# MORAL HAZARD INDEX FOR CREDIT RISK TO SMEs


***Abstract***

This article proposes a methodology to calculate the effect of moral hazard on credit risk to small and medium-sized enterprises (SMEs). To this end, the four categories of moral hazard ratios defined by Castillo et al. (2018) are employed to determine default probability based on a logit model. Moreover, a novel Colombian database is used to calculate a moral hazard index that considers the percentages of the odds ratios of the moral hazard variables for positive coefficients on the defaults probability. The empirical analysis result in an index measuring the impact of moral hazard on odds ratio mainly based on underinvestment moral hazard category in the sample of companies analyzed for the period 2007-2014.



**Keywords**

SME credit, credit risk, moral hazard, moral hazard index

JEL classification: G320

# 1. INTRODUCTION

Credit risk models have undergone an increasing interest in the last decades triggered, among other reasons, by the need of providing accurate credit rankings and risk premia for corporate and sovereign bonds, see e.g. Gastelum et. Al. (2017), Chang et al. (2018), Jian et. al. (2019), Kirikkaleli & Gokmenoglu (2019). Overall, credit risk is the risk associated to potential losses resulting from the default of a counterparty in a financial transaction or as a deterioration in the creditworthiness of the counterparty or of the agreed collateral. Traditionally, it been measured on the basis of parametric techniques or particular models developed to evaluate these transactions (Bluhm, Overbeck, & Wagner, 2010).

One of the causes of credit default is the presence of moral hazard (Berger, Scott Frame, & Ioannidou, 2011), which is related to the problems that arise in contractual relationships associated with the effort to comply with the agreements (Ross, 1973). Since moral hazard is an unobservable behavior, it is manifested directly on its consequences (Mirrlees, 1999). Due to this fact, in moral hazard dilemmas it is essential to determine the level of risk and to establish a guideline or an index to monitor it. However, there is no index to assess moral hazard (Jeanne & Zettelmeyer, 2005), although Zinman (2014) cites a methodological reference for a moral hazard measure (based on a linear regression model) of credit extended to individuals. In this regard, the definition of a moral hazard index for credit default becomes an important tool within the scope of risk analysis.

On the subject of moral hazard in credit transactions, there are theoretical studies such as those by Dixit and Besley (1997), Csóka et al. (2015), Lee and Yu (2002), and Myerson (2014), as well as empirical studies such as those by Dell'Ariccia et al. (2002), Uesugi et al. (2010), Berger et al. (2011), Ono et al. (2012) and Castillo et al. (2018), among others. The latter authors incorporate variables for measuring moral hazard in credit risk to small and medium-sized enterprises (SMEs) in an emerging market case. These variables are defined in terms of four categories: asset substitution, low effort, underinvestment and alternate use. However, the authors do not establish an index to measure such risk, which is the main objective of this article.

In addition to the introduction, this paper has three sections. Section two reviews the literature on the evaluation of credit risk and moral hazard; section three presents the empirical evidence for creating the moral hazard index in credit transactions; and the last section summarizes the conclusions.

# 2. LITERATURE REVIEW

## 2.1. CREDIT RISK EVALUATION

In banking, two types of models are used to evaluate credit risk; traditional ones and those based on parametric techniques (Bluhm, Overbeck, & Wagner, 2010).The former, are based on the creation of borrowers' profiles based on their solvency, reputation and credit repayment history. Other factors are also considered, such as the company's ability to repay a loan, its capital structure, shareholder exposure to risk and credit history, collateral to secure the creditor's exposure to risk, and the cyclical conditions of the economy. This is known as the five Cs of credit: Character, Capacity, Capital, Collateral and Conditions.

Furthermore, the existing financial literature groups the models based on parametric techniques into three categories: (i) econometric models, which include linear discriminant analysis and multiple linear regression (Altman Z-score model), and logit and probit models, wherein the independent variables are mainly financial ratios and variables that measure macroeconomic effects; (ii) the Kecholfer, McQuom and Vasicek (KMV) or Moody's model, also called Credit Monitor, based on the theory of financial options, which enables the simulation of loan behavior using a put option; and (iii) models of artificial neural networks with computational models that try to simulate the human learning process by imitating a network of interconnected neurons (De Lara, 2008).

