Duty calls: Prediction of failure in reorganization processes

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ABSTRACT

Purpose: Using data from business reorganization processes under Act 1116 of 2006 in Colombia during the period 2008 to 2018, a model for predicting the success of these processes is proposed. The paper aims to validate the model in two different periods. The first one, in 2019, characterised by stability, and the second one, in 2020, characterised by the uncertainty generated by the COVID-19 pandemic.

Design/Methodology/Approach: A set of five financial variables comprising indebtedness, profitability and solvency proxies, firm age, macroeconomic conditions, and industry and regional dummies are used as independent variables in a logit model to predict the failure of reorganization processes. In addition, an out-of-sample analysis is carried out for the 2019 and 2020 periods.

Findings: The results show a high predictive power of the estimated model. Even the results of the out-of-sample analysis are satisfactory during the unstable pandemic period. However, industry and regional effects add no predictive power for 2020, probably due to subsidies for economic activity and the relaxation of insolvency legislation in Colombia during that year.

Originality/Value: In a context of global reform in insolvency laws, the consistent predictive ability shown by the model, even during periods of uncertainty, can guide regulatory changes to ensure the survival of companies entering into reorganization processes, and reduce the observed high failure rate.

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Duty calls: Prediction of failure in reorganization processes

1. Introduction

The economic and social costs of bankruptcy (Quintiliani, 2017) affect capital allocation efficiency, labour productivity, employment, and access to credit (Mcgowan et al., 2017). This is driving policymakers to seek optimal insolvency regimes consistent with the design of reforms aimed at economic growth and the financial standardization resulting from economic globalization. Company reorganization is one of the insolvency proceedings with the greatest potential consequences for the stability and growth of the business fabric.

Indeed, fear of a wave of bankruptcies caused by the COVID-19 pandemic led several legislations to opt for flexibility in a bid to avoid massive business liquidations and support reorganization procedures in countries that applied strict lockdowns or were more severely hit by the pandemic. While countries such as the United Kingdom, Netherlands, Poland and Colombia, adopted new quasi-judicial and hybrid reorganization procedures others, such as Australia, Singapore or the United States, pursued the same objective by facilitating simplified liquidation and restructuring processes for Small and Medium Enterprises (Menezes and Gropper, 2021).

The literature has extensively studied corporate default prediction, defining the term in different ways, ranging from inability of a firm to fulfil its financial obligations (Beaver, 1966), to business failure (Platt and Platt, 2004) or bankruptcy (Altman, 1968; Ohlson, 1980; Li and Faff, 2019).

However, research on prediction of corporate reorganizations is scant, especially in relation to emerging countries. This paper therefore aims to fill this research gap with evidence from a prediction model for success in corporate reorganization processes that includes financial variables, economic-context proxies, and industry and region dummies. In particular, data on reorganization agreements in Colombia for the period 2008-2018 enable the use of logistic regression to assess the relative importance of specific one- or two-period lagged predictors of failure and test the congruence of an "ad hoc" forecast model with one-year lagged predictors.

The particular conditions generated by the COVID-19 pandemic suggested running an out-of-sample predictive analysis for the years 2019 and 2020. The results show that the model has good predictive capacity, even for the year 2020 when the chances of success in reorganization processes could have been conditioned by the lockdowns forced by the pandemic, government aid to support businesses, or modifications of the Act to reduce the risk of a reorganization failing. Thus, the results obtained in the modelling and post-estimation processes conducted with the analysed predictors provide valuable information for policymakers, owners, managers, and creditors.

Although previous evidence on the prediction of the failure of reorganization processes is scarce, our model has shown predictive ability. This ability is maintained even in the event of economic shocks, such as the coronavirus pandemic. The results could serve as a guide in the development of legislation aimed at preventing the failure of reorganization processes.

2. Literature Review

The range of papers on bankruptcy shine a light on the widespread interest in predicting firm failure and the availability of effective analytical and predictive techniques with which to study it. However, the features of this phenomenon vary according to the perspective from which it is approached, and forecasting the success of reorganization procedures is one that requires further investigation (Camacho-Miñano et al., 2013; Cepec and Grajzl, 2021). This need has been reinforced by the various economic crises of recent decades.

The legal framework for insolvency singles out the U.S. Bankruptcy Code and the U.K. Insolvency Law as international reference systems that can be seen as facilitators of screening processes designed to recover viable companies and liquidate those that are not (Hotchkiss et al., 2008; John et al., 2013). Corporate reorganization is one of the most commonly accessed insolvency procedures when the economic recovery appears to be a strong choice for leveraging resources and minimizing costs at the social and private levels (Gurrea-Martínez, 2020a).

Chapter 11 of the U.S. Bankruptcy Code is the framework from which corporate reorganization legislation has spread. Although the processes of admission, negotiation and resolution of agreements delimited in this chapter have been studied and emulated in the systems of other countries (Alanis and Quijano, 2019; Cepec and Grajzl, 2021), some studies indicate that successful reorganization processes are infrequent, despite being considered the preferred instrument for rescuing businesses (Laitinen, 2011; Wang, 2012). These considerations, therefore, indicate that insolvency can be explored using different contexts and specific legal procedures.

The recent crisis, brought on by the COVID-19 pandemic, highlighted the need for legislative reform to cover restructuring processes. Proposals for the pandemic period included both temporary and permanent measures (Routledge, 2021; Gurrea-Martínez, 2020b). However, once the pandemic can be considered overcome, recommendations are proposed for the improvement of insolvency frameworks focusing on small and medium-sized companies (Gurrea-Martínez, 2021) or emerging markets (Gurrea-Martínez, 2020c), although in the latter the future development of legislation to promote efficient insolvency frameworks is as important as improving judicial systems and creating a sophisticated body of insolvency practitioners.

In particular, for the development of bankruptcy theory, predicting the success or failure of corporate reorganizations is as crucial as regulating to guarantee the economic recovery of companies undergoing these procedures. However, literature relating these two factors is still scarce and we detect a gap between predicting the outcome of reorganization processes and using the results to guide the creation of more efficient insolvency regimes. Thus, White (1989) questions the efficiency of the U.S. bankruptcy system, which screens out failed and liquidated businesses whose resources are more valuable if they remain in business, as well as others that continue to operate even when their resources could be put to new and better uses. Since this situation arises where bankruptcy reorganization is preferred to liquidation, the author conceives that a unified procedure reduces the costs of controlling unproductive resources. However, although this approach aims at the efficient use and mobility of assets through market-regulated compensation mechanisms for creditors and owners (Hotchkiss et al., 2008), predicting the failure of reorganization processes could provide novel insights into proposals for insolvency regime improvements.

