Prediction of failure in reorganization agreements under Colombia's corporate insolvency act

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ABSTRACT

Purpose: The aim of this paper is to provide an overview of the impact of the implementation of Colombian Corporate Insolvency Act 1116 of 2006 in the period 2008-2018 and to assess the relevance of a broad set of financial predictors, as well as variables related to the economic context or the characteristics of the process itself, in explaining the failure of reorganization processes.

Design/Methodology/Approach: Both logit and probit models are estimated, starting from a large number of variables proposed in the literature which are then narrowed down to a final selection based on their individual significance and machine learning.

Findings: The results show the prevalence of a limited number of financial variables related to equity, indebtedness, profits, and liquidity as predictors of the failure of reorganization processes. The use of financial information from the year prior to the completion of the reorganization improves predictive accuracy and reliability. The debt-to-equity indicator provides no significant explanatory power, while voluntary entry into a reorganization process favors its success.

Originality/Value: While financial and accounting information is used across the literature to predict insolvency events, it is used here to predict success or failure in reorganization processes under the conditions imposed by a specific legislative act in a Latin American context.

Keywords: Insolvency, reorganization, failure, financial predictors, machine learning.
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Prediction of failure in reorganization agreements under Colombia's corporate insolvency act / Predictores financieros del fracaso de los procesos de reorganización en Colombia

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1.- Introduction

The issue of corporate bankruptcy forecasting is one that has attracted significant ongoing attention in the financial literature. Entry into insolvency proceedings burdens companies with a series of costs linked not only to the management of the process but also to the company's productive activity (Brogaard *et al.*, 2017). Any legislation for regulating this type of process must therefore aim, not only at reducing reorganization costs, but also at ensuring that as many companies as possible are able to continue their activity.

The literature on predicting the failure or success of reorganization agreements is scarce and little is known about the determinants behind corporate reorganization under different legal regimes. A series of papers on firm survival in Slovenia after bankruptcy and re-organizational success analyze the influence of ownership structure, property changes and management turnover on creditors' acceptance of a business reorganization plan (Cepec and Grajzl, 2020, 2021a and 2021b) in a post-Socialist economy that successfully coped with the transition to capitalism.

Another way to complement the literature on the determinants behind the success or failure of reorganization processes is to turn to the largely neglected Latin American context, which provides new research options for further understanding of the impact of the reorganization process on the company and how it should be addressed. In the specific case of Colombia, Act 1116 of 2006 is a basic rule with 126 articles condensing 66 years' experience of modern bankruptcy law (Vélez, 2011) and seeking to guarantee credit protection and maintain the company as a going concern and source of employment by means of reorganization and specified judicial liquidation procedures.

Within this context, the goal of this act is to establish an agreement permitting the survival of viable companies by normalizing their credit and commercial relations through administrative, operational and accounts restructuring. The Act also emphasizes that the initiation of a debtor's reorganization process necessarily requires the assumption of cessation of payments or imminent inability to pay, while the agreement terminates upon fulfillment of the contractual obligations, uncorrected breach of the said obligations, or non-payment of administrative or social security expenses.

In fact, although most countries include the possibility of corporate reorganization among their legislative provisions, either as an exclusive act or as part of an insolvency code that has evolved over time, successful reorganization processes are not as common as would be desirable (Komera and Lukose, 2013), despite a significant trend in recent decades towards the use of this type of procedures as a corporate safeguard (Wang, 2012).

This legislative approach, aimed at ensuring the survival of viable businesses, gathered force in the wake of the shock caused by the outbreak of the COVID-19 pandemic, when many regulations were relaxed to avert business liquidation (Menezes and Gropper, 2021). With the crisis over, however, several papers have described recommendations to improve insolvency mechanisms applicable to small and medium-sized companies (Gurrea-Martinez, 2021) or emerging markets (Gurrea-Martinez, 2020). In all of them, reorganization processes are considered as a preferred alternative.

In the literature, insolvency has been generally related to any event involving partial or future cessation of payments (Beaver, 1966; Chava and Jarrow, 2004; Alanis and Quijano, 2019), illiquidity (Altman, 1981), over-indebtedness (Altman, 1988), or economic losses and the deterioration of equity (Deakin, 1972). It is implicitly assumed that insolvency has economic roots and is a sign of corporate failure, or bankruptcy. However, some studies have chosen to use some of these events as criteria for classifying firms as healthy vs troubled, regardless of whether they are immersed in insolvency proceedings, such as those introduced by the U.S. Bankruptcy Code or the U.K. Insolvency Act (Correa *et al.*, 2003; Staszkiewicz and Witkowski, 2018).

Insolvency prediction models commonly rely on financial and accounting information, following what is standard practice from the classic models (Altman, 1968; Ohlson, 1980) right up to the latest (Li and Faff, 2019). Despite criticism for lack of theoretical support (Serrano-Cinca, et al. 2019), the power of accounting information to predict corporate insolvency has withstood the test of time (Agarwal and Taffler., 2007; Altman et al., 2017) and it is widely used in models designed to explain a range of phenomena related to corporate failure. With respect to the resolution of insolvency processes, Stef and Bissieux (2022) use a series of financial ratios with empirical power to explain firms' exit paths, including reorganization. However, these authors only cite previous empirical evidence (Stef and Zenou, 2021; Irfan et al. 2018) to support the use of these ratios.

Focusing on the specific issue of corporate insolvency prediction, the selected methodologies and variables can be seen to differ from one paper to another. Altman

(1968) criticizes previous ratio analyses for the predominantly univariate nature of the methodology and suggests combining several measures to obtain a meaningful predictive model. Ohlson (1980) presents some empirical results from a model predicting corporate failure, although only one of the independent variables coincides with those proposed by Altman (1968). Originally used as a means to avoid the common problems associated with Multiple Discriminant Analysis (MDA), conditional logit analysis was to become the most popular technique for bankruptcy studies using vectors of predictors. According to Lo (1986), logit is more robust than DA and has demonstrated applicability across a wider variety of distributions than is possible with normal DA. He compares the logit estimation with DA, taking into account six variables, two of which are in line with Ohlson's (1980) proposal.

