		0.2163	1.47		0.2163	1.47	
FF2 (+)	-0.3130	-0.40		-0.3130	-0.40		-0.3130	-0.40	
FF3	1.7888	1.63		-0.0448	-0.41		-4.8764	2.82	***
FF4 (+)	-4.7530	-3.13	***	-4.7530	-3.13	***	-4.7530	-3.13	***
SR	-2.8124	-3.34	***	-3.2259	-2.67	***	1.8664	1.83	
CP (+)	-0.6930	-1.82		-0.6930	-1.82		-0.6930	-1.82	
Intercept	-48.8929	-3.77	***	-34.1051	-3.26	***	-0.6215	-0.10	
N	75								
LR chi2(12)	104.74	***							
Pseudo R2	0.5186								
Panel B: Before the COVID-19 crisis									
	From AAA/AA to A			**From A to BBB**			**From BBB to BB/C**		
	Threshold coefficients								
Variables	**Value**	**t value**		**Value**	**t value**		**Value**	**t value**	
FrmSz (+)	4.9710	4.94	***	4.9710	4.94	***	4.9710	4.94	***
Lev (+)	-1.2755	-0.48		-1.2755	-0.48		-1.2755	-0.48	
EA	0.0815	0.55		0.4688	2.35	**	2.1105	3.55	***
FF2	-1.0854	-0.89		-1.1888	-1.26		-4.6889	-3.03	***
FF3 (+)	-1.6717	-1.51		-1.6717	-1.51		-1.6717	-1.51	
FF4 (+)	-3.1856	-2.51	**	-3.1856	-2.51	**	-3.1856	-2.51	**
SR (+)	-0.9839	-2.14	**	-0.9839	-2.14	**	-0.9839	-2.14	**
CP (+)	0.9943	2.69	***	0.9943	2.69	***	0.9943	2.69	***
Intercept	-39.1758	5.00	***	-36.7298	-4.80	***	-34.0436	-4.56	***
N	75								
LR chi2(12)	101.17	***							
Pseudo R2	0.5279								

Note: *Likelihood ratio test of proportional odds assumption: during COVID-19: chi2 = 71.21(Prob > chi2 = 0.00); pre-COVID-19: chi2 = 45.60 (Prob > chi2 = 0.00). (+) The same coefficient for all rating categories.*
FrmSz = Firm size; Lev = Leverage; EA = Interest coverage ratio; FF2 = Medium financial flexibility; FF3 = Moderate financial flexibility; FF4 = Limited financial flexibility; SR =Sector risk; CP = Competitive position.
****Significant at 1%; **Significant at 5%.*
Source: *Elaborated by the authors.*

Panel B presents the results of the GOLR estimates in the pre-COVID-19 crisis period. The variables EA and FF2, with respect to FF1, violate the proportional odds assumption, while the remaining variables maintain the same coefficient for all rating categories. The variables FrmSz, FF4, SR, and CP show a significant coefficient for all rating categories, with the FrmSz and CP coefficients being positive, and the FF4 and SR coefficients being negative. Additionally, the AE variable has a significant positive coefficient in discriminating between the A *vs*. BBB and BBB *vs*. BB/C rating categories.

Applying GOLR shows that during the COVID-19 crisis, firm size and sector risk are relevant factors in determining the credit rating of firms with a rating above BBB, with firm size having a positive effect and sector risk having a negative effect. Limited and moderate financial flexibility are also relevant in determining the credit rating of firms with a BB/C rating. This means that firms with limited and moderate financial flexibility, as determined by the proxy used, experienced losses for three and two years, respectively.

Before the COVID-19 crisis, firm size, limited financial flexibility, sector risk, and competitive position were relevant in all rating categories. Firm size and competitive position have a positive impact on the rating categories, while limited financial flexibility and sector risk have a negative impact. The interest coverage ratio variable is relevant for the categories below the BBB rating.