According to Laitinen (2011), the viability analysis of firms in reorganization is an approach that links failure prediction with the efficiency of the reorganization procedure. In this paper, viability, viewed as the state in which the firm is able to cover its future liabilities, is analyzed using financial and non-financial variables in a logistic regression to predict the outcomes of a sample of firms that filed for bankruptcy and reorganization under the Finnish Bankruptcy Act and Finnish Company Reorganization Act. Overall, the results show that most of the firms in reorganization are not viable, while many of the firms in bankruptcy are. This not only confirms that filtering failures can be observed in different bankruptcy systems around the world, as shown by Wang (2012) for an international sample of 30 countries on different continents, Lukason and Urbanik (2013) in the case of Estonia and its reorganization law, and Cepec and Grajzl (2019) in an analysis of company reorganization proposals in post-socialist Slovenia; but also indicates that ex-ante evaluation comparing financial and non-financial predictors can help in forecasting successful reorganizations and more efficient insolvency proceedings (Blazy and Nigam, 2019; Antill and Grenadier, 2019; Blazy and Stef, 2020).

This raises the need for reorganization-success prediction models to improve efficiency in modern bankruptcy regimes. While some of the patterns of failure observed in countries' insolvency regimes are attributable to standard features of reorganization laws or procedures, differences in regime design due to country idiosyncrasies and state policies are likely to generate other efficiency-determining factors (Mcgowan et al., 2017). With respect to the COVID-19 pandemic, Stef and Bissieux (2022) report a relationship between government-decreed lockdowns and the outcomes of insolvency proceedings in France, where, after lockdowns were lifted, the number of judicial liquidations increased with respect to the pre-pandemic period.

The specific features of the Colombian case are considered in some papers addressing bankruptcy prediction. Thus, Arroyave (2018) verifies the effectiveness of some of the most widely used corporate bankruptcy prediction models in three of the country's largest companies, while Valencia et al. (2019) analyze various bankruptcy prediction models for small and medium-sized firms for the two-year period 2012 to 2013.

Addressing success prediction for reorganization processes, Abinzano et al. (2021) estimate the predictive ability of classical insolvency prediction models when applied to corporate reorganizations, finding that, although some financial variables relating to solvency, indebtedness, or profitability show some predictive ability, none of the models is entirely satisfactory.

In relation to the possible impact of the COVID-19 pandemic on corporate insolvency and reorganization processes in Colombia, the government launched loan programs targeting the sectors worst hit by the pandemic for an amount greater than 1% of GDP

(Guerrero-Amezaga et al., 2022) and introduced two temporary modifications to Act 1116 of 2006 establishing two new out-of-court processes (Alarcón-Lora et al., 2022; Menezes and Gropper, 2021). However, none of these measures affects the results of the present study, given that all the reorganization processes analyzed start prior to 2019.

Against this background, and since the literature does not provide a model for predicting the success or failure of reorganization processes, this paper aims to propose and test a failure prediction model for reorganization processes by considering both financial and non-financial variables. The context is interesting for two reasons: firstly, because the reorganization processes of interest take place in an emerging economy under Act 1116/2006 during the first decade of its implementation; and secondly, because the validity of the model is tested with an out-of-sample analysis using data for 2019 and 2020 when the consequences triggered by the COVID-19 pandemic were already visible.

The remainder of the paper is structured as follows. Section 3 describes the database, sample selection, and methodology. Section 4 gives the results of the models estimated to predict failure in reorganization processes, and of the out-of-sample analysis. Section 5 discusses the findings and, finally, section 6 highlights the main conclusions and practical implications.

3. Database and methodology

3.1. Database

This paper uses the business reorganization and judicial liquidation database from the Colombian Superintendence of Companies (SSC), which provides information from 2008 to 2020. For the various analyses proposed, we have considered those reorganization processes that were completed by 2020 and started prior to 2018 within the framework of Act 1116/2006. This choice stems from our interest in evaluating the determinants of the failure of business reorganization using data accumulated between 2008 and 2018, that is, during the first decade of application of Act 1116/2006. The SSC has the most complete historical and publicly accessible database in existence, given that the only information currently available refers to processes in progress. Thus, estimates from failure forecast models should provide valuable information on the resilience of businesses for avoiding liquidation and ensuring survival.

Out of a total of 2,591 reorganization processes initiated between 2008 and 2018, 1,868 involved companies and 723 individuals. Focusing on corporate proceedings, 508 processes were completed in the 2008-2018 period (277 relapsed into a judicial liquidation process and 231 successfully completed the reorganization plan). Subsequently, the sample was reduced to 111 companies with financial information for the year ending prior to the agreement closure date. Five observations were dropped due to missing data in the Cash Flow Statement (CFS) and four more due to inconsistencies detected in the Statement of Comprehensive Income (SCI). The final sample obtained for period t-1 comprises 102 observations. Using a similar procedure, another sample of 163 observations was obtained for period *t-2*[1].

Subsequently, in order to analyze the ability of the estimated models to provide predicted values for companies outside the study, we run an out-of-sample test of the models previously estimated, starting from a sample of 125 companies that initiated their reorganization agreements in the period 2008-2018 and completed them in 2019 or 2020. This analysis enables us to verify the ability of the model to anticipate reorganization failure in an uncertain environment such as that created by the lockdowns forced by the COVID-19 pandemic during the year 2020.

3.2. Methodology

Previous works that have reviewed the literature on bankruptcy show the variety of methodologies and models used for bankruptcy prediction. Bellovary et al. (2007) highlights the importance of taking advantage of the existing empirical structure to apply it or refine it if necessary. Meanwhile, Tascón and Castaño (2012) argue that the findings obtained with some methodologies and business failure models show commonalities across different geographical settings and time periods. However, they also conclude that "ad hoc" model design can be useful, depending on the context and its evolution.

The considerations outlined above, together with the characteristics of the selected samples and the high predictive capacity that binary logistic regression has shown in previous studies, justify the use of this methodology to construct a failure prediction model for reorganization processes. Since companies are classified as failed or non-failed according to the status reported by the SSC at the closing of the reorganization agreement and not based on subjective assessment criteria, misclassification bias is no obstacle to

[1] As the end of the restructuring process approaches, some observations are lost. This is why there are more observations for period *t-2* than for period *t-1*. However, some companies have data for period *t-1* but not for period *t-2*. A total of 74 companies have data for both periods.

selecting a logit model in this context. However, care must be taken to avoid multicollinearity between the independent variables to ensure statistically significant results (Balcaen and Ooghe, 2006).

The logit model for estimating business failure probability can be written mathematically as follows:

$$P(Failure_{it} = 1) = \frac{1}{1+e^{-f\left(\Psi_{h_{i,t-j}}\right)}} \tag{1}$$

with:

$$f\left(\Psi_{h_{i,t-j}}\right) = Y_{i,t} = \beta_0 + \beta_1\Psi_{1_{i,t-j}} + \beta_2\Psi_{2_{i,t-j}} + \ldots + \beta_k\Psi_{k_{i,t-j}}$$

where $\Psi_{h_{i,t-j}}$ represents the value of the independent variable Ψ_h, with $h=1, 2, \ldots, k$, for company i, at time t-j.