For the selection of independent variables, Tascón and Castaño (2012) start from a sample of 40 papers using a broad range of methodologies and variables. Their review shows that the most commonly used variables in insolvency prediction models include accounting ratios such as profitability, indebtedness, economic balance, and structure, which serve as proxies for firm performance. While noting the limited use of non-accounting variables, Tascón and Castaño (2012) mention that the results generally point to an improvement in the explanatory power of the models when some variables of this type are included. Tian and Yu (2017) attempt to provide some insights into bankruptcy prediction across the international market, observing an overriding focus on US companies and scant literature on international markets. They use a state-of-the-art variable selection technique, known as adaptive LASSO (Least Absolute Shrinkage and Selection Operator), to automatically select the bankruptcy predictors and study their forecasting performance. They analyze bankruptcy prediction in Japan using logit and discrete hazard models. Finally, taking a combined approach, Li and Faff (2019) propose a hybrid bankruptcy prediction model incorporating both accounting and market-based information. They show that size, book-to-market (BTM), volatility, liquidity, and profitability are key attributes for predicting a company’s future default probability.
Romero (2013) studies the specific case of Colombia, and explores the identification of the financial variables that can best explain business failure in a sample of small and medium-size enterprises (SMEs) which entered into insolvency procedures under Acts 222 of 1995 and 1116 of 2006 between 2005 and 2011. Their methodological approach complements the view of Martinez (2003) in that it uses logit rather than probit models

and the analysis incorporates financial and other categorical variables such as age, industry, and size.

The above literature lays open an interesting question regarding the choice and relevance of financial variables for predicting the success or failure of reorganization processes within the context of specific insolvency regimes, an issue which has received little attention in predictive models for processes regulated by a specific legislative act (Ruiz and Aguiar, 2017; Rosslyn-Smith and Pretorius, 2018).

As already stated, the quest for optimal insolvency regimes has not missed the emerging or transition economies (Gurrea-Martínez,2020; Cepec and Grajzl, 2021b). In the particular case of Colombia, the growing number of companies that have filed for insolvency under Act 1116 of 2006 is warrant enough for us to examine the outcome of its first decade of enactment, and analyze the financial factors underlying the success or failure of the reorganization agreements signed under its auspices.

The objective of this paper, therefore, is twofold; first, to provide an overview of the results achieved by the new Colombian Corporate Insolvency Act implemented a decade ago; and, subsequently, to assess which financial predictors, in conjunction with other independent variables, provide some foresight of the potential failure of reorganization agreements negotiated under the new Act between 2008 and 2018. Particular attention is paid to financial predictors used in previous literature, which relate to liquidity and solvency, rotation, leverage, profitability or size. Given the specificities of the Colombian case, we also consider some of the predictors used by Romero (2013), while adding new variables to assess the role of debt-to-equity conversion, proven by Cepec and Grajzl (2020) to be a determinant of success in reorganizations; and the part played by economic crisis (Hernández, 2022; Ibáñez; 2020). The issue of voluntary vs. non-voluntary entry into the reorganization agreement is also examined in the light of evidence for a higher success rate for voluntarily-initiated processes carried out under the Colombian Corporate Insolvency Act.

The results of this research show that a limited number of one-period lagged financial variables have explanatory power for failure in reorganizations undertaken in Colombia between 2008 and 2018. These results hold both for the stepwise variable-selection method based on individual significance and for the A-Lasso selection method (Tian and

Yu, 2017), and for both logit and probit estimations, although they also show that the two-period lagged variables have little predictive power. Other variables proposed in the literature as proxies for debt-to-equity conversion also fail to provide any significant explanatory capacity in this particular context.

Nevertheless, the higher success rate of out-of-court reorganization processes (over 51%), all of them voluntary, suggests that extrajudicial agreements between creditors and debtors may contain potentially valuable information for explaining reorganization failure. The results show that the inclusion of a variable reflecting voluntary vs. non-voluntary engagement in the process improves the explanatory power of most of the estimated models.

The rest of the paper is structured as follows. A description of the database and an overview of the reorganization processes carried out in Colombia under Act 1116 of 2006 are given in section two. The methodology and results of the application of the prediction models are presented in sections tree and four, respectively. Finally, section five contains the discussion and main conclusions.

2.- Database

2.1. Database

The database for this paper was obtained from the official website of the Colombian Superintendence of Companies (SSC), an entity which, until the first quarter of 2019[1], provided accumulated data for as far back as 2007 on companies and individuals who initiated reorganization and judicial liquidation processes under Act 1116 of 2006[2]. The database, which enables the identification of the economic activity segment (industry), is also cross-referenced with other databases and official sources in Colombia through the Tax Identification Number (NIT).

Figure 1 shows that, in the period under study, 2008–2018, a total of 1,868 company reorganization processes were initiated, 508 of which were completed within that period. The accounting data for these companies, lagged one year prior to the completion of the

[1] Currently, however, the only available data are for ongoing processes.

[2] https://www.supersociedades.gov.co/delegatura_insolvencia/Documents/Informes_Periodicos_Marzo_31_2019/Reorganizacion_Empresarial_Validacion_Judicial_Acumulado_31Marzo2019.htm

reorganization process, were obtained by crossing the NIT with the databases of the companies that had submitted annual financial statements to the SSC over the period 2008–2018[3].

INSERT FIGURE 1 ABOUT HERE

INSERT FIGURE 2 ABOUT HERE

2.2. Reorganization processes undertaken within the framework of Colombian Corporate Insolvency Act 1116/2006

Any rules governing corporate insolvency processes require a dual focus. They not only need to protect the creditors of the company initiating the reorganization process, but, once the reorganization is complete, they should also provide it, in the best-case scenario, with the necessary tools to continue with its activity while avoiding insolvency costs as far as possible, or at least enable it to carry out an orderly liquidation.

This section provides a brief overview of the main data on reorganization processes carried out under the new Corporate Insolvency Regime in Colombia. Firstly, it is worth noting, as can be inferred from Figure 1, that the rate of process completion during the period of investigation was 27.19%. In other words, 508 of the 1,868 initiated proceedings were brought to conclusion. Table 1 shows the period spent in reorganization proceedings by firms which completed the process between 2008 and 2018, together with the success and failure rates in relation to the number of years before completion. It can be seen that over 30% of the completed reorganization processes take one year or less and that over 60% are completed in under three years. In addition, over 45% of completed corporate reorganizations are successful (i.e., firms successfully avoid liquidation after a reorganization process), and it follows that firms taking between three and four years are more likely to succeed in the endeavor.