In conclusion, both methods produce similar results. However, the main difference is that GOLR captures the nonlinearity of the relationship between covariables and independent variables, as pointed out by Gray et al. (2006). The difference between the determinant before and during the COVID-19 crisis is due to the through-the-cycle approach used by Fitch Ratings, which considers the COVID-19 crisis as a transitory event. According to this approach, the permanent components are firm size, sector risk, and financial flexibility, while the transitory components are interest coverage ratio and competitive position.

Firm size and potential sector risk are considered permanent factors due to their intrinsic long-term behavioral characteristics. Financial flexibility, as measured by cumulative negative net income, is also considered a permanent factor due to the low possibility of short-term reversal. Although the literature suggests that the interest coverage ratio is a key determinant of credit rating, it is viewed as a transitory factor because of the probability of short-term reversal if the firm maintains its refinancing capacity. The pandemic affected the competitive position of some firms, which is regarded as a transitory factor due to the possible reversal of such a situation.

4.2 Prediction

4.2.1 In-sample

First, the predictive power of the model is examined using in-sample data. Predictive accuracy is measured by comparing the predicted credit rating to the actual rating for each firm and calculating the ratio of correctly classified firms to the total number of firm observations. Table 13 shows that the model has higher predictive accuracy during the pre-COVID-19 period than during the pandemic, using both the OLR and GOLR methods. However, GOLR shows a greater difference between the pre-COVID-19 period and the COVID-19 crisis (78.67 > 65.33) than OLR (69.33 > 64.00). This suggests that the predictability of the model decreased during the pandemic compared to the pre-COVID-19 period. This can be explained by the cycle approach applied by the rating agencies.

Table 13
Predictive accuracy with in-sample data

Rating	Ordinal logistic regression	Generalized ordinal logistic regression
Panel A: During the COVID-19 crisis		
AAA/AA	50.00%	68.75%
A	88.46%	80.77%
BBB	52.38%	57.14%
BB/C	50.00%	41.67%
Total	64.00%	65.33%
Panel B: Pre-COVID-19 crisis		
Rating	**Ordinal logistic regression**	**Generalized ordinal logistic regression**
AAA/AA	76.92%	76.92%
A	76.92%	80.77%
BBB	67.86%	78.57%
BB/C	37.50%	75.00%
Total	69.33%	78.67%

Source: *Elaborated by the authors.*

Moreover, Panel A shows that during the COVID-19 crisis period, the OLR and GOLR methods have similar predictive accuracy rates (64.00% ≈ 65.33%) for the aggregate categories. The GOLR method outperforms OLR in terms of accuracy for the AAA/AA rating category (68.50%>50.00%), while the difference in accuracy for the A and BB/C rating categories is smaller (80.77% < 88.46%; 41.67% < 50.00%, respectively). In Panel B of Table 13, the GOLR method has higher predictive accuracy than ORL for the pre-COVID-19 crisis period (78.67% > 69.33%). The individual rating categories also show high predictive accuracy in nearly all rating categories, particularly in the BB/C category (75.00%>37.50%). However, the AAA/AA category has the same predictive accuracy in both methods.

4.2.2 Out-of-sample

The statistical method used to predict the accuracy includes OLR, GOLR, and SVM. The out-of-sample validation is implemented by resampling the cross-validation through 10 folds and repeating it five times. The radial basis function (RBF) kernel used for SVM is more accurate than the linear method. Two parameters are associated with the RBF kernel: cost of misclassification (C) and gamma (γ). Technically, the gamma parameter is the inverse of the standard deviation of the RBF kernel. High gamma values usually produce highly flexible decision limits, and low gamma values often result in a more linear decision limit. The optimal values of the cost and gamma parameters (C and ϱ) were obtained using five-fold cross-validation.

Table 14 presents the results of the study on the predictive accuracy of the OLR, GOLR, and SVM statistical methods. The results show that in the pre-COVID-19 period, the three statistical methods used had greater predictive accuracy compared to the COVID-19 crisis period. The GOLR has the highest accuracy rate (70.40% > 56.61%), especially in the AAA/AA and BB rating categories. In the A and BB/C categories, OLR and SVM both show high accuracy.