The dependent variable takes values in the interval [0, 1] and indicates the probability of belonging to the group of non-failed vs failed companies. In this particular case, the financial independent variables for the construction of the "ad hoc" model were extracted from a compendium of accounting and financial variables identified in previous studies as potential predictors of insolvency and bankruptcy (Abinzano et al., 2021), using univariate analysis and multicollinearity tests to establish the selection criteria. Financial variables are commonly used both for bankruptcy prediction and as control variables to explain the results of reorganization proceedings (Stef and Bissieux, 2022; Corbae and D'Erasmo, 2021). The following five variables, based on the criteria used by Abinzano et al. (2021), were selected: (Current Assets – Inventories) / Current Assets ((CA-I)/CA); Cash / Current Assets (C/CA); Cash/Total Assets (C/TA); Total Liabilities / Total Assets (TL/TA) and Net Income / Total Assets (NI/TA).

Firm age is considered as an additional factor in failure prediction for corporate reorganization agreements. This variable is measured as the age of the company in years at the beginning of the reorganization agreement, and both the natural logarithm (LN_Age) and the square of the natural logarithm (SLN_Age) are used in the estimations, to control for quadratic effects. The analysis of firm age is motivated by the use of age as a non-financial predictor in previous works (Back, 2005; Altman et al., 2015; Steff and Bissieux, 2022).

Macroeconomic conditions have been identified in several studies as a factor to be taken into account. In particular, Fallanca et al. (2020) cite the macroeconomic climate as a key determinant in predicting bank credit vulnerability; Afzal and Firdousi (2022) show that the cost of bank capital is influenced by GDP growth; Berninger et al. (2021) describe the effect of financial crises on corporate bond yields; while Cincinelli and Piatti (2021) find that the increase in bank NPLs is related to the economic recession in Italy. For the specific case of corporate failure and business reorganization processes, our literature review reveals the common use predictors relating to economic activity (Li and Faff, 2019; Stef and Bissieux, 2022). In our case, economic activity is proxied by acceleration or slowdown in the growth rates of the Colombian Investment Component of GDP (ΔINVt)[2].

Dummy variables for the industry and the region in which the company is located are also considered, since the impact of financial crises on firm solvency and performance varies across sectors of activity. In particular, the Covid-19 crisis has had significant effects on the travel & leisure sectors (Salisu and Tchankam, 2022). Given that each company is linked to a single industry according to the International Standard Industrial Classification (ISIC) prepared by the National Administrative Department of Statistics (DANE), binary variables were constructed to indicate belonging or not to one of the five industries identified in the sample (Agriculture, Commerce, Construction, Manufactures, and Services). Likewise, binary variables were created for Colombia's main vs other cities based on the categories observed in the company domicile data (Bogota, Medellin, Cali, Barranquilla, and the rest of the country).

Finally, the results obtained with the estimation of the Logit models with data for 2008-2018 are used to test their goodness of fit to the data for the sample of reorganization processes initiated during the law's first decade and completed in 2019 and 2020.

4. Results

4.1. Descriptive statistics

The descriptive statistics of the financial variables summarised in Table 1 are taken from the firms' annual statements for each of the last two years prior to the completion of the

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[2] Other variables potentially capturing the evolution of economic activity, such as ΔGDP_t (Acceleration in GDP growth rate at t) or ΔPE_t (Acceleration in Public Expenditure growth rate at t) considered initially yielded poorer results than the investment growth rate variable.

reorganization process. In both samples, the solvency indicators[3] of failed and non-failed companies have averages below unity and fairly uniform standard deviations in the two accounting years preceding the closing of the agreement. When no distinction is made between failed and non-failed companies (Panel C), a higher level of indebtedness can be observed on average, albeit with lower average losses, at *t-1* than at *t-2*. However, Panel B poses an exception to this pattern, because the average aggregate indebtedness in period *t-1* is lower for successful firms.

Based on the characteristics of the database, a robust mean difference test for independent samples is in order[4]. Thus, firms are classified as failed or non-failed in periods *t-1* and *t-2*. After testing for normality and homoscedasticity using the Kolmogorov-Smirnof and Snedecor's F-tests, respectively, the results of the test for the sample at *t-1* revealed that, even without controlling for other factors, there are significant differences in solvency (CA - I)/CA, indebtedness (TL/TA) and profitability (NI/TA) ratios between firms that failed and those that reorganized successfully. In other words, successful firms are more solvent, carry less debt, and show better average returns. However, the only significant difference between the two groups of firms according to the test at *t-2* is in their TL/TA ratios. This can be interpreted as a first sign that financial variables in period *t-1* may have explanatory power for success in reorganization processes, while in period *t-2* their role will be less relevant.

INSERT TABLE 1 ABOUT HERE

The correlation coefficients of the financial variables for both samples, at *t-1* and at *t-2*, are shown in Table 2. Although some seem to indicate high levels of correlation between certain explanatory variables, these are not sufficient to imply multicollinearity (Maddala and Lahiri, 2009). Since these variables are valuable indicators of a firm's future financial performance, the variance inflation factor (VIF) is a more appropriate way to determine their inclusion in the modelling process (Table 3). This diagnosis can be obtained with an OLS estimation, where the main concern is with the relationship between the independent variables rather than the functional form of the model (Menard, 2002).

INSERT TABLE 2 ABOUT HERE

[3] The solvency indicators for our study are: (CA – I)/CA, C/CA and C/TA.

[4] The mean difference test results (not shown for lack of space) are available from the authors upon request.

INSERT TABLE 3 ABOUT HERE

As can be seen in Table 3, in no case is it observed that the maximum tolerable limits of the VIF from which multicollinearity problems regularly arise are far from being reached (10 according to Hair et al., 1995; and 5 according to Akinwande et al., 2015). Tolerance, measured as the percentage of variance in a given predictor that cannot be explained by other predictors, also lies below the aforementioned thresholds.

4.2. Logit Estimation

Table 4 shows the results of the model estimation given by expression (1) with the financial predictors identified in the previous section, the age variables, the ΔINVt, and the variables selected to include regional and industry effects.

INSERT TABLE 4 ABOUT HERE

The independent variables used in the estimation of Model 1 are the five financial ratios that showed individual predictive ability in the analysis of failure in reorganization processes, together with the variables ΔINVt, LN_Age and SLN_Age. The results with the sample variables at *t-1* indicate that the model correctly predicts 78.4% of the cases and achieves a pseudo R2 of 41.1%. The coefficients show that all the variables are significantly associated with failure, as expected. The coefficients of the (CA – I)/CA ratio and the C/TA ratio are positive and significant at the 5% and 1% levels, respectively, such that higher values of these indicators increase the probability of failure in a reorganization process. Although in previous insolvency studies (Lo, 1986; Romero, 2013) the observed association between these variables and corporate failure was negative, our finding provides new evidence on the determinants of corporate failure when specifically analyzing reorganization procedures and the insolvency regime of an emerging country. The C/CA ratio, which, together with the two previous ones, is among the group of variables that proxy for solvency, is significant at the 1% level with a negative sign. This indicates that the probability of failure is greater for firms with less cash in proportion to liquid assets, in line with what was observed by Romero (2013) regarding the failure of small and medium-sized companies in Colombia. The coefficients of the ratios of indebtedness and profitability are significant with opposite signs. The TL/TA ratio is positively associated with failure, thus showing that higher indebtedness increases the probability of liquidation. This result is supported by previous insolvency studies (Ohlson, 1980; Tascón and Castaño, 2012). The negative sign of the NI/TA ratio, meanwhile, is consistent with the notion that a higher ratio of profitability to assets reduces the probability of failure in a reorganization process (Ohlson, 1980; Tian and Yu, 2017; Abinzano et.al, 2021).