INSERT TABLE 1 ABOUT HERE

[3] Financial statements data up to the year 2014 were obtained from the Business Information and Report System of the SSC (SIREM) and the data for the period 2016-2018 from its Business Information Portal (PIE). It is worth noting, therefore, that the total number of financial reports submitted to the SSC decreased between 2007 (21,734) and 2017 (18,364) due to changes in the country's normative frameworks and information systems. From November 2020, access to the financial information of Colombian companies must be through the Integrated Company Information System (SIIS).

Due to its judicial nature, the reorganization procedure also provides valuable information on processes registered between 2008–2018, because some companies were admitted for reorganization after submitting a formal request in accordance with the internal procedures outlined in Act 1116 (non-extrajudicial reorganizations), while others benefited from a judicial validation of out-of-court agreements between the creditors and the debtor (extrajudicial reorganizations). Among the advantages of non-extrajudicial processes is that they allow the company to continue its operations without creditor harassment (Chaterjee et al., 1996). The main dissuading factor is their costliness (see Jensen, 1989 and Gilson et al., 1990), which encourages firms to negotiate directly with their creditors. In addition, it is important to keep in mind that the reorganization may be voluntary, i.e., requested directly by the debtor, or non-voluntary, i.e., implemented at the initiative of the creditors or another competent authority. For the purposes of this study, reorganizations are classified as non-extrajudicial or extrajudicial, and voluntary or non-voluntary.

It can be seen from Table 2 that extrajudicial processes achieve a much higher completion rate (43.2%) than is the case for non-extrajudicial processes (25.1%). It is also clear that all extrajudicial processes are voluntary, which makes sense given that the debtor's consent is required for the process to be validated within the framework of Act 1116.

INSERT TABLE 2 ABOUT HERE

As shown in Table 3, the success rate is higher in non-extrajudicial reorganizations filed voluntarily by the debtor (45.48%) than in those that were not (27.59%). The success rate for out-of-court reorganization agreements exceeds 51% (Table 4).

INSERT TABLE 3 ABOUT HERE

INSERT TABLE 4 ABOUT HERE

The revealed pattern of outcomes for corporate reorganizations in Colombia during the period 2008–2018 shows that the chances of success appear to be enhanced when the process is undertaken voluntarily by the debtor. The observed enforcement rate is also higher in out-of-court reorganizations, where the judicial validation of the prior external agreements between creditors and debtors reduces the likelihood of failure.

3.- Methodology

3.1. Variable selection based on individual significance.

As stated previously, the accounting and financial variables for the study of insolvency prediction issues (Serrano-Cinca et al., 2019) or the outcome of exit paths, including reorganization (Stef and Bissieux, 2022) are selected on the basis of previous empirical evidence. One of the main criticisms associated with this method of selection is the lack of theoretical support.

The thirty-six financial variables selected for this study are taken from six previous international benchmark studies (Altman, 1968; Ohlson, 1980; Lo, 1986; Tascón and Castaño, 2012; Tian and Yu, 2017; Li and Faff, 2019) and one work of reference in the Colombian economy (Romero, 2013)[4]. The variables in question are described in Table 5 and their descriptive statistics at *t-1* are shown in Table 6.

INSERT TABLE 5 AND 6 ABOUT HERE

Although these models were originally developed to predict business failure in a broad sense, the variables included provide a useful starting point for predicting success or failure in reorganization processes. However, in order to provide a more accurate depiction of the context of interest, this study considers the variables with the greatest explanatory power for the failure of reorganizations in Colombia, before incorporating additional variables for further analysis.

3.2. Variable Selection with the Least Absolute Shrinkage and Selection Operator (LASSO) and Adaptive LASSO

Selecting financial variables by their relevance and frequency of use in the study of insolvency is common practice. However, contextual diversity deriving from national peculiarities and the heterogeneity of insolvency regimes makes it difficult to create a potential theoretical framework for predicting the failure of reorganization agreements. In the specific case of this study, complementary to the selection of variables based on an international reference framework, we apply Machine Learning techniques to develop an empirical selection method that takes into account the singularities of the Colombian

[4] The logit estimates using reorganization failure as the dependent variable and the predictors proposed in each of these papers individually are available upon request from the authors. The results show that none of the models is able to provide a satisfactory explanation and that most of the variables are without significance.

institutional framework and business fabric. Thus, we use the Least Absolute Shrinkage and Selection Operator (LASSO) under the constrained penalty approach (Tibshirani, 1996; Tian *et al*., 2015) and the Adaptive LASSO (A-LASSO) (Zou, 2006; Tian and Yu, 2017).

To select a predetermined set of predictor variables, we randomly split the sample at t-1 and define 70% of the observations as the training data set and the remaining 30% as the test data set. This process is repeated 100 times to reduce potential prediction bias due to random sample splitting. In each iteration, LASSO logistic regression is used to identify possible predictors of reorganization failure, and the results of the Cross Validation (CV) method are compared with those obtained via Adaptive Selection (AS). In addition, the Bayesian Information Criterion (BIC) is used to compare these results with those of the most parsimonious variable selection model observed in each iteration.

The variables in question are described in Table 7. They are listed in the order of selection frequency identified by the Machine Learning algorithm and their descriptive statistics at *t-1* are given in Table 6. Variables with more than 20 repetitions in the CV method and more than 10 repetitions in AS were used in the second stage of the estimations.

INSERT TABLE 7 ABOUT HERE

3.3. Model

Logistic regression, also known as logit, has been used in several business failure forecasting studies (Ohlson, 1980; Huang *et al.*, 2013; Altman *et al.*, 2016). The rationale for the use of this technique includes the high degree of predictive power it has demonstrated in previous studies and its potential for bias reduction, as compared to discriminant analysis, for example.

Some of the strengths of logit models relate to the fact that the scores generated for the dependent variable as a function of the explanatory variables are bounded between zero and one, making it easier to determine the probability of the two alternatives. It also admits the use of categorical variables, and the explanatory power of the estimated coefficients becomes individually relevant in the absence of outliers, missing values, and multicollinearity.

In the specification of the dependent variable in the various estimated models, failure is defined as entry into judicial liquidation proceedings after completing a reorganization agreement. As already stated, the proposal for determining the probability of this happening under Act 1116 of 2006 uses logistic regression, as per the following equation:

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

where:

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

$X_{h_{i,t-j}}$ indicates the value of the independent variable X_h, with $h=1, 2, \ldots, k$, for company i, at time $t\text{-}j$.