When comparing the methods used, the GOLR method has the highest accuracy in the pre-COVID-19 crisis period (70.40% > 65.10% > 47.66%). However, the SVM methods show slight superiority (59.10% > 57.00% > 56.61) during COVID-19. Moreover, there is no uniformity in all categories; for example, during the COVID-19 crisis, OLR has the highest accuracy in rating category A (80.69%) and SVM has the highest accuracy in rating category BB/C (73.13%).

Table 14
Predictive accuracy cross-validation data

Rating	Ordinal logistic regression		Generalized ordinal logistic regression		Support vector machine	
	Periods		Periods		Periods	
	COVID-19	Pre-COVID-19	COVID-19	Pre-COVID-19	COVID-19	Pre-COVID 19
AAA/AA	41.31%	83.24%	58.59%	89.29%	47.42%	83.24%
A	80.69%	66.86%	50.59%	63.70%	68.30%	66.86%
BBB	44.64%	59.89%	65.88%	70.00%	48.57%	58.71%
BB/C	48.13%	47.66%	58.33%	69.70%	73.13%	47.66%
Total	57.00%	65.10%	56.61%	70.40%	59.10%	64.60%
C					200	200
ϱ					0.01	0.01

Source: *Elaborated by the authors.*

In summary, the conclusions obtained from the out-of-sample and in-sample data are similar. Predictability decreases during the pandemic crisis due to the use of the through-the-cycle approach by the rating agencies. This conclusion is consistent with the results of the determinants of credit rating. Overall, the generalized ordinal logistic regression method showed superior predictive performance in this study.

5. CONCLUSIONS

First, this study seeks to identify the determinants of domestic credit rating in Argentina, explicitly issued by Fitch Ratings, before and during the COVID-19 crisis. The results indicate that the determinants of credit rating during the pre-COVID-19 period are firm size, sector risk, financial flexibility, interest coverage ratio, and competitive position. However, during the COVID-19 crisis, interest coverage ratio and competitive position are not found to be relevant determinants. The difference in the determinants before and during the COVID-19 crisis is due to the through-the-cycle approach used by rating agencies, in which the COVID-19 crisis is viewed as a transitory event.

According to previous results, firm size, sector risk, and financial flexibility are classified as permanent components, while interest coverage ratio and competitive position are classified as transitory components. Firm size is particularly relevant in the upper categories (A/AA), and moderate and limited financial flexibility is a parameter for rating firms in the lower categories (BB/CCC). The interest coverage ratio variable is relevant for the categories below the BBB rating, confirming the non-linearity of the variables across rating categories. Although the literature suggests that the interest coverage ratio is a determinant of credit rating, it was considered a transitory component during the COVID-19 period.

We also examine how the predictability of credit ratings was affected by COVID-19. The models used to assess this predictability suggest that the accuracy of credit ratings decreased during the COVID-19 crisis period. This result is consistent with the through-the-cycle approach adopted by credit rating agencies, which considers the pandemic event to be transitory. This approach led to less predictability and more stable credit ratings, as pointed out by Löffler (2004). This conclusion is consistent with the results of the determinants of credit ratings.

The main limitation of this work was the small number of observations in some categories. These categories were grouped together to address this, but this approach may have led to some loss of information.

This paper contributes significantly to understanding the impact of the application of the through-the-cycle method on the determinants and predictability of credit ratings. The findings of the study can help investors and financial analysts make more informed decisions and assess the creditworthiness of companies during an economic crisis. This study contributes to the development of the domestic bond credit market in emerging economies, improving the readability and transparency of credit rating agencies. The conclusions make an important academic contribution, as they will allow researchers to improve credit risk assessment studies, considering the differences between the through-the-cycle approach and the point-in–time approach. Future research on credit ratings should incorporate contextual variables that capture the application of the through-the-cycle approach.

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