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Insolvency Prediction for the Chinese Real Estate Industry

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ABSTRACT

This paper focuses on predicting the insolvency of Chinese real estate companies using financial indicators. Specifically, it analyzes data collected from the financial statements of 30 real estate firms in China spanning from 2010 to 2021. The study employs the fixed effect model to predict the likelihood of insolvency. It assesses the significance of various financial ratios, such as the current ratio, returns on assets to the return on total equity ratio, and retained earnings. By analyzing the financial indicators of these companies, the paper sheds light on the factors contributing to the risk of insolvency. However, it also acknowledges the limitations of the model and highlights the need for further research to include additional variables and expand the sample size. The results of this study provide valuable insights for investors, regulators, and policymakers in assessing the stability and financial viability of the Chinese property market.

Keywords: insolvency prediction, Chinese real estate companies, financial indicators, risk assessment

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Introduction

This academic research presented here focuses on analyzing the financial indicators of Chinese real estate companies and developing a predictive regression model for insolvency. The purpose of this study aims to provide valuable insights into the related factors that affect the insolvency of companies in the background of the Chinese real estate market.

In recent years, the Chinese housing price has been rising significantly, and the housing bubble remains a serious structural problem, according to Ning from Financial Times (2023). Moreover, there is growing concern about a contagion effect in 2021 due to the crisis of Evergrande, which has liquidity problems because of its high indebtedness. Evergrande had lots of unfinished projects in China. There are nearly 1.6 million people eagerly awaiting the completion of these projects. (Lu & Keller, 2022). Evergrande's no-major operations have exhausted its cash reserves (Lu & Keller, 2022). Furthermore, this financial crisis threatens China's financial system's stability and may cause a spillover effect on the international market (Lu & Keller, 2022).

The research question that prompted this study is rooted in the author's curiosity surrounding Evergrande's insolvency problems and their underlying causes. The author seeks to investigate the primary factors contributing to Evergrande's financial difficulties and determine if other real estate companies face similar challenges. By delving into the financial and accounting data of real estate companies, this research aims to uncover the specific circumstances of each company and provide a comprehensive understanding of the overall state of the sector. The research question can be summarized as follows: What are the key factors contributing to Evergrande's insolvency, and are these factors common in other real estate companies? Analyzing real estate companies from an internal perspective, focusing on their financial and accounting data, will reveal the current situation of individual companies as well as the broader real estate sector.

The main objectives of this research are to determine the dominant factors contributing to corporate insolvency and test insolvency prediction. By analyzing key financial indicators, such as liquidity ratios, profitability index, leverage ratios, and solvency metrics, this study seeks to identify the factors that leading to the insolvency risks of the real estate sector in China.

The methodology employed in this study involves the use of a representative sample of 28 Chinese real estate companies. The study utilizes a panel dataset spanning 2010 to 2021 to run regression analysis using Microsoft Excel and STATA/SE 16.0. The analysis will consider various financial indicators as independent variables and examine their impact on company insolvency, which is scaled with the company's credit rating. The statistical significance and economic significance of the relationships will be assessed, and appropriate diagnostic tests and analysis will be conducted to ensure the validity and reliability of the findings.

The results of this study highlight the significance of the fixed effects regression model in assessing insolvency risk for companies. The analysis reveals that several financial ratios and indicators have a notable impact on the likelihood of insolvency. Notably, variables such as the current ratio, ROA, ROA/ROE_T, and retained earnings consistently demonstrate statistical significance across the fixed effects regression models. Higher current ratios, indicating better short-term obligation management, and increased profitability measures, such as ROA and ROA/ROE_T, are associated with reduced insolvency risk. In addition, companies with higher levels of retained earnings are more likely to avoid insolvency. Although the model's explanatory power remains limited, this research offers valuable insights for stakeholders, including investors, creditors, and policymakers, enabling them to make informed decisions and effectively manage risks.