In this functional form, the covariances can be assessed for their relative importance in explaining the dependent variable (probability of failure), which takes values in the interval [0, 1] and indicates the probability of belonging to the group of non-failed or the group of failed companies.

4.- Determinants of the outcomes of reorganization processes in Colombia

4.1. Estimation of logit models with financial predictors based on individual significance and other independent variables

After univariate logit analysis to determine which of the variables described in Table 5 are individually significant, they are used together with other independent variables proposed in the literature (Table 8) to estimate the failure of reorganization agreements under Act 1116.

Financial indicators with previously documented predictive power are used as independent variables for the estimation of Model 1, while controlling for potential multicollinearity.

INSERT TABLE 8 ABOUT HERE

For the sake of parsimony, we specify Model 1 using five significant financial predictors of reorganization failure. The percentage of correctly classified cases is 75.49%. The variable Current Assets-Inventories)/Current Assets ((CA-I)/CA) appears referenced in Romero's (2013) study on Colombia and is included in our analysis as a means to measure the effect of the weight of the most liquid corporate assets on the probability of reorganization failure. The C/CA variable (Cash/Current Assets), which proxies for firm liquidity, has the expected negative sign, i.e., higher liquidity prior to the conclusion of the reorganization process is associated with lower probability of failure. However, the positive sign on the coefficient for C/TA (Cash/Total Assets) could be proxying for the use of non-current assets to create liquidity, in which case the impact on the firm's economic structure would reduce its probability of completing a successful reorganization. These variables offer an idea of the importance of liquidity in determining the success of these processes. The fourth variable included is TL/TA (Total liabilities / Total Assets) which proxies for corporate indebtedness and is expected to have a positive coefficient. Higher indebtedness is associated with a greater probability of failure. Finally, NI/TA (Net Income/Total Assets), which proxies for firm profitability, is expected to have a negative coefficient. That is, higher profitability reduces the likelihood of failure.

Secondly, using the data provided for firm reorganizations over the period 2008-2018 and based on Cepec and Grajzl (2020), we construct a binary indicator for the impact of debt-to-equity conversion on the failure of reorganization deals (IMPROVE_DEC). The dummy variable IMPROVE_DEC takes the value 1 for an improvement in the debt-to-equity ratio, proxied in our model by the Total Liabilities/Equity ratio, between *t-1* from the start of the reorganization and *t-1* from its conclusion.

In addition, given that previous studies have highlighted the impact of national economic crises in increasing the probability of corporate bankruptcy and insolvency filings in Colombia over the last two decades (Hernandez, 2022; Ibañez; 2020), we construct two dummy variables to measure the association between an economic slowdown or crisis and business reorganization failures. According to Ibañez (2020), 2008-2010 and 2015-2016 were periods of economic crisis in which real GDP growth was below its potential, mainly due to external shocks to the Colombian economy. Thus, the variable CRISIS_S takes the value 1 for reorganizations initiated during a year in either crisis period and 0 otherwise, while CRISIS_C takes the value 1 for reorganizations concluded in such a year.

Finally, we add the variable VOLUNT, which takes the value 1for voluntary entry into the reorganization process and 0 otherwise; voluntary entry being associated with a higher percentage of success, as indicated in the sample description.

Model 2 is an extension of Model 1 to include the indicator, IMPROVE_DEC. In this case the estimated pseudo R^2 is 37.2%. Although the negative sign of the estimator is consistent with expectations, in the sense that an improvement in the firm's debt-to-equity conversion during reorganization proceedings reduces the probability of failure, the estimator is non-significant and the result is therefore inconclusive. This contrasts with the findings of Cepec and Grajzl (2020), who find a negative and significant relationship, albeit with a different sample and explanatory variables.

Model 3, which includes the variables IMPROVE_DEC, CRISIS_S and CRISIS_C, yields a higher pseudo R^2 (38,2%) and the percentage of correctly classified cases rises to 77.33%. In this model, CRISIS_S is significant with a positive sign, indicating that the probability of failure increases if the reorganization started in a year of economic crisis.

The results of Model 4, which also includes VOLUNT, show this variable to have a non-significant negative relationship with failure in reorganization processes. Finally, Model 5, which excludes the IMPROVE_DEC indicator, thereby increasing the number of observations, yields a pseudo R^2 of 39.8% and a predictive accuracy rate of 81.37%. While all the variables maintain their signs, VOLUNT now becomes significant. In other words, voluntary entry into the reorganization process is associated with less likelihood of failure.

4.2. Estimation of logit models using machine learning-generated predictors and other independent variables

The variables identified in subsection 3.2. are subjected to a univariate analysis to evaluate their relevance in the prediction of failure in reorganizations undertaken within the Colombian institutional framework. The results provide statistical evidence to support the individual significance of 8 of the 13 machine learning-generated variables with predictive relevance for failure: Equity/Total Liabilities, Dummy OENEG (One if total liabilities are greater than total assets, zero otherwise), (Current Assets - Inventories)/Current Assets, (Current Assets - Inventories)/Total Assets, Equity, Current Assets/Total Assets, Operating Income/Total Assets, and Total Liabilities/Total Assets. Based on these findings, a stepwise logistic regression is used to obtain a set of predictor variables for consideration in the prediction of reorganization failure, based on their economic meaningfulness and overall significance in the estimation. Table 9 condenses the results of the above process together with the logit estimates including other independent variables considered in the previous subsection. Model 1a has 76.47% of correctly classified cases and includes the most important financial variable for each of the three groups as determined via machine learning: Leverage/Indebtedness, Liquidity and Solvency, and Profitability (See Table 7). The Total Equity/Liability ratio, a traditional Z-Score ratio, has a negative sign, indicating that a greater ability to satisfy current liabilities reduces the likelihood of failure in reorganization processes. The ratio (Current Assets – Inventories)/Current Assets maintains the positive sign shown in the estimates in the previous section, as does the ratio (Current Assets – Inventories)/Total Assets, which is included to measure the impact of asset structure in reorganization failure. The sign and significance of the Operating Income/Total Asset ratio verify a negative relationship between generated revenue before tax and reorganization failure, such that higher profitability reduces the probability of failure.

INSERT TABLE 9 ABOUT HERE

Model 2a adds the indicator IMPROVE_DEC and, in this case, the pseudo R^2 drops to 27.3%. While the non-significant negative sign of the coefficient is consistent both with expectations and the findings of the previous section, other model variables lose individual significance, and the percentage of correctly classified cases reaches 77.3%.