The statistical significance of the variable ΔINVt is verified at the 5% level and its negative sign reflects that failure is less likely for periods showing higher rates of growth in private investment[5]. These results highlight the importance of using information based on the dynamics of the economy and the market context when undertaking the study of corporate failure. Therefore, these findings are consistent with those obtained in previous insolvency studies (Wang, 2012; Li and Faff, 2019).

The significant negative sign of the natural logarithm of age indicates that the age of a company (LN_Age) contributes towards reducing the probability of failure in a reorganization agreement, which is consistent with the findings of Altman et al. (2015) for financially distressed Finnish companies. We should stress that this effect dissipates over time as indicated by the positive and significant coefficient associated with the age-squared variable (SLN_Age).

In Model 2, which adds industry dummies, both the correctly classified cases and the pseudo R-square show substantial improvements as compared with the results of Model 1. The former stands at 82.4% and the latter at 45.6%. The results reveal that the highest probability of failure in a reorganization agreement lies in the commercial sector, followed in order by manufacturing, agriculture, services, and construction, which is the reference category in this case.

Model 3 adds regional dummies to Model 1. The results suggest that, in comparison to the country as a whole, the probability of failure is higher in companies domiciled in Barranquilla, Bogotá, and Cali and lower in those registered in Medellín. These results are novel given the focus of this study and the institutional insolvency framework being analyzed. Based on the Accuracy Ratio (AR) and the AIC and BIC information criteria obtained in models 2 and 3, industry effects appear to be stronger than regional effects[6].

[5] Estimations performed with other economic context variables showed that the acceleration of public expenditure (ΔPE_t) also has a negative and significant relationship with failure. However, its inclusion in replacement of the variable ΔINV_t, worsens the model fit and reduces the percentage of correctly classified cases to 76.5%.

[6] Models 1 to 3 have also been estimated with information for period *t-2*. In general, the models are not jointly significant, although the coefficients associated with the dummy variables are consistent with the estimates shown for period *t-1*.

Finally, the complete "ad hoc" model is estimated with the financial predictors and variables representing the firms' environmental and economic characteristics (Table 5). The results, once again, confirm that the best predictions are obtained with the data one year prior to the closing of the reorganization agreement. The pseudo R2 is above that obtained for the previous models, 48.3%, and the greater explanatory capacity of this model is clearly evident in the 85.3% of cases correctly predicted. The accuracy rate drops slightly to 81.4% when the cut-off point for the classification of failed vs non-failed companies is raised from 0.5 to 0.53, which is the value established with the intersection of the sensitivity and specificity curves of the model[7].

The coefficients of the financial and investment growth rate predictors remain the same with respect to the observed association with failure in the previous estimations and still have admissible confidence levels. In the case of the dummy variables, the construction sector prevails in the model as a predictor associated with a lower probability of failure, while the city of Barranquilla remains significantly positively associated with failure.

INSERT TABLE 5 ABOUT HERE

According to Altman et al. (1977), a model is adequate as long as the Accuracy Ratio (AR) indicator is greater than 50%, so the Failure Prediction Model ("ad hoc" model) is by far the most accurate of all those estimated. These results confirm that the "ad hoc" model is by all accounts the best of all, even after observing that for models 1-3 the null hypothesis of the Hosmer-Lemeshow test (no difference between observed and predicted values) was not rejected, thus indicating that all the models are well fitted. Although the Akaike (AIC) and Bayesian (BIC) information criteria are higher in the "ad hoc" model, the results show that adding parameters does not worsen the goodness of fit in this case.

4.3. Post-estimation

The post-estimation analysis indicates that the results obtained with Model 1 correctly classify 58% of the companies that completed reorganization processes in 2019 and 62% of those that did so in 2020 (Table 6). Adding industry dummies improves reorganization outcome prediction (Model 2), this model being more accurate in predicting failure than

[7] Sensitivity determines the percentage of failed agreements that were correctly classified by the model (88.6% when the cut-off point is 0.5 and 82.1% when the cut-off point is 0.53), while specificity indicates the percentage of successful agreements that were correctly classified (80% when the cut-off point is 0.5 or 0.53).

success (Table 7). A similar effect is observed after performing a new post-estimation by adding regional dummies to capture the domicile effect, i.e., using the "ad hoc" Model (Table 8). In both tests, the improvements take the form of an increase in correctly identified cases for the year 2019 as evidenced by percentages of correct classification close to 70% and 73%, in each case, while the year 2020 registered no improvement in correctly classified cases.

INSERT TABLE 6 ABOUT HERE

INSERT TABLE 7 ABOUT HERE

INSERT TABLE 8 ABOUT HERE

As mentioned above, the models tend to be more accurate in predicting reorganization failure than success, something that might have to do with the higher frequency of this phenomenon in the reorganization processes analyzed during the first 10 years of effective application of Act 1116 of 2006. The "ad hoc" model correctly classifies more cases for the year 2019 (73%) than for 2020 (62%). The latter was a critical year for companies, with business erosion due to the pandemic. The post-estimation results are robust even under this stress scenario and are consistent for two compelling reasons. Firstly, the year 2020 is further away from the training sample with which parameters have been estimated, and secondly, during 2020 the Colombian government intervened in the economy with different emergency measures aimed at mitigating the effects of the COVID-19 lockdowns and avoiding, among other risks, a catastrophe at the corporate level. This may have resulted in the higher reorganization success rates observed in 2020 (15) as compared to 2019 (6).

5. Discussion

With the escalation of reforms and systematization of insolvency regimes taking place around the world in recent decades, the issue of business failure has taken on an international dimension (Stef, 2022). Circumstances such as those brought about by the latest financial crises and the COVID-19 pandemic have also fuelled the discourse on the prediction of success in reorganization processes (Greenwood et al., 2020); a topic which has attracted less research, despite the fact that governments propose corporate reorganization procedures as a credit protection strategy and as an assistance mechanism for the recovery of still viable companies.

This work contributes to filling the research gap by focusing on the Latin American context and the specific case of Colombia, an emerging economy whose insolvency regime was modernized by the Act 1116/2006.

Although previous studies have shown that a variety of financial variables have some predictive capacity for insolvency, this paper shows that, for predicting success in reorganization processes, sufficient data can be extracted from five accounting ratios; three relating to solvency and liquidity (Current Assets – Inventories) /Total Assets; Cash/Current Assets; Cash/Total Assets), one to indebtedness (Total Liabilities/Total Assets) and one to profitability (Net Income/Total Assets). These predictors increase their predictive capacity for failure (or success) at horizons close to process closure, thus highlighting the need for periodic monitoring or even set ratio thresholds.