Literature review

Evergrande Crisis Analysis

The Evergrande crisis unfolded in September 2021 when the company failed to pay interest on its foreign bonds (Lu & Keller, 2022). Since the debt increased significantly, this debt crisis has been compared to China's Lehman Brothers moment (Lu & Keller, 2022). Consequently, concerns have been raised regarding the interplay between financial stability, investor protection, and the multifaceted nature of investors in the real estate industry (Lu & Keller, 2022). After the Evergrande crisis occurred, it prompted extensive analysis to understand the reasons behind its occurrence. Researchers have employed various methods to investigate the factors contributing to Evergrande's financial troubles. By comparing its financial mode, it has been observed that Evergrande heavily relied on bank loans and had a high asset-liability ratio, especially with a significant amount of current liability (Sun & Cao, 2021).

Furthermore, an examination of profitability, solvency, operational capacity, and growth capability ratios revealed that Evergrande had utilized overly high leverage for its bland diversification expansion plan, resulting in generating less profit than expected and not having enough liquidity cash to pay the debt (Wang et al., 2022). In the same way, Zheng (2022) conducted an assessment using the same ratios and incorporated them into the Altman Z-score model for the period from 2018 to 2020. The findings indicated a continuous decline in z-score every year, with results consistently below 1.8, signaling a grave financial risk (Zheng, 2022).

Moreover, concerns regarding contagion and spillover effects have emerged. Some studies suggest that large corporations in the real estate industry may face a higher probability of default (Altman et al., 2022). However, there are no clear reactions of the stock and bond market towards the Evergrande credit event and no direct impact on the systemic risk in the financial system (Altman et al., 2022).

The Evergrande crisis is a crucial case study within the literature, providing valuable insights into the factors that led to its insolvency. For example, the analysis of Evergrande's financial indicators, such as leverage, liquidity, profitability, and solvency ratios. These findings highlight the importance of effective financial management practices, adequate liquidity management, and a cautious approach to leverage in the real estate sector. Understanding the lessons from the Evergrande crisis is essential for investors, regulators, and policymakers to reduce risks and ensure the stability of the Chinese real estate market.

Insolvency Prediction

Insolvency prediction plays a crucial role in financial analysis as it helps identify the likelihood of a company facing financial distress or bankruptcy. In the context of the real estate industry, accurate insolvency prediction is significant due to the significant capital intensity involved in various aspects of the industry (Xu et al., 2022). The real estate sector in China is a key driver of economic development and has a profound impact on multiple sectors (Xu et al., 2022). Understanding the relevance of insolvency prediction specifically for the Chinese real estate industry is crucial for risk management.

Several models and techniques have been developed for predicting insolvency in different industries. These models typically employ financial ratios, statistical models, and machine learning algorithms to assess companies' financial health and bankruptcy risk (Jackson & Wood, 2013). Hilbert summarized and proved the five most common models with 124

Mexican companies. The five models include Altman Z1 and Z2 models (1966), the Fulmer model (1984), the Springate model (1978), and the CA Score model. These models used weighted equations with different financial ratios to assess the possibility of bankruptcy.

These models include variables related to working capital, such as working capital to total assets in the Altman Z-score and Springate model and current liabilities to total assets in the Fulmer model, emphasizing the significance of liquidity and the ability to meet short-term obligations in assessing insolvency risk. Profitability measures, such as EBIT to total assets in the Altman Z-score and Springate models and EBIT to current liabilities in the Springate model, are consistently included. Strong profitability indicates the company's ability to generate earnings and cover its obligations, thereby reducing the risk of insolvency. Variables related to debt and leverage ratios are standard in the models. For instance, the market value of equity to total liabilities in the Altman Z-score model, total debt to total equity in the Fulmer model, and total debt to total assets in both the Fulmer model and CA models highlight the importance of assessing the company's debt levels and the proportion of debt to equity in determining insolvency risk. Revenue or sales-related variables, such as revenue to total assets in the Altman Z-score, the Fulmer, and CA models and sales to total assets in the Springate and CA models, are included in multiple models. Notably, the ability to generate revenue and manage assets effectively dramatically affects the risk of insolvency.