Model 3a includes the variables CRISIS_S and CRISIS_C, while Model 4a is extended to include VOLUNT, which, notably, has negative significance, indicating that, in reorganization processes, voluntary entry is positively related to success.

Finally, the coefficient estimates of Model 5a, where the variable IMPROVE_DEC is dropped for its lack of significance and negative sample-size effect, show the same tendency as those of the financial indicators and crisis/non-crisis and voluntary/non-voluntary dummies included in this model, which has a pseudo R^2 of 33.1% and 80.39% of correctly classified cases.

4.3. Robustness tests

The above estimations are replicated by replacing the Total Equity/Liability ratio with the OENEG debt dummy, the second most important predictor of failure according to the machine learning results. Table 10 presents the estimates of all the models, which show no substantial differences with respect to those obtained in the first estimation. In particular, the positive sign of OENEG in models 1b to 5b indicates that the probability of failure increases for companies whose liabilities exceed their assets. The remaining predictor variables keep their levels of significance and present the expected signs.

INSERT TABLE 10 ABOUT HERE

A further check, whereby each model is estimated using probit, yields conclusions similar to those obtained with the logit models. Finally, repeat estimation of all the models with t-2 variables replacing t-1 variables results in a substantial loss of goodness of fit[5].

5.- Conclusions

This paper examines the determinants of failure in reorganization processes in Colombia during the first decade of Colombian Corporate Insolvency Act 1116, introduced in 2006. Albeit in the absence of theoretical support for the predictive power of the selected financial predictors of failure, the results are consistent with previous empirical evidence for other countries. In particular, it emerges that the success of reorganization processes is explained mainly by variables related to indebtedness, firm profitability and liquidity. The sets of variables differ slightly according to whether they are selected with a machine learning technique or based on individual significance.

The findings of this research indicate that companies whose reorganization agreements end in failure have shown previous signs of inventory depletion and under-use of installed capacity and fixed assets. High indebtedness, likewise, emerges as a possible factor in the failure of reorganization processes, thus begging the question whether it might be worth relaxing pre- and mid-reorganization debt restrictions. Higher return ratios are, overall and unsurprisingly, associated with lower probabilities of failure.

Other relevant variables emerging from this analysis are whether or not the process is entered into voluntarily and whether or not it is undertaken during economic crisis. Other variables proposed in the literature as proxies for debt-to-equity conversion appear to lack explanatory power in this particular context, although reorganization processes are seen to thrive following out-of-court negotiations between creditors and debtors.

[5] The results of the probit estimation and those of the models with *t-2* variables replacing *t-1* variables are available upon request from the authors.

Moreover, given that one of the stated purposes of the Act is the protection of the company's credit and creditors, the success rate of over 51% in Completed Extrajudicial Reorganizations (CER) begs the question as to the efficiency gains that could be achieved in reorganization processes carried out under the auspices of the Act. This observation is all the more striking because the success rate of Completed Non-Extrajudicial Reorganizations (CNER) is just over 44%. These results suggest that negotiations between creditors and debtors tend to run more smoothly and conclude more successfully when the parties have pre-established rights and obligations. This is hardly surprising, given that CERs are voluntary; unlike CNERs, where the formal request for the initiation of judicial reorganization proceedings sometimes comes from an external agent other than the debtor.

Whether the company manages, in the best-case scenario, to continue its activity without resorting to judicial liquidation proceedings is a highly nuanced issue. Thus, caution is required when interpreting the outcomes of reorganizations undertaken during the period 2008–2018. The overall low (27.19%) completion rate of corporate reorganizations during that period does not necessarily indicate that the Act is inadequate for saving companies from bankruptcy, as testified by the 45%-plus success rate in completed cases and the increased probability of success among companies that persevere with proceedings for a period of between three and four years.

What finds more support is the notion that both firms and their creditors benefit from voluntary reorganization processes and that procedural efficiency could be improved by prior consensus between debtors and creditors regarding their respective rights and obligations.

In terms of theoretical implications, this paper contributes an exhaustive analysis of the determinants of reorganization processes to a body of literature heavily focused on the determinants of bankruptcy with scant attention to corporate reorganizations. Starting from the variables used in other bankruptcy studies, this one extends the research selecting variables on the basis of their individual significance or through a machine learning process. The inclusion of variables related to crisis scenarios and voluntary versus non-voluntary undertaking of the process improves the fit of the models.

In terms of the policy implications of the results presented above, our recommendation is that corporate segment regulators in Colombia should focus on the financial predictors identified in this study when designing monitoring guidelines, which might include an initial assessment prior to the onset of reorganization proceedings. Out-of-court settlements between creditors and debtors should also be encouraged to ensure the success of reorganization processes.

Finally, future research might overcome one of the limitations of this study by validating our findings regarding success or failure in business reorganizations in Colombia using a sample period extending beyond 2018. Other potentially useful contributions to this dissertation would be the study of variables alluding to the characteristics of reorganization agreements and the surrounding macroeconomic context.