While these variables have an important predictive capacity, non-financial variables have also been shown to be relevant in this study. Thus, the growth rate of private investment in GDP as well as industry and domicile dummies are analyzed. In particular, the probability of failure in reorganization processes has been found to be negatively linked to firms in the construction industry and positively linked to those domiciled in the city of Barranquilla. Our observations also show that a higher national investment growth rate prior to the reorganization process reduces the probability of failure. For this reason, we consider that reorganizations that begin in an unfavorable economic environment for the private sector require a more exhaustive monitoring analysis of the companies' accounting information.

These results have been confirmed by an out-of-sample analysis with data for of 2019 and 2020, which proves the robustness of the estimates even for a period such as 2020 when the economic effects of the COVID-19 pandemic began to be seen in corporate solvency and thereby in corporate reorganization processes. However, industry and region variables add no predictive power to the model in the out-of-simple analysis for 2020. There are two possible reasons for this; namely, the aforementioned temporary softening of bankruptcy legislation in 2020, and the significant financial support provided by governments to stave off insolvency for companies short of liquidity (Dörr et al., 2022). However, for the Latin American case, Guerrero-Amezaga et al. (2022) show that the subsidies and loans received had a limited impact on small and medium-sized enterprises, whose share in the aid was smaller, in line with their lower demand for assistance.

6. Conclusions, limitations and further research

Although it has been a long time since the first business failure prediction studies appeared in the 1930s, the issue still takes a central place in the financial economics literature. However, the specific topic of corporate reorganization procedures has received much less attention. Therefore, this paper takes advantage of available data from the database of the Colombian Superintendence of Companies (SSC) to study the determinants of the success or failure in reorganization processes during the period 2008 to 2018 using both financial and non-financial variables.

The results obtained in this study are supported by previous literature and point towards reducing the research gap in the prediction of reorganization failure. The evidence provides information of interest not only for policy-makers, in Colombia and other emergent economies, but also for the supervisory bodies involved in reorganization proceedings. The theoretical contributions and practical implications of this study may provide a point of reference for creditors, debtors, and company managers.

In theoretical terms, in particular, this paper makes two substantial contributions to the literature; first, by identifying the firm financial characteristics that determine the success or failure of corporate reorganization processes, and then by providing a process outcome prediction model. In addition, unlike previous works, it jointly considers the financial, non-financial and macroeconomic variables involved in the success or failure of the processes.

From the practical and managerial perspective, the findings of this analysis may be useful to regulators and managers when it comes to determining eligibility criteria for admission to a reorganization process, monitoring it to increase the chances of success, and even setting minimum solvency, liquidity or profitability requirements throughout its duration. In this regard, the results suggest that more attention should be paid to the role of industry and geographical effects in the probability of reorganization processes meeting with failure, since the production environment and local conditions may be underlying factors.

This study may be useful in the context of a global reconsideration of insolvency laws. The failure rate observed in reorganization proceedings is too high, considering that the fundamental objective of the agreements is to recover and preserve viable companies. The implications of business failure following a reorganization process extend beyond the erosion of capital and loss of labour productivity. Thus, it is preferable to concentrate efforts on reorganizing companies that show clear viability potential and promptly liquidate those in which such potential is lacking.

Given that the model has consistent predictive capacity, even during periods of uncertainty, it might help policymakers to introduce the necessary reforms to ensure the survival of companies entering reorganization processes. These legal reforms should be accompanied, as Gurrea-Martínez (2020c) points out, by a general improvement of the judicial system and training for insolvency practitioners.

Although this paper presents highly predictive models for 2020, one of its acknowledged shortcomings is the non-consideration of the potential role of the new social and corporate practices brought in after Covid-19 and the temporary legislative reform relaxing Act 1116/2006 as failure factors in reorganization processes. Therefore, future research could be directed at investigating the usefulness of our findings as guidelines for avoiding failure and achieving success in reorganization processes.

Future research also should delve into the underlying sources of regional and industry effects. The long-term consistency of the findings and the relevance of characteristics pertaining to the process and to the trustees involved would also merit attention. Another potential contribution would be to introduce a measure of default risk to be taken just prior to the reorganization process as an aid in forecasting the probability of success. Finally, by widening its scope to other types of insolvency proceedings and new information sources, future researchers could use our proposed model to gain further valuable insights into the success probabilities of reorganization processes.

References

Abinzano, I., Bonilla, H., and Muga, L. (2021), "Prediction of the failure of reorganization agreements under Colombia's corporate insolvency act", Available at SSRN: https://ssrn.com/abstract=3954952 or http://dx.doi.org/10.2139/ssrn.3954952.

Afzal, A., and Firdousi, S. F. (2022). "Does the market discipline banks? Evidence from Balkan states" *The Journal of Risk Finance*, Vol 23 No. 4, pp 418-436.

Akinwande, M., Dikko, H. and Samson, A. (2015), "Variance Inflation Factor: As a Condition for the Inclusion of Suppressor Variable(s) in Regression Analysis", *Open Journal of Statistics*, Vol. 5, pp. 754-767.

Alanis, E., and Quijano, M. (2019), "Investment-cash flow sensitivity and the Bankruptcy Reform Act of 1978", *The North American Journal of Economics and Finance*, Vol. 48, pp. 746-756.

Alarcón-Lora, A., Álvarez-González, G., and Arias-Romero, L. (2022), "Transitional Insolvency Regime in Colombia: Impact of the New Bankruptcy Processes Created by the Emergency Decrees Issued by the National Government in Cartagena de Indias D.T. y C. during the year 2020", *Revista Saber, Ciencia y Libertad*, Vol. 17 No. 1, pp. 199 – 218.

Altman, E.I. (1968), "Financial Ratios, Discriminant Analysis and Prediction of Corporate Bankruptcy", *Journal of Finance,* Vol. 22, pp. 589-610.

Altman, E. I., Haldeman, R. G., and Narayanan, P. (1977), "ZETA Analysis: A New Model to Identify Bankruptcy Risk of Corporations", *Journal of Banking and Finance*, Vol. 1, pp. 29-54.

Altman, E. I., Iwanicz-Drozdowska, M., Laitinen, E. K., and Suvas, A. (2015), "Financial and non-financial variables as long-horizon predictors of bankruptcy", Available at SSRN: https://ssrn.com/abstract=2669668 or http://dx.doi.org/10.2139/ssrn.2669668

Antill, S., and Grenadier, S. R. (2019), "Optimal capital structure and bankruptcy choice: Dynamic bargaining versus liquidation", *Journal of Financial Economics*, Vol. 133 No. 1, pp. 198-224.

Arroyave, J. (2018), "A comparative analysis of the effectiveness of corporate bankruptcy prediction models based on financial ratios: Evidence from Colombia", *Journal of International Studies*, Vol. 11 No. 1, pp. 273-287.