The purpose of credit risk assessment is to determine the probability that the borrower or the bond issuer will default (Saavedra García & Saavedra García, 2010). The literature on econometric models for financial default assessment generally considers four elements in its analysis:

(i) Definition of the cause of the financial difficulty. Two well-defined lines of thinking emerge here. One is associated with the concept of bankruptcy, as in Zhao et al. (2016), Blanco-Olivero et al. (2014), Altman et al. (2010), and Liou and Smith (2007). The other is related to the concept of insolvency as viewed by Altman and Sabato (2007) and Grunert et al. (2005).

(ii) The explanatory variables, which usually correspond to financial ratios, see e.g. Brédart (2014), Liou and Smith (2007), Altman (1968) and Beaver (1966). In some cases, cash flows are considered, such as in Sharma and Iselin (2003) and Gentry et al. (1987), or macro variables such as in Filipe et al. (2016) and Liou and Smith (2007).

(iii) A methodology that extensively uses a logit model, as in the studies by Zhao et al. (2016), Filipe et al. (2016), Becchetti and Sierra (2003), Keasey and Watson (1987) and Ohlson (1980).

(iv) A theory that primarily based on Beaver's (1966) theory and other previous related studies.

On the other hand, Castillo et al. (2018) incorporate a logit model that includes the economic interest of the borrower when modeling financial default in credit contracts, which gives rise to the moral hazard assessment. Thus, they establish an argument based on agency theory to incorporate this type of risk in the financial performance of the borrower, specifically regarding credit to SMEs. Their argument consider four different categories of moral hazard: (i) substitution of assets for the purpose of finding riskier investments and better performance; (ii) low effort, characterized by high costs and expenses; (iii) underinvestment, characterized by the use of financial resources for non-operating expenses; and (iv) alternate use, when the loan is used for activities other than those established in the credit agreement. These authors find that the variables for the first three categories are statistically significant, but they do not provide an explicit link between the coefficients of the significant variables of the different categories and the concept of moral hazard. This paper establishes this relationship.

## 2.2. MORAL HAZARD EVALUATION

To understand moral hazard, we will first discuss the agency relationship that manifests itself between two or more parties when one (the agent) acts on behalf of the other (the principal) in contractual relationships, such as employer and employee, and in financial intermediation. In this relationship, the agent obtains benefits resulting from the way he acts, states of nature (unpredictable events), and remuneration received for his effort. Furthermore, the principal will receive benefits depending on the agent’s effort as conditioned by payments made by the principal, and the states of nature. This contractual relationship generates problems of moral hazard (Ross, 1973). Therefore, moral hazard, in economic terms, is related to the role of incentives in the framework of the principal-agent relationship and has nothing to do with a judgment about ethics (Rowell & Connelly 2012). Furthermore, moral hazard is an unobservable behavior that can be inferred from its consequences (Mirrlees, 1999), and thus, it can be argued that that credit non-compliance might result from moral hazard (Berger et al., 2011).

The influence of moral hazard on credit have been studied in the literature at both theoretical and empirical levels. Theoretical studies have focused on the implementation of incentives that ensure proper efforts exerted by the borrower, which consequently benefits the lender (Dixit & Besley 1997), or its influence on loans between an SME and its clients (Csóka et al., 2015). Additionally, moral hazard is considered in the evaluation of insurance hedges, such as in the study by Lee and Yu (2002). Moreover, there are arguments that analyze macroeconomic instability as a cause of moral hazard, as illustrated by an agent responsible for making large investments using the savings of individual investors (Myerson, 2014).

As far as the empirical strand of literature concerns, some studies have analyzed the existence of distortions in the price of credit to emerging economies (Martinez-Vazquez & Mina, 2003) and the determination of the extent to which banking safety nets or the financial bailouts by the International Monetary Fund (IMF) stimulate moral hazard, see e.g. Dell'Ariccia et al. (2002), Lee and Shin (2008) and Dam and Koetter (2012). Other investigations studied the effects of the collateral on business sectors and for some credit channels – Honig and Jain-Chandra (2006), Uesugi et al. (2010), Berger et al. (2011), Ono et al. (2012), and Ono et al.