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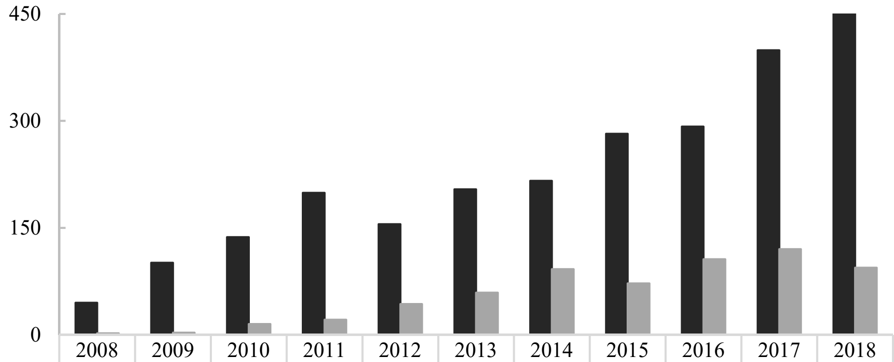
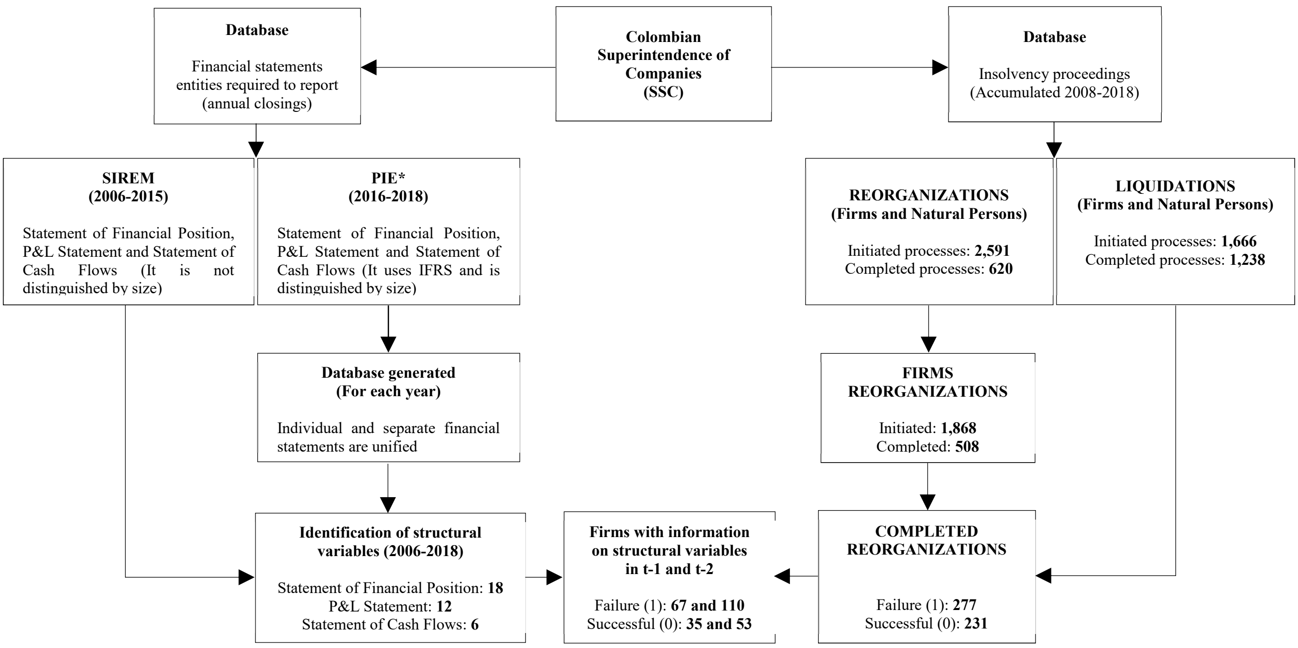
Figure 1. Initiated and completed processes per year.



	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
■ Initiated	45	101	137	199	155	204	216	282	292	399	561
■ Completed	2	3	15	21	43	59	92	72	106	120	94

Figure 2. Sample selection process.



*Financial Statements under IFRS from the year 2016.

Table 1. Time of permanence of the firms that completed a reorganization agreement.

Years	Firms	%	Successful Firms	Success Rate	Failured Firms	Failure Rate
9	6	1.18%	2	0.39%	4	0.79%
8	5	0.98%	2	0.39%	3	0.59%
7	17	3.35%	5	0.98%	12	2.36%
6	23	4.53%	15	2.95%	8	1.57%
5	40	7.87%	19	3.74%	21	4.13%
4	95	18.70%	48	9.45%	47	9.25%
3	99	19.49%	51	10.04%	48	9.45%
2	68	13.39%	34	6.69%	34	6.69%
1	94	18.50%	31	6.10%	63	12.40%
< 1	61	12.01%	24	4.72%	37	7.28%
Total	**508**	**100%**	**231**	**45.47%**	**277**	**54.53%**

The table shows the number of firms that have completed reorganization processes disaggregated by the number of years they have been in reorganisation. It is further broken down by successful and failed processes.

Table 2. Reorganizations initiated and completed in the 2008-2018 period, by type of agreement and judicial nature of the process.

Type of agreement	Non-extrajudicial initiated reorganizations	Non-extrajudicial completed reorganizations	%	Extrajudicial initiated reorganizations	Extrajudicial completed reorganizations	%
Voluntary	1,567	387	24.7%	213	92	43.2%
Non-voluntary	88	29	33.0%	0	0	NA
Total	**1,655**	**416**	**25.1%**	**213**	**92**	**43.2%**

The table shows the number of voluntary and non-voluntary reorganizations initiated and completed. It also shows the percentage of completed over initiated (%).

Table 3. Success and failure rates of non-extrajudicial reorganizations completed in the 2008-2018 period, by type of agreement.

Type of agreement	Non-extrajudicial reorganizations	Successful cases	Success rate	Failured cases	Failure rate
Voluntary	387	176	45.48%	211	54.52%
Non-voluntary	29	8	27.59%	21	72.41%
Total	**416**	**184**	**44.23%**	**232**	**55.77%**

The table shows the success and failure rates of completed non-extrajudicial reorganizations.

Table 4. Success and failure rates of extrajudicial reorganizations completed in the 2008-2018 period, by type of agreement.

Type of agreement	Extrajudicial completed reorganizations	Successful cases	Success rate	Failured cases	Failure rate
Voluntary	92	47	51.09%	45	48.91%
Non-voluntary	0	NA	NA	NA	NA
Total	**92**	**47**	**51.09%**	**45**	**48.91%**

The table shows the success and failure rates of completed extra-judicial reorganizations.

Table 5. Variable definitions.

Variables	Definition
Liquidity and solvency group	
CA/TA	Current Assets/Total Assets
CA/CL	Current Assets/Current Liabilities
WC/TA	Working Capital/Total Assets
(CA – I)/CL	(Current Assets - Inventories)/Current Liabilities
(CA – I)/TA	(Current Assets - Inventories)/Total Assets
(CA – I)/CA	(Current Assets - Inventories)/Current Assets
C/CL	Cash/Current Liabilities
C/CA	Cash/Current Assets
C/TA	Cash/Total Assets
*Estructural group**	
NI	Net Income
TL	Total Liabilities
E	Equity
Cash flow group	
CFO/TL	Cash Flow from Operations/Total Liabilities
Rotation group	
S/TA	Sales/Total Assets
RE/TA	Retained Earnings/Total Assets
Leverage and debt group	
TL/TA	Total Liabilities/Total Assets
D/TA	Debt/Total Assets
CL/CT	Current Liabilities/Total Liabilities
E/TA	Equity/Total Assets
CL/TA	Current Liabilities/Total Assets
LTL/TA	Long Term Liabilities/Total Assets
CL/S	Current Liabilities/Sales
E/TL	Equity/Total Liabilities
CL/CA	Current Liabilities/Current Assets
OENEG	One if total liabilities are greater than total assets, zero otherwise
EBT/S	Earnings Before Tax/Sales
NI/S	Net Income/Sales
(CL – C)/TA	(Current Liabilities - Cash)/Total Assets
I/S	Inventories/Sales
Profitability group	
EBT/TA	Earnings Before Tax/Total Assets
NI/TA	Net Income/Total Assets
OI/TA	Operating Income/Total Assets
OI/S	Operating Income/Sales
RE/CL	Retained Earnings/Current Liabilities
Size group	
SIZE	The natural logarithm of the total assets
LOG(S)	The natural logarithm of the sales

The table shows the definition of the financial variables used throughout the paper. Structural variables are defined in COP millions.