Back, P. (2005), "Explaining financial difficulties based on previous payment behavior, management background variables and financial Ratios", *European Accounting Review* Vol. 14 No. 4, pp. 839–868.

Balcaen S., and Ooghe H. (2006), “35 years of studies on business failure: an overview of the classic statistical methodologies and their related problems”, *British Accounting Review,* Vol. 38 No. 1, 63–93.

Beaver, W.H. (1966), “Financial ratios as predictors of failure”, *Journal of Accounting Research,* Vol. 4, pp. 71–111.

Bellovary, J.L., Giacomino, D.E., and Akers, M.D. (2007), “A review of bankruptcy prediction studies: 1930 to present”, *Journal of Financial Educati*on, Vol. 1 No. 1, pp. 3-41.

Berninger, M., Fiesenig, B., and Schiereck, D. (2021), “The performance of corporate bond issuers in times of financial crisis: empirical evidence from Latin America”, *Journal of Risk Finance,* Vol. 22 No. 1, pp. 78-92.

Blazy, R., and Nigam, N. (2019), “Corporate insolvency procedures in England: the uneasy case for liquidations*”, European Journal of Law and Economics,* Vol. 47 No. 1, pp. 89-123.

Blazy, R., and Stef, N. (2020), “Bankruptcy procedures in the post-transition economies”, *European Journal of Law and Economics*, Vol. 50 No. 1, pp. 7-64.

Camacho-Miñano, M.-M., Pascual-Ezama, D., and Urquía-Grande, E. (2013), “On the efficiency of bankruptcy law: Empirical evidence in Spain”, *International Insolvency Review*, Vol. 22 No. 3, pp. 171–187.

Cepec, J., and Grajzl, P. (2019), “Measuring the effectiveness of bankruptcy institutions: filtering failures in Slovenian financial reorganizations”, *Journal of Institutional Economics,* Vol. 15 No. 3, pp. 553-567.

Cepec, J., and Grajzl, P. (2021), “Creditors, Plan Confirmations, and Bankruptcy Reorganizations: Lessons from Slovenia”, *European Business Organization Law Review,* Vol. 22, pp. 559–589.

Cincinelli, P., and Piatti, D. (2021). “How inefficient is an inefficient credit process? An analysis of the Italian banking system”. *The Journal of Risk Finance*. Vol. 22 No 3/4, pp 209 -239.

Corbae, D., and D’Erasmo, P. (2021), “Reorganization or liquidation: Bankruptcy choice and firm dynamics”, *The Review of Economic Studies*, Vol. 88 No. 5, pp. 2239-2274.

Dörr, J.O., Licht, G., and Murmann, S. (2022), “Small firms and the COVID-19 insolvency gap”, *Small Business Economics*, Vol. 58 No. 2, pp. 887-917.

Fallanca, M.G., Forgione, A.F., and Otranto, E. (2020), “Forecasting the macro determinants of bank credit quality: a non-linear perspective”, *Journal of Risk Finance*, Vol. 21 No. 4, pp. 423-443.

Greenwood, R., Iverson, B., and Thesmar, D. (2020), "Sizing Up Corporate Restructuring in the COVID-19 Crisis", *Brookings Papers of Economic Activity,* Fall 2020, pp. 391-441.

Guerrero-Amezaga, M.E., Humphries, J.E., Neilson, C.A., Shimberg, N., and Ulyssea, G. (2022), "Small firms and the pandemic: Evidence from Latin America", *Journal of Development Economics*, Vol. 155, 102775.

Gurrea-Martínez, A. (2020a), "The future of reorganization procedures in the era of pre-insolvency law", *European Business Organization Law Review,* Vol. 21 No. 4, pp. 829-854.

Gurrea-Martínez, A. (2020b), "Insolvency Law in Times of COVID-19", *Ibero-American Institute for Law and Finance*, Available at SSRN: https://ssrn.com/abstract=3562685.

Gurrea-Martínez, A. (2020c), "Insolvency Law in Emerging Markets*", Ibero-American Institute for Law and Finance*, Available at SSRN: https://ssrn.com/abstract=3606395.

Gurrea-Martínez, A. (2021), "Implementing an insolvency framework for micro and small firms", *International Insolvency Review*, Vol. 30 S1, S46– S66.

Hair, J.F., Anderson, R.E., Tatham, R.L., and Black, W.C. (1999), *Análisis multivariante*, Madrid: Prentice-Hall.

Hotchkiss, E. S., John, K., Mooradian, R.M., and Thorburn, K.S. (2008), 'Bankruptcy and the Resolution of Financial Distress', in B. E. Eckbo, (ed.), *Handbook of Corporate Finance: Empirical Corporate Finance*, Vol. 2 No. 14, pp. 235-287. https://doi.org/10.1016/B978-0-444-53265-7.50006-8

John, K., Mateti, R. S., and Vasudevan, G. (2013), "Resolution of financial distress: A theory of the choice between Chapter 11 and workouts", *Journal of Financial Stability*, Vol. 9 No. 2, 196-209.

Laitinen, E.K. (2011), "Assessing viability of Finnish reorganization and bankruptcy firms", *European Journal of Law and Economics*, Vol. 31 No. 2, pp. 167-198.

Li, L., and Faff, R. (2019), "Predicting corporate bankruptcy: What matters? *International Review of Economics and Finance*, Vol. 62, pp. 1–19.

Lukason, O., and Urbanik, A. (2013), "Why Reorganization of Firms Fails: Evidence from Estonia", *Estonian Discussions on Economic Policy,* Vol. 21, pp. 73–84.

Maddala, G.S., and Lahiri, K. (2009), *Introduction to econometrics* (4th ed.). The Jon Wiley and Sons, Ltd., Publication.

Mcgowan, M. A., Andrews, D., and Millot, V. (2017), "Insolvency regimes, zombie firms and capital reallocation", *OECD Economics Department Working Papers*, No. 1399.

Menard, S. (2002), *Applied logistic regression analysis* (Vol. 106). Sage.

Menezes, A., and Gropper, A. (2021), "Overview of Insolvency and Debt Restructuring Reforms in Response to the COVID-19 Pandemic and Past Financial Crises: Lessons for Emerging Markets", *Equitable Growth, Finance and Institutions COVID-19 Notes;* World Bank, Washington, DC.

Ohlson, J. (1980), "Financial ratios and probabilistic prediction of bankruptcy", *Journal of Accounting Research*, Vol 18 No. 1, pp. 109-131.

Platt, H., and Platt, M. (2004), "Industry-relative ratios revisited: the case of financial distress" (pp. 6-9). Paper presented at the FMA 2004 Meeting, New Orleans (USA).

Quintiliani, A. (2017), "Financial distress cost of Italian small and medium enterprises: A predictive and interpretative model", *Journal of Risk Finance*, Vol. 18 No. 5, pp. 564-580.

Routledge, J. (2021), "Rethinking insolvency law amid the COVID-19 pandemic", *Pacific Accounting Review*, Vol. 33 No. 2, pp. 231-237.