(2013) – or mortgage credit – Agarwal et al. (2016). On the other hand, only Zinman (2014) attempt to propose a methodology (see also Bryan et al. 2013) for providing a moral hazard measure, based on a linear regression model, related to credit risk of credit. However, the literature still lacks the provision of an index to measure moral hazard (Jeanne & Zettelmeyer, 2005). Recently, Castillo et al. (2018) introduced the financial ratios for moral hazard, which improve the predictive capacity of credit risk models for SMEs, although they do not establish a general index for moral hazard.

# 3. METHODOLOGY AND EMPIRICAL EVIDENCE

## 3.1. MORAL HAZARD INDEX

Since moral hazard is unobservable and only its consequences can be seen, one must think about an index that is necessarily based on the effect of the event examined – the non-compliance event, in this case. In other words, until the probability of default (PD) is calculated, the index cannot be established. Given that PD ($P_i$) can be properly modeled according to logistic function and in terms of a set of variables $X \in \Re^m$, the corresponding logit model can be expressed in terms of the so-called odds ratio ($P_i/1 - P_i$) as

$$\frac{P_i}{1-P_i} = e^{\beta_0 + \sum_{i=1}^{m} \beta_i X_i} \quad . \tag{1}$$

Thus, the logarithm of the odds ratio (LOR) can be formulated in a simple linear relation on the variables included in *X*,

$$\ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \sum_{i=1}^{m} \beta_i X_i, \tag{2}$$

where $\beta_\mathrm{i}$ captures the marginal effect of the variable *i* in the logit model, that is, on the logarithm of the probabilities in favor of the occurrence of the examined event, and $e^{\beta_\mathrm{i}}$ measures the marginal impact of the variable *i* on the odds ratio, i.e. on the ratio of the probability of occurrence and non-occurrence of the default.

In addition, the vector $X$ can be partitioned in two groups of variables: those related to the traditional (common) financial ratios (CFR), and other ratios accounting for moral hazard financial ratios (MHFR). This allows us to straightforward quantify the effect of both types of factors on LOR,

$$LOR = \beta_0 + \sum_{j=1}^{n} CFR_j \, \beta_j + \sum_{k=n+1}^{m} MHFR_k \, \beta_k, \tag{3}$$

and built a moral hazard index based on the weights captured by $e^{\beta_i}$. Particularly, we can establish the degree to which the coefficients $e^{\beta_i}$ of the moral hazard ratios have a positive impact on the default probability ratio. This degree is determined by the percentage of $e^{\beta_i}$ higher than one (i.e. where $\beta_i > 0$) for the moral hazard variables over the total amount of $e^{\beta_i}$ higher than one on the entire regression (degree of moral hazard or moral hazard index for credit risk). This is interpreted as the percentage of effect of the moral hazard variables on the probability ratio.

### 3.2. EMPIRICAL EVIDENCE

The purpose of this section is to obtain a moral hazard index for credit risk (MHICR). Here, we will work with the significant coefficients of the moral hazard variables defined in default probability modeling. To this end, the databases and logit models defined in Castillo et al. (2018) were used. However, this article employs a reduced sample only covering the period 2012-2014, whilst we extend the sample from 2007 to 2014, thus including the informative period of the subprime crisis where credit default and moral hazard are particularly relevant. We also consider two models, the first model considers just traditional financial ratios, and the second model combines the traditional financial ratios with moral hazard ratios. These two models are compared with the aim of verifying any improvement in predictive capacity once the moral hazard ratios are incorporated in the calculation of the MHICR.

### 3.3. DATA

The data for calculating default probabilities come from two sources: the National Credit Guarantee Fund of Colombia (*Fondo Nacional de Garantías de Colombia* - FNG) and the Superintendency of Corporations of Colombia (*Superintendencia de Sociedades de Colombia*). The financial ratios for both moral hazard and traditional risk are calculated using these data for the period 2007-2014.