Table 6. Descriptive statistics of the financial variables at t-1

Variables	Obs	Mean	S.D.	Min	Max
Liquidity and solvency group					
CA/TA	102	0,47	0,29	0,01	1,00
CA/CL	102	2,94	7,96	0,01	60,66
WC/TA	102	-0,12	0,74	-4,80	0,93
(CA – I)/CL	102	2,06	6,78	0,00	60,66
(CA – I)/TA	102	0,35	0,27	0,00	0,99
(CA – I)/CA	102	0,73	0,26	0,08	1,00
C/CL	102	0,08	0,16	0,00	1,07
C/CA	102	0,06	0,11	0,00	0,89
C/TA	102	0,02	0,06	0,00	0,34
*Estructural group**					
NI	102	-2.376	7.801	-50.000	7.758
TL	102	16.900	27.900	189	135.000
E	102	5.948	23.000	-26.800	190.000
Cash flow group					
CFO/TL	102	-0,19	1,61	-15,79	0,87
Rotation group					
S/TA	102	0,75	0,95	0,00	5,94
RE/TA	102	-1,10	4,72	-43,92	0,73
Leverage and debt group					
TL/TA	102	1,50	3,70	0,04	36,49
D/TA	102	0,43	0,58	0,00	3,92
CL/CT	102	0,54	0,33	0,01	1,00
E/TA	102	-0,50	3,70	-35,49	0,96
CL/TA	102	0,60	0,73	0,01	5,50
LTL/TA	102	0,90	3,62	0,00	35,86
CL/S	100	3,60	11,00	0,02	79,25
E/TL	102	0,63	2,52	-0,97	21,97
CL/CA	102	3,15	13,78	0,02	139,24
OENEG	102	0,39	0,49	0,00	1,00
EBT/S	100	-0,89	2,54	-18,34	0,78
NI/S	100	-0,96	2,59	-18,34	0,76
(CL – C)/TA	102	0,57	0,73	-0,02	5,47
I/S	100	0,77	3,20	0,00	28,81
Profitability group					
EBT/TA	102	-0,19	0,38	-2,04	0,38
NI/TA	102	-0,20	0,38	-2,05	0,22
OI/TA	102	-0,15	0,34	-2,04	0,49
OI/S	100	-0,76	2,29	-18,34	0,79
RE/CL	102	-1,61	7,50	-70,02	16,69
Size group					
SIZE	102	15,67	1,72	10,42	19,22
LOG(S)	100	14,74	1,92	10,06	19,07

The table shows the descriptive statistics for the financial variables defined in table 1. Obs number of observations; mean; S.D. Standard Deviation; Min minimum; Max maximum

Table 7. Predetermined predictors with artificial intelligence using logistic LASSO regression

Variable	Group	Cross Validation (CV)		Adaptive Selection (AS)		BIC (Minimum)	
		Repetitions	%	Repetitions	%	Repetitions	%
Constant		100	100,0%	100	100,0%	100	100,0%
E/TL	Leverage and debt	91	91,0%	78	78,0%	49	49,0%
OENEG		88	88,0%	67	67,0%	78	78,0%
(CA-I)/CA	Liquidity and solvency	47	47,0%	42	42,0%	11	11,0%
CL/CA		47	47,0%	24	24,0%	3	3,0%
(CA-I)/CL		44	44,0%	32	32,0%	9	9,0%
(CA-I)/TA		42	42,0%	31	31,0%	10	10,0%
C/CA		37	37,0%	25	25,0%	3	3,0%
E	Structural	33	33,0%	18	18,0%	7	7,0%
NI		30	30,0%	16	16,0%	1	1,0%
CA/TA	Liquidity and solvency	27	27,0%	18	18,0%	3	3,0%
OI/TA	Profitability	27	27,0%	20	20,0%	2	2,0%
CA/CL	Liquidity and solvency	25	25,0%	23	23,0%	0	0,0%
TL/TA	Leverage and debt	21	21,0%	14	14,0%	0	0,0%
RE/CL	Profitability	17	17,0%	7	7,0%	2	2,0%
CL/CT	Leverage and debt	14	14,0%	5	5,0%	1	1,0%
EBT/TA	Profitability	13	13,0%	5	5,0%	0	0,0%
CL/TA	Leverage and debt	11	11,0%	7	7,0%	0	0,0%
SIZE	Size	8	8,0%	4	4,0%	0	0,0%
EBT/S	Profitability	8	8,0%	3	3,0%	0	0,0%
I/S	Rotation	8	8,0%	4	4,0%	0	0,0%
NI/TA	Profitability	7	7,0%	2	2,0%	0	0,0%
S/TA	Rotation	6	6,0%	2	2,0%	0	0,0%
CL/S	Leverage and debt	6	6,0%	3	3,0%	0	0,0%
LOG(S)	Size	6	6,0%	0	0,0%	0	0,0%
TL	Structural	6	6,0%	2	2,0%	0	0,0%
C/CL	Liquidity and solvency	5	5,0%	0	0,0%	0	0,0%
C/TA	Liquidity and solvency	3	3,0%	4	4,0%	0	0,0%
D/TA	Leverage and debt	2	2,0%	1	1,0%	0	0,0%
E/TA		2	2,0%	0	0,0%	0	0,0%
OI/S	Profitability	2	2,0%	0	0,0%	0	0,0%
(CL-C)/TA	Leverage and debt	2	2,0%	3	3,0%	0	0,0%
LTL/TA	Size	1	1,0%	0	0,0%	0	0,0%
NI/S	Profitability	1	1,0%	0	0,0%	0	0,0%

The table shows the order of frequency and importance of the variables selected through the artificial intelligence procedure.