Salisu, A., and Tchankam, J.P. (2022), "Uncertainty due to pandemics and epidemics and the behavior of Travel & Leisure stocks in the UK, the USA and Europe", *Journal of Risk Finance*, Vol. 23 No. 5, pp. 619-638.

Stef, N., and Bissieux, J.J. (2022), "Resolution of corporate insolvency during COVID-19 pandemic. Evidence from France", *International Review of Law and Economics*, Vol. 70, 106063.

Tascón, M., and Castaño, F. (2012), "Variables and Models for the Identification and Prediction of Business Failure: Revision of Recent Empirical Research Advances", *Revista de Contabilidad-Spanish Accounting Review*, Vol. 15 No. 1, pp. 7-58.

Valencia, C., Cabrales, S., Garcia, L., Ramirez, J., and Calderona, D. (2019), "Generalized additive model with embedded variable selection for bankruptcy prediction: Prediction versus interpretation", *Cogent Economics & Finance*, Vol. 7 No. 1, 1597956.

Wang, C.-A. (2012), "Determinants of the Choice of Formal Bankruptcy Procedure: An International Comparison of Reorganization and Liquidation", *Emerging Markets Finance and Trade*, Vol. 48 No. 2, pp. 4–28.

White, M. J. (1989), "The corporate bankruptcy decision", *Journal of Economic Perspectives,* Vol. 3, pp. 129-151.

Table 1. Descriptive statistics for the financial variables.

Panel A	Failed companies									
	t-1					t-2				
Variable	Obs	Mean	S.D.	Min	Max	Obs	Mean	S.D.	Min	Max
(CA – I)/CA	67	0,77	0,25	0,08	1,00	110	0,72	0,26	0,10	1,00
C/CA	67	0,04	0,07	0,00	0,38	110	0,06	0,10	0,00	0,57
C/TA	67	0,03	0,06	0,00	0,34	110	0,03	0,06	0,00	0,41
TL/TA	67	1,94	4,52	0,36	36,49	110	1,60	3,74	0,02	34,97
NI/TA	67	-0,27	0,45	-2,05	0,22	110	-0,38	1,83	-14,96	0,44
Panel B	Non-Failed companies									
	t-1					t-2				
Variable	Obs	Mean	S.D.	Min	Max	Obs	Mean	S.D.	Min	Max
(CA – I)/CA	35	0,65	0,26	0,16	1,00	53	0,72	0,28	0,02	1,00
C/CA	35	0,08	0,17	0,00	0,89	53	0,09	0,17	0,00	0,96
C/TA	35	0,02	0,05	0,00	0,31	53	0,03	0,07	0,00	0,36
TL/TA	35	0,66	0,32	0,04	1,54	53	0,96	0,83	0,21	5,18
NI/TA	35	-0,06	0,09	-0,31	0,11	53	-0,27	0,647	-3,54	0,228
Panel C	All companies									
	t-1					t-2				
Variable	Obs	Mean	S.D.	Min	Max	Obs	Mean	S.D.	Min	Max
(CA – I)/CA	102	0,73	0,26	0,08	1,00	163	0,72	0,26	0,02	1,00
C/CA	102	0,06	0,11	0,00	0,89	163	0,07	0,13	0,00	0,96
C/TA	102	0,02	0,06	0,00	0,34	163	0,03	0,06	0,00	0,41
TL/TA	102	1,50	3,70	0,04	36,49	163	1,39	3,12	0,02	34,97
NI/TA	102	-0,20	0,38	-2,05	0,22	163	-0,35	1,55	-14,96	0,44

This table presents the descriptive statistics of the financial variables before the end of the reorganization procedure. Obs: Observations. S.D.: Standard deviation. Min: Minimum value. Max: Maximum value. The sample at *t-1* consists of 102 companies with financial information one year before the end of the reorganization process and the sample at *t-2* consists of 163 companies. (CA – I)/CA: (Current Assets – Inventories)/Total Assets. C/CA: Cash/Current Assets. C/TA: Cash/Total Assets. TL/TA: Total Liabilities/Total Assets. NI/TA: Net Income/Total Assets.

Table 2. Correlation matrices.

Variable	t-1					t-2				
	(CA – I)/CA	*C/CA*	*C/TA*	*TL/TA*	*NI/TA*	*(CA – I)/CA*	*C/CA*	*C/TA*	*TL/TA*	*NI/TA*
(CA – I)/CA	1					1				
C/CA	0.141	1				0.216	1			
C/TA	0.167	0.600	1			0.205	0.768	1		
TL/TA	0.146	-0.069	-0.032	1		0.153	0.055	0.126	1	
NI/TA	-0.125	0.090	0.097	-0.245	1	-0.141	-0.205	-0.306	-0.799	1

This table presents the correlation coefficients of financial variables. The definition of the variables and the samples are analogous to those in Table 1.

Table 3. Variance Inflation Factor (VIF).

t-1			t-2		
Variable	VIF	TOLERANCE	Variable	VIF	TOLERANCE
C/TA	1.59	0.63	*NI/TA*	3.14	0.32
C/CA	1.58	0.63	*TL/TA*	2.94	0.34
NI/TA	1.09	0.92	*C/TA*	2.62	0.38
TL/TA	1.08	0.92	*C/CA*	2.48	0.40
(CA – I)/CA	1.07	0.93	*(CA – I)/CA*	1.07	0.93

This table presents the variance inflation factor (VIF) and tolerance of financial variables. Tolerance = 1/VIF or 1-R^2, where R^2 is obtained from the regression of each independent variable on all remaining independent variables. The definition of the variables and the samples are analogous to those in Table 1.

Table 4. Logit estimates.

Variable	Model 1		Model 2		Model 3	
	Coef.	O.R.	Coef.	O.R.	Coef.	O.R.
Constant	2.995	19.977	3.140	23.108	1.915	6.784
(CA-I)/CA	2.486**	12.017	2.797**	16.402	2.929**	18.706
C/CA	-43.834***	9.19e-20	-49.152***	4.50e-22	-47.257***	3.00e-21
C/TA	59.724***	8.67e+25	66.443***	7.18e+28	63.642***	4.36e+27
TL/TA	4.005***	54.854	4.313***	74.652	4.331***	76.002
NI/TA	-7.749**	0.000	-7.803**	0.000	-9.165**	0.000
ΔINV_t	-0.206**	0.814	-0.222**	0.801	-0.230**	0.7948
LN_Age	-6.4284**	0.002	-7.852**	0.000	-5.987*	0.003
SLN_Age	1.300**	3.669	1.534**	4.650	1.195*	3.303
Agricultral			1.692	5.428		
Commerce			2.263**	9.616		
Manufactures			1.824*	6.198		
Services			1.271	3.566		
Bogotá					0.045	1.046
Medellín					-1.088	0.337
Cali					-0.197	0.821
Barranquilla					1.601	4.958
Prob > Chi2	0.000		0.000		0.000	
Pseudo R^2	0.411		0.456		0.443	
Observations	102		102		102	
Correctly classified	78.43%		82.35%		80.39%	
Accuracy Ratio	77.92%		82.34%		80.46%	
Prob > Chi2 Test H-L	0.927		0.847		0.452	
AIC	95.322		97.338		99.063	
BIC	118.947		131.463		133.188	