From the FNG source, company credit information is taken for a period less than or equal to 12 months. This is because the database does not allow identifying the dates on which a customer may have defaulted on loan payments. Therefore, with data for the period indicated above, the company's financial information for the year in which the collateral became effective and the completion of the credit term will not be significantly different, unless the company entered bankruptcy, which was verified. This organizes the work into annual cohorts,[1] which provide an instant and complete picture of the SMEs' credit performance (guaranteed by the FNG) for each year. Balance sheets and income statements for these same companies with FNG credit guarantees were obtained from the Colombian Superintendency of Corporations.

The number of records obtained (filtered by company size[2]) with regard to the number of SMEs in Colombia was 2,234, 2,451, 3,469, 3,498, 3,896, 3,760, 3,615, and 3,228 for the years 2007 to 2014, respectively. These records consist of two groups. The first corresponds to companies for which the collateral was paid to the financial intermediary by the FNG; in other words, these companies defaulted. There were 8, 5, 10, 6, 9, 17, 17 and 20 companies that defaulted in each of the years examined, respectively. The second group consists of the

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[1] With this type of data, endogeneity problems due to simultaneity are unlikely. However, this was verified, and no evidence of such was found.

[2] For this purpose, in addition to the size classification of Colombian SMEs established by Law 905 in 2004, the amount of the legal monthly minimum wage was used. The amounts were: 2007 (COP 433,700), 2008 (COP 461,500), 2009 (COP 496,900), 2010 (COP 515,000), 2011 (COP 535,600), 2012 (COP 566,700), 2013 (COP 589,500) and 2014 (COP 616,000).

remaining companies for which the collateral was terminated without a claim; that is, the borrower paid back the entire loan.

In the modeling, the focus is on the behavior of the company at the end of the collateral period because either the company defaulted or it did not. Additionally, given that a company can have multiple loans, the company's response regarding the entire credit package was taken into account; that is, whether it complied or not. A single loan default was enough to consider the entire credit package to be in breach of contract.

In the two logit models used, the dependent variable in all cases corresponded to the state of compliance with the terms of the credit package (in default or not). In the first model, the independent variables were the traditional financial ratios and the number of loans[3]; a one (1) was assigned when there was a single loan, and a zero (0) was assigned for all other cases. In the second model, the moral hazard ratios were added.

A descriptive analysis of the data highlight that the average values of the traditional financial ratios that convey repayment capacity are higher for solvent companies (not defaulted), except for the cash/total assets ratio in 2007, 2008, 2009, 2011 and 2013, and the retained earnings/total assets ratio in 2014. Meanwhile, solvent companies had a lower average level of short-term debt/equity – the ratio that conveys debt levels – except in 2011 and 2012.

Regarding the moral hazard ratios, the average values do not reveal a dominant pattern in either case (insolvency or solvency). However, it is worth mentioning that these values were higher for all cases from 2008-2012, and the only variable with a consistently higher average value was non-operating expenses/total assets (underinvestment).

[3] The traditional financial ratios are based on Altman and Sabato (2007). On the other hand, Altman, Sabato, and Wilson (2010) demonstrate the importance of qualitative variables that reflect the risk of operating the company. In this sense, the variable number of loans is considered.

## 3.4. RESULTS

Tables 1 and 2 present the coefficients of the models used to calculate the SMEs[4] default probabilities. Model 1 (Table 1) uses traditional financial ratios, and Model 2 (Table 2) incorporates moral hazard ratios. These models exceed the global significance tests of the variables and have a good fit with the data. Model 2 is the best model according to -2log likelihood criterion, and the coefficients of the significant variables have theoretical consistency except for two years (2007 and 2009) in which the cash/total assets ratio is positive. This result may be due to the 2007 international financial crisis because agents have a preference for liquidity in such situations.

[INSERT TABLES 1 -2]

Table 3 presents the results of the coefficients of the moral hazard variables in Model 2, the coefficients of the traditional financial ratios, and the corresponding values of $e^{\beta_i}$ for each case. In the positive coefficients the values of $e^{\beta_i}$ of the moral hazard ratios correspond to the value for the moral hazard effect, which represent a high relative risk in 2007, 2010 and 2012 (represented by the underinvestment category)

[INSERT TABLES 3]

Table 4 shows, for each ratio category, the percentage of (positive or negative) effect of the $e^{\beta_i}$ on the default probability ratio. The percentages for each moral hazard ratio category correspond to the degree of effect within the default probability ratio.