Table 8. Estimation results of logit models with relevant financial predictors and other independent variables.

Variable	Model 1		Model 2		Model 3		Model 4		Model 5	
	Coef.	O.R.	Coef.	O.R.	Coef.	O.R.	Coef.	O.R.	Coef.	O.R.
Constant	-2.971***	0.051	-3.723***	0.024	-4.443***	0.012	-1.866	0.155	-0.562	0.570
(CA-I)/CA	2.111**	8.255	2.403**	11.059	2.823**	16.828	2.373	10.728	1.892*	6.631
C/CA	-31.457**	2.18e-14	-33.657**	2.41e-15	-48.037**	1.37e-21	-58.745**	3.07e-26	-41.188***	1.29e-18
C/TA	43.280**	6.25e+18	75.824**	8.51e+32	87.430*	9.34e+37	107.568*	5.20e+46	52.369***	5.54e+22
TL/TA	2.548***	12.778	2.796**	16.381	3.614**	37.124	4.500***	90.028	3.730***	41.665
NI/TA	-5.400*	0.005	-6.613**	0.001	-7.792**	0.000	-9.633**	0.000	-6.447*	0.002
IMPROVE_DEC			-0.440	0.644	0.080	1.084	0.390	1.477		
CRISIS_S					1.877**	6.537	2.082**	8.023	0.966	2.629
CRISIS_C					-2.259**	0.104	-2.836***	0.059	-1.918***	0.147
VOLUNT							-3.060	0.047	-2.718**	0.066
Prob > Chi2	0.000		0.000		0.000		0.000		0.000	
Pseudo R^2	0.324		0.372		0.382		0.485		0.398	
Observations	102		75		75		75		102	
Classified	75.49%		81.33%		77.33%		84.00%		81.37%	

This table presents the results of the estimation of the logistic regression of the different models that includes relevant financial predictors, IMPROVE_DEC that proxies the debt-to-equity conversion measures, dummy VOLUNT takes the value 1 if voluntary and 0 otherwise, and dummy variables for crisis periods (CRISIS_S and CRISIS_C) for the sample in t-1. The definition of the financial variables is shown in table 1. Coef.: Estimated coefficient of the independent variable. O.R.: Odds Ratio. ***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

Table 9. Estimates of logit models using predictors obtained with Machine Learning and other independent variables

Variable	Model 1a		Model 2a		Model 3a		Model 4a		Model 5a	
	Coef.	O.R.	Coef.	O.R.	Coef.	O.R.	Coef.	O.R.	Coef.	O.R.
Constant	-2.205**	0.110	-1.937	0.144	-2.028	0.132	1.789	5.981	1.817	6.151
E/TL	-0.690*	0.502	-0.718	0.488	-0.749	0.473	-1.212**	0.298	-1.191**	0.304
(CA-I)/CA	2.640**	14.012	2.566**	13.018	2.760**	15.806	2.280*	9.778	2.239**	9.385
CA/TA	2.128**	8.400	1.756	5.789	1.898	6.674	1.843	6.314	1.831*	6.238
OI/TA	-6.587**	0.001	-5.352**	0.005	-5.579**	0.004	-7.626**	0.000	-8.117***	0.000
IMPROVE_DEC			-0.062	0.940	0.059	1.061	0.256	1.291		
CRISIS_S					0.886	2.425	1.009	2.744	0.544	1.723
CRISIS_C					-1.160*	0.313	-1.613**	0.199	-0.154*	0.342
VOLUNT							-3.414*	0.033	-3.334**	0.036
Prob > Chi2	0.000		0.000		0.000		0.000		0.000	
Pseudo R^2	0.280		0.273		0.310		0.353		0.331	
Observations	102		75		75		75		102	
Classified	76.47%		77.33%		77.33%		80.00%		80.39%	

This table presents the results of the estimation of the logistic regression of the different models that includes relevant financial predictors, IMPROVE_DEC that proxies the debt-to-equity conversion measures, dummy VOLUNT takes the value 1 if voluntary and 0 otherwise, and dummy variables for crisis periods (CRISIS_S and CRISIS_C) for the sample in t-1. The definition of the financial variables is shown in table 1. Coef.: Estimated coefficient of the independent variable. O.R.: Odds Ratio. ***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

Table 10. Estimates of logit models using specific predictors obtained with Machine Learning and other independent variables

Variable	Model 1b		Model 2b		Model 3b		Model 4b		Model 5b	
	Coef.	O.R.	Coef.	O.R.	Coef.	O.R.	Coef.	O.R.	Coef.	O.R.
Constant	-2.555***	0.078	-2.135**	0.118	-2.406**	0.090	-0.873	0.418	-1.072	0.342
OENEG	1.039*	2.826	0.958	2.607	1.847**	6.337	2.022**	7.556	1.707**	5.511
(CA-I)/CA	2.190**	8.932	2.081*	8.009	2.415**	11.190	2.134*	8.445	2.076**	7.972
CA/TA	2.229**	9.287	1.983*	7.263	2.300*	9.976	2.438**	11.453	2.323**	10.206
OI/TA	-5.117**	0.006	-4.098*	0.017	-3.499	0.030	-4.401	0.012	-5.230**	0.005
IMPROVE_DEC			-0.817	0.442	-0.886	0.412	-0.901	0.406		
CRISIS_S					1.189*	3.283	1.190*	3.287	0.647	1.909
CRISIS_C					-1.645**	0.193	-1.865**	0.155	-1.284**	0.277
VOLUNT							-1.465	0.231	-1.373	0.253
Prob > Chi2	0.000		0.001		0.002		0.001		0.000	
Pseudo R^2	0.220		0.201		0.271		0.285		0.262	
Observations	102		75		75		75		102	
Classified	71.57%		70.67%		77.33%		78.67%		76.47%	

This table presents the results of the estimation of the logistic regression of the different models that includes relevant financial predictors, IMPROVE_DEC that proxies the debt-to-equity conversion measures, dummy VOLUNT takes the value 1 if voluntary and 0 otherwise, and dummy variables for crisis periods (CRISIS_S and CRISIS_C) for the sample in t-1. The definition of the financial variables is shown in table 1. Coef.: Estimated coefficient of the independent variable. O.R.: Odds Ratio. ***, ** and * denote significance at the 1, 5 and 10% levels, respectively.