This table presents the estimates of the logistic regression for the sample in *t-1*. In model 2, Construction is the reference category. In model 3, Rest of the country is the reference category. Coef.: Estimated coefficient of the independent variable. O.R.: Odds Ratio. The definition of the financial variables and the samples are analogous to those in Table 1. ΔINV_t: Investment growth rate taking as references the year of start of the agreement and one year before. LN_Age: Natural logarithm of the age of the company at the start of the reorganization agreement. SLN_Age: Square of the natural logarithm of the company at the start of the reorganization agreement. AR: Accuracy Ratio. Test H-L: Test Hosmer-Lemeshow. AIC: Akaike's information criterion. BIC: Bayesian information criterion. ***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

Table 5. Logit estimates for the "ad hoc" model.

Variables	t-1		t-2	
	Coef.	O.R.	Coef.	O.R.
Constant	1.488	4.430	1.768	5.857
(CA-I)/CA	3.127**	22.800	0.077	1.080
C/CA	-52.860***	1.10e-23	-4.087	0.0168
C/TA	69.735***	1.93e+30	5.541	255.051
TL/TA	4.905***	134.922	0.969**	2.635
NI/TA	-9.253**	0.000	0.912*	2.490
ΔINV_t	-0.264***	0.768	0.060	1.062
LN_Age	-7.121*	0.001	-1.940	0.144
SLN_Age	1.375*	3.953	0.387	1.473
Agricultral	1.891	6.628	-0.045	0.956
Commerce	2.185**	8.887	0.737	2.089
Manufactures	1.869*	6.484	0.458	1.580
Services	1.767	5.853	0.705	2.023
Bogotá	0.141	1.151	0.056	1.057
Medellín	-0.864	0.421	-0.542	0.581
Cali	-0.796	0.451	0.430	1.537
Barranquilla	1.739	5.691	0.546	1.727
Prob > Chi2	0.000		0.254	
Pseudo R^2	0.483		0.094	
Observations	102		163	
Correctly classified	85.29%		72.39%	
Accuracy Ratio	83.72%		42.40%	
Prob > Chi2 Test H-L	0.939		0.946	
AIC	101.883		220.315	
BIC	146.508		272.909	
Correctly classified'	81.37%		64.42%	

This table presents the results of the estimation of the "ad hoc" model with financial independent variables in *t-1* and *t-2*.
In model 2, Construction is the reference category. In model 3, Rest of the country is the reference category. Coef.: Estimated coefficient of the independent variable. O.R.: Odds Ratio. The definition of the financial variables and the samples are analogous to those in Table 1. ΔINV_t: Investment growth rate taking as references the year of start of the agreement and one or two years before. LN_Age: Natural logarithm of the age of the company at the start of the reorganization agreement. SLN_Age: Square of the natural logarithm of the company at the start of the reorganization agreement. AR: Accuracy Ratio. Test H-L: Test Hosmer-Lemeshow. AIC: Akaike's information criterion. BIC: Bayesian information criterion. ***, ** and * denote significance at the 1, 5 and 10% levels, respectively. Correctly classified' denotes a cutoff of 0.53 for the sample at *t-1* and 0.68 for the sample at *t-2*. See tables 1-3 for variable definitions and sample descriptions. ***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

Table 6. Post-estimation classification. Model 1

Firms with agreements completed after 2018				
Concept	Pr	2019 U 2020	2019	2020
Sensitivity	Pr(+| D)	54,81%	56,60%	52,94%
Specificity	Pr(-|~D)	85,71%	66,67%	93,33%
Positive predictive value	Pr(D| +)	95,00%	93,75%	96,43%
Negative predictive value	Pr(~D| -)	27,69%	14,81%	36,84%
False + rate for true ~D	Pr(+|~D)	14,29%	33,33%	6,67%
False - rate for true D	Pr(-| D)	45,19%	43,40%	47,06%
False + rate for classified +	Pr(~D| +)	5,00%	6,25%	3,57%
False - rate for classified -	Pr(D| -)	72,31%	85,19%	63,16%
Number of companies		125	59	66
Failured		104	53	51
Non Failured		21	6	15
Correctly classified		60,00%	57,63%	62,12%

This table presents the estimates using the coefficient values obtained with Model 1 in Table 4 and the structure specified in equation (1). D: failed companies. ~D: non-failed companies. +: companies classified as failed. -: companies classified as non-failed.

Table 7. Post-estimation classification. Model 2

Firms with agreements completed after 2018				
Concept	Pr	2019 U 2020	2019	2020
Sensitivity	Pr(+| D)	65,38%	69,81%	60,78%
Specificity	Pr(-|~D)	66,67%	66,67%	66,67%
Positive predictive value	Pr(D| +)	90,67%	94,87%	86,11%
Negative predictive value	Pr(~D| -)	28,00%	20,00%	33,33%
False + rate for true ~D	Pr(+|~D)	33,33%	33,33%	33,33%
False - rate for true D	Pr(-| D)	34,62%	30,19%	39,22%
False + rate for classified +	Pr(~D| +)	9,33%	5,13%	13,89%
False - rate for classified -	Pr(D| -)	72,00%	80,00%	66,67%
Number of companies		125	59	66
Failured		104	53	51
Non Failured		21	6	15
Correctly classified		65,60%	69,49%	62,12%

This table presents the estimates using the coefficient values obtained with Model 2 in Table 4 and the structure specified in equation (1). D: failed companies. ~D: non-failed companies. +: companies classified as failed. -: companies classified as non-failed.

Table 8. Post-estimation classification. “Ad hoc” model.

Firms with agreements completed after 2018				
Concept	Pr	2019 U 2020	2019	2020
Sensitivity	Pr(+| D)	67,31%	73,58%	60,78%
Specificity	Pr(-|~D)	66,67%	66,67%	66,67%
Positive predictive value	Pr(D| +)	90,91%	95,12%	86,11%
Negative predictive value	Pr(~D| -)	29,17%	22,22%	33,33%
False + rate for true ~D	Pr(+|~D)	33,33%	33,33%	33,33%
False - rate for true D	Pr(-| D)	32,69%	26,42%	39,22%
False + rate for classified +	Pr(~D| +)	9,09%	4,88%	13,89%
False - rate for classified -	Pr(D| -)	70,83%	77,78%	66,67%
Number of companies		125	59	66
Failured		104	53	51
Non Failured		21	6	15
Correctly classified		67,20%	72,88%	62,12%

This table presents the estimates using the coefficient values obtained with the failure prediction model in Table 5 and the structure specified in equation (1). D: failed companies. ~D: non-failed companies. +: companies classified as failed. -: companies classified as non-failed.