[INSERT TABLES 4]

Table 5 shows The MHICR in each year that is given by the sum of the positive effect percentages, considering the results of the coefficients of the moral hazard variables.

[INSERT TABLES 5]

[4] The supporting data is available upon request, as well as the correlation tests.

- Tables 3-5 present the calculations of the moral hazard index for credit risk. The following can be stated based on the above tables: The underinvestment component of moral hazard was prevalent in the various years analyzed, and although it reached its highest point ($\beta_i$) in 2007 (8.887), its most significant influence was in 2010 and 2012, as its contributions to the probability ratio were 98.647% and 100%, respectively (Table 4).
- The moral hazard components of low effort and asset substitution contributed negatively to the default probability (PD). That is, where there was statistical significance, they contributed to better performance regarding the financial obligations of the companies (Table 4).
- Not present in any of the PD calculations for the years analyzed was the alternative use of borrowed money to acquire long-term assets that had a slower recovery rate than short-term money obtained through credit transactions.
- In the years where moral hazard was present, the positive impact on the PD was very significant.

## 4. CONCLUSIONS

The moral hazard index for the data in consideration was established based on underinvestment moral hazard category with a 38.485% in 2007, 98.647% in 2010 and 100% in 2012 of impact on the default probability of the SMEs.

This article sheds light on the impact of moral hazard on default probability (measured in terms of the odds ratio) and quantifies this effect through a moral hazard index. For this purpose the moral hazard variables proposed by Castillo et al. (2018), grouped into the categories of asset substitution, low effort, underinvestment and alternative use of the credit, are used and reveled as significant sources of credit risk. In the sample, which extends the analysis to the period 2007-2014, at least three of the moral hazard variables defined by the aforementioned authors (short- and long-term investments/total assets, operating costs + operating expenses/total assets, and non-operating expenses/total assets) allowed the identification or rejection of the influence of moral hazard on the default probability by the companies backed by the Colombia's FNG from 2007-2014.

Although the FNG's guarantee of the resources channeled to SMEs does not mitigate the moral hazard problems, when significant results were found in 2010 and 2012, it is noteworthy that the credit non-compliance rates of the sample only ranged from a maximum of 0.62% (2014) to a minimum of 0.17% (2010). Furthermore, the fact that the alternative use category (property, plant and equipment/total assets) of the moral hazard ratios did not have any statistical significance in the years analyzed reveals the lack of interest by the sampled companies in applying aggressive financing strategies because short-term credit was not affected by investments in long-term assets.

Given that the consequences of moral hazard are not observable and only its consequences can be seen, the moral hazard index provides a tool to monitor the evolution of its effect on credit compliance. Both the positive and negative signs of the moral hazard ratios for credit default have theoretical meaning because the former indicates the existence of moral hazard, while the latter indicates its absence.

When calculating default probability, the times when the effects of the moral hazard ratios are greater than the combined influence of the ratios for liquidity, profitability, leverage, or any other traditional financial ratios should be considered critical, given that the loan is negatively impacted by a conflict of interest rather than by the company's own operations; this conflict should be rectified by the collateral. Future studies could be conducted to extend the empirical validation of the moral hazard index for credit offered to other companies and markets.