The BP neural network model has also been utilized for financial early warning. Sun & Lei (2021) confirmed the high prediction accuracy using data from Chinese mining listed companies. The financial indicators used in the model can be classified into the following categories: profitability, operation capacity, solvency, development ability, and cash flow (Sun & Lei, 2021). Xu et al. (2015) mentioned that multivariate discriminate analysis (MDA), Logistic, and Probit regression were employed for the early-warning model of financial problems. Their paper utilized partial least-squares logistic regression to predict 132 Chinese real estate companies (Xu et al., 2015). As a result, the regression had 87% accuracy (Xu et al., 2015).

Moreover, Han (2022) approached insolvency prediction from a cash flow perspective and employed machine learning techniques to develop a prediction model for Chinese real estate companies from 2013 to 2017. With the Light Gradient Boosting Machine algorithm, the model achieved an accuracy of 96% (Han, 2022). The model incorporated important variables such as the long-term asset suitability ratio, current ratio, cash dividend coverage ratio, long-term equity investment ratio, and other ratios. (Han, 2022).

Key Findings and Research Gap

As we can observe from the above models, almost all insolvency prediction models use variables from the seven categories: profitability, operation capacity, solvency or liquidity, leverage, development ability, revenue, and cash flow. Real estate is a crucial industry for the Chinese economy, and it is essential for individuals, related corporations, and the government to understand the actual situation of these companies. From a financial indicators' perspective, there needs to be more research regarding Chinese real estate companies in recent years. Therefore, there is a need for more comprehensive studies that specifically focus on insolvency prediction models in the Chinese real estate industry.

Methodology

Subjects

This study used a sample of approximately 30 Chinese companies operating in the real estate industry as a representative sample for our analysis. The chosen sample comprises a diverse range of company sizes, including both middle and large-sized companies. The market sizes of these selected companies varied significantly, spanning from 2 billion to over 200 billion.

A regression model was employed to explore the factors that affect the company's insolvency, treating company insolvency as the dependent variable in the analysis. Specifically, the credit ratings assigned to each company were used as indicators of their insolvency risk.

Credit ratings offer an objective measure of a company's creditworthiness and provide insights into its financial stability and risk of insolvency.

Initially, the sample size consisted of 30 companies. However, during the data collection process, it was encountered that credit rating information for the two companies took much work to obtain. As a result, these three companies were excluded from the final sample, reducing it to a size of 28 companies. It is worth noting that efforts were made to gather the necessary credit rating data for all companies in the sample. However, obtaining data for those companies proved challenging for various reasons, such as limited availability or confidentiality.