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## APPENDIX

**Table 1**: Logit regression 2007-2014 – traditional financial ratios

| | Model 1 | 2007 | 2008* | 2009 | 2010 | 2011* | 2012 | 2013 | 2014 |
|---|---|---|---|---|---|---|---|---|---|
| **No.** | **Variable** | | | | **Coefficients** | | | | |
| 1 | Cash/total assets | 9.949 | 5.043 | 7.234 | -163.389 | | -33.284 | 4.248 | -0.716 |
| | | **(0.028)** | **(0.438)** | **(0.000)** | **(0.403)** | | **(0.068)** | **(0.161)** | **(0.925)** |
| 2 | EBITDA/total assets | 0.718 | | -1.232 | -0.961 | | -1.451 | -1.075 | -3.117 |
| | | **(0.856)** | | **(0.050)** | **(0.593)** | | **(0.037)** | **(0.133)** | **(0.064)** |
| 3 | EBITDA/financial expenses | -0.011 | | -0.006 | -0.013 | | -0.004 | 0.000 | 0.003 |
| | | **(0.481)** | | **(0.587)** | **(0.560)** | | **(0.705)** | **(0.955)** | **(0.879)** |
| 4 | Retained earnings/total assets | 1.609 | | -11.362 | -19.341 | 4.341 | -1.316 | -2.664 | 0.763 |
| | | **(0.664)** | | **(0.077)** | **(0.167)** | **(0.279)** | **(0.616)** | **(0.376)** | **(0.294)** |
| 5 | Short-term debt/capital | -0.374 | 0.124 | 0.003 | 0.044 | | 0.035 | 0.110 | 0.199 |
| | | **(0.255)** | **(0.530)** | **(0.874)** | **(0.146)** | | **(0.834)** | **(0.344)** | **(0.216)** |
| 6 | D_Number_c | -3.272 | -2.722 | -1.081 | 15.006 | -1.156 | -2.554 | -1.254 | -2.310 |
| | | **(0.010)** | **(0.018)** | **(0.107)** | **(0.988)** | **(0.086)** | **(0.002)** | **(0.037)** | **(0.004)** |
| 7 | (Short- and long-term investments)/total assets | | | | | | | | |
| 8 | (Operating costs + operating expenses)/total assets | | | | | | | | |
| 9 | Non-operating expenses/total assets | | | | | | | | |
| 10 | Property, plant and equipment/total assets | | | | | | | | |
| 11 | Constant | -4.618 | -5.039 | -4.627 | -19.728 | -4.935 | -3.392 | -4.455 | -4.375 |
| | | **(0.000)** | **(0.000)** | **(0.000)** | **(0.984)** | **(0.000)** | **(0.000)** | **(0.000)** | **(0.000)** |
| | Tests | | | | | | | | |
| | -2log likelihood | 57.386 | 63.222 | 117.925 | 60.856 | 122.498 | 128.762 | 145.072 | 124.578 |
| | $R^2$ Nagelkerke | 0.178 | 0.116 | 0.134 | 0.190 | 0.038 | 0.176 | 0.055 | 0.175 |
| | Omnibus: $\chi^2$ | 12.206 | 8.205 | 17.844 | 14.071 | 4.750 | 26.731 | 8.238 | 25.581 |
| | | **(0.058)** | **(0.042)** | **(0.007)** | **(0.029)** | **(0.093)** | **(0.000)** | **(0.221)** | **(0.000)** |
| | Hosmer and Lemeshow: $\chi^2$ | 10.523 | 1.248 | 4.088 | 0.718 | 5.912 | 2.620 | 6.622 | 3.600 |
| | | **(0.230)** | **(0.996)** | **(0.849)** | **(0.999)** | **(0.657)** | **(0.956)** | **(0.578)** | **(0.891)** |

* Model 1 did not pass the Omnibus test for 2008 and 2011. Therefore, using this model and applying the (Wald) backward elimination, a modified Model 1 is obtained with the variables shown in the table. Source: By authors.

**Table 2**: Logit regression 2007-2014 – traditional financial ratios and moral hazard ratios

| | Model 2 | 2007 | 2008* | 2009 | 2010 | 2011* | 2012 | 2013 | 2014 |
|---|---|---|---|---|---|---|---|---|---|
| **No.** | **Variable** | | | | | **Coefficients** | | | |
| 1 | Cash/total assets | 9.356 | 8.106 | 8.173 | -179.958 | | -43.444 | 3.645 | 1.294 |
| | | **(0.062)** | **(0.193)** | **(0.000)** | **(0.342)** | | **(0.047)** | **(0.232)** | **(0.853)** |
| 2 | EBITDA/total assets | -2.646 | | -1.668 | -1.138 | | -0.709 | -2.378 | -3.194 |
| | | **(0.450)** | | **(0.292)** | **(0.470)** | | **(0.569)** | **(0.042)** | **(0.084)** |
| 3 | EBITDA/financial expenses | -0.001 | | -0.005 | -0.013 | | -0.005 | 0.000 | -0.002 |
| | | **(0.660)** | | **(0.644)** | **(0.591)** | | **(0.567)** | **(0.953)** | **(0.908)** |
| 4 | Retained earnings/total assets | 1.420 | | -11.793 | -21.575 | -4.335 | -1.463 | -2.782 | 1.064 |
| | | **(0.648)** | | **(0.066)** | **(0.141)** | **(0.277)** | **(0.611)** | **(0.349)** | **(0.133)** |
| 5 | Short-term debt/capital | 0.435 | 0.209 | 0.004 | 0.053 | | 0.033 | 0.067 | 0.238 |
| | | **(0.287)** | **(0.262)** | **(0.834)** | **(0.098)** | | **(0.856)** | **(0.490)** | **(0.136)** |
| 6 | D_Number_c | -3.179 | -2.999 | -1.199 | 15.073 | -1.234 | -2.660 | -1.321 | -2.368 |
| | | **(0.015)** | **(0.013)** | **(0.083)** | **(0.988)** | **(0.071)** | **(0.002)** | **(0.030)** | **(0.003)** |
| 7 | (Short- and long-term investments)/total assets | -3.179 | 0.125 | -1.127 | -6.891 | -40.362 | 1.764 | -681.296 | 0.702 |
| | | **(0.015)** | **(0.986)** | **(0.882)** | **(0.685)** | **(0.362)** | **(0.689)** | **(0.235)** | **(0.871)** |
| 8 | (Operating costs + operating expenses)/total assets | -1.594 | -2.098 | -0.086 | -0.091 | -1.359 | -0.237 | -1.161 | -0.904 |
| | | **(0.142)** | **(0.059)** | **(0.648)** | **(0.728)** | **(0.039)** | **(0.402)** | **(0.028)** | **(0.114)** |
| 9 | Non-operating expenses/total assets | 8.887 | 5.210 | -0.834 | 4.342 | 0.958 | 4.065 | 2.913 | 0.869 |
| | | **(0.034)** | **(0.186)** | **(0.836)** | **(0.057)** | **(0.209)** | **(0.001)** | **(0.253)** | **(0.801)** |
| 10 | Property, plant and equipment/total assets | 0.960 | 2.499 | 2.352 | 2.738 | -0.744 | 0.257 | -1.638 | 0.574 |
| | | **(0.706)** | **(0.230)** | **(0.144)** | **(0.195)** | **(0.710)** | **(0.888)** | **(0.414)** | **(0.742)** |
| 11 | Constant | -3.763 | -3.871 | -4.810 | -20.531 | -3.005 | -3.420 | -2.369 | -3.601 |
| | | **(0.012)** | **(0.002)** | **(0.000)** | **(0.984)** | **(0.001)** | **(0.000)** | **(0.007)** | **(0.000)** |
| | Tests | | | | | | | | |
| | -2log likelihood | 44.811 | 55.402 | 115.459 | 57.629 | 113.420 | 121.909 | 127.313 | 120.966 |
| | $R^2$ Nagelkerke | 0.360 | 0.227 | 0.152 | 0.233 | 0.110 | 0.221 | 0.174 | 0.200 |
| | Omnibus: $\chi^2$ | 24.781 | 16.025 | 20.309 | 17.298 | 13.828 | 33.585 | 25.997 | 29.193 |
| | | **(0.006)** | **(0.025)** | **(0.026)** | **(0.068)** | **(0.032)** | **(0.000)** | **(0.004)** | **(0.001)** |
| | Hosmer and Lemeshow: $\chi^2$ | 5.144 | 3.111 | 5.235 | 0.533 | 5.326 | 2.963 | 3.778 | 11.891 |
| | | **(0.742)** | **(0.927)** | **(0.732)** | **(1.00)** | **(0.722)** | **(0.937)** | **(0.877)** | **(0.156)** |

* For the years 2008 and 2011, Model 2 (modified) considers the modification of Model 1 and adds the moral hazard ratios. Source: By authors.

**Table 3**: Significant coefficients and values for $e^{\beta_i}$ for Model 2

| | **Moral hazard ratios** | | | | | | **Traditional financial ratios** | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Underinvestment | | Low effort | | Asset substitution | | **Liquidity** | | **Profitability 1** | | **Profitability 2** | | **Leverage** | |
| Year | Non-operating expenses/total assets | Exp(βi) | (Operating costs + operating expenses)/ total assets | Exp(βi) | (Short- and long-term investments)/total assets | Exp(βi) | Cash/total assets | Exp(βi) | EBITDA/ total assets | Exp(βi) | Retained earnings/ total assets | Exp(βi) | Short-term debt/equity | Exp(βi) |
| 2007 | 8.887 | 7,237.275 | | | -3.179 | 0.0416 | 9.356 | 11,568.024 | | | | | | |
| 2008 | | | -2.098 | 0.123 | | | | | | | | | | |
| 2009 | | | | | | | 8.173 | 3,543.960 | | | -11.793 | 7.56E-6 | | |
| 2010 | 4.342 | 76.861 | | | | | | | | | | | 0.053 | 1.054 |
| 2011 | | | -1.359 | 0.257 | | | | | | | | | | |
| 2012 | 4.065 | 58.265 | | | | | -43.440 | 1.36E-19 | | | | | | |
| 2013 | | | -1.161 | 0.313 | | | | | -2.378 | 0.093 | | | | |
| 2014 | | | | | | | | | -3.194 | 0.041 | | | | |

| Year | Const. | Exp(βi) | D_Number_c | Exp(βi) | Total Exp(βi) | |
|---|---|---|---|---|---|---|
| | | | | | Positive Effect | Negative Effect |
| 2007 | -3.763 | 0.023 | -3.179 | 0.042 | 18,805.299 | 0.106 |
| 2008 | -3.871 | 0.021 | -2.999 | 0.050 | | 0.193 |
| 2009 | -4.810 | 0.008 | | | 3,543.960 | 0.008 |
| 2010 | | | | | 77.916 | |
| 2011 | -3.005 | 0.050 | | | | 0.306 |
| 2012 | -3.420 | 0.033 | -2.660 | 0.070 | 58.265 | 0.103 |
| 2013 | -2.369 | 0.094 | -1.321 | 0.267 | | 0.766 |
| 2014 | -3.601 | 0.027 | -2.368 | 0.094 | | 0.162 |

Source: By authors.

**Table 4:** Percentage of the effect of the $e^{\beta_i}$ on the probability ratios in Model 2

| | Moral hazard ratios | | | Traditional financial ratios | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Underinvestment | Low effort | Asset substitution | Liquidity | | Profitability 1 | Profitability 2 | Leverage | Constant | D_Number_c |
| Year | Effect + | Effect - | Effect - | Effect + | Effect - | Effect - | Effect - | Effect + | Effect - | Effect - |
| 2007 | 38.485% | | 39.098% | 61.515% | | | | | 21.804% | 39.098% |
| 2008 | | 63.452% | | | | | | | 10.776% | 25.772% |
| 2009 | | | | 100.000% | | | 0.093% | | 99.907% | 0.000% |
| 2010 | 98.647% | | | | | | | 1.353% | | |
| 2011 | | 83.835% | | | | | | | 16.165% | 0.000% |
| 2012 | 100.000% | | | | 0.000% | | | | 31.865% | 68.135% |
| 2013 | | 40.865% | | | | 12.101% | | | 12.210% | 34.823% |
| 2014 | | | | | | 25.318% | | | 16.853% | 57.830% |

Source: By authors.

**Table 5:** Moral Hazard Index for Credit (MHICR)

| Year | Effect + | Effect - | MHIC |
|---|---|---|---|
| 2007 | 38,485% | -39,0982% | 38,485% |
| 2008 | 0,000% | -63,452% | 0,000% |
| 2009 | 0,000% | 0,000% | 0,000% |
| 2010 | 98,647% | 0,000% | 98,647% |
| 2011 | 0,000% | -83,835% | 0,000% |
| 2012 | 100,000% | 0,000% | 100,000% |
| 2013 | 0,000% | -40,865% | 0,000% |
| 2014 | 0,000% | 0,000% | 0,000% |

Source: By authors.