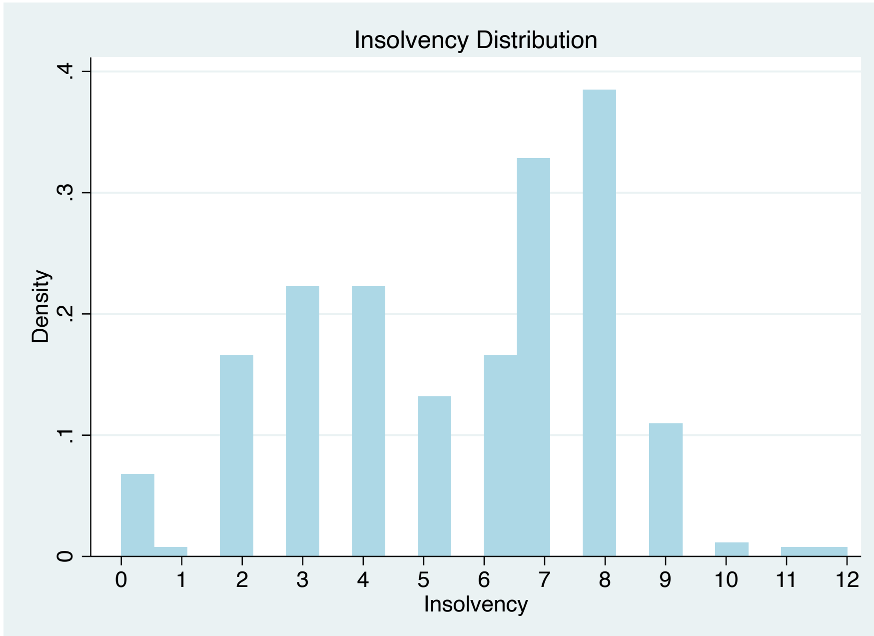
The credit ratings utilized in the analysis were sourced from reputable entities, with Moody's as the primary source and Standard & Poor's as a complementary source (2023). These two entities provide comprehensive assessments of a company's creditworthiness, where a higher grade presents a lower probability of default. These ratings provided an objective measure of the companies' creditworthiness and were crucial in assessing their risk of insolvency. It is important to realize that not all companies in the sample had participated in the credit rating process at the time of their establishment. In such cases, we adopted a reasonable assumption that the credit rating level of the first available rating represents the company's initial rating. Additionally, if there were instances where data was missing for certain periods, we filled in the gaps by assuming the same credit rating level that had been observed in preceding periods.

The credit ratings ranged from 0 (A2 level), denoting a lower risk of insolvency, to 12 (CC level), indicating a higher risk of encountering insolvency problems. The data provided in Table 1 reveals that the majority of companies fell within the Baa3 to B1 insolvency levels, with B1 insolvency level 8 being the most frequently observed category.

Table 1: Frequency table of the dependent variable, source: own elaboration

Credit rating	Insolvency	Frequency	Percent	Cumulative
A2	0	18	3.70	3.70
A3	1	2	0.41	4.12
Baa1	2	44	9.05	13.17
Baa2	3	59	12.14	25.31
Baa3	4	59	12.14	37.45
Ba1	5	35	7.20	44.65
Ba2	6	44	9.05	53.70
Ba3	7	87	17.90	71.60
B1	8	102	20.99	92.59
B2	9	29	5.97	98.56
B3	10	3	0.62	99.18
CC	11	2	0.41	99.59
C	12	2	0.41	100.00
	Total	486	100.00	
	Std. Dev.	2.5026	Mean	5.5638

Figure 1: Insolvency distribution, source: own elaboration



Objects

The data were compiled from semi-annual financial reports from 2010 to 2021. These reports were obtained from Bloomberg (2023), a reputable financial data source. The data included a comprehensive set of financial indicators derived from the balance sheet and annual accounts of the selected Chinese real estate companies. A total of 34 potential independent variables were identified based on these financial indicators, such as debts, sales, inventories, free cash flow, accounts receivable, and profit, among others.

Table 2: Summary table of the independent variable, source: own elaboration

Variable	Observation	Mean	Std. Dev.	Min	Max
ROA (%)	451	4.41	4.16	-2.67	73.99
ROE _ Common (%)	451	18.66	13.55	-10.91	212.47
ROE _ Total (%)	451	18.35	13.45	-10.91	212.47

Variable	Observation	Mean	Std. Dev.	Min	Max
ROCE (%)	450	11.64	10.82	-13.40	208.14
ROA/ROE_C	451	4.89	2.61	1.84	19.57
ROA/ROE_T	451	4.79	2.43	1.84	16.48
ROE_C/ROCE	450	1.66	0.54	-1.62	4.40
ROE_T/ROCE	450	1.63	0.51	-1.62	3.36
Financial Debt (CNY, in thousands)	461	59,387.72	83,035.61	1,432.58	732,625.00
LT Debt (CNY, in thousands)	464	41,898.27	52,316.48	676.94	381,192.00
ST Debt (CNY, in thousands)	464	17,694.76	33,576.23	0.00	356,381.00
Revenue (CNY, in thousands)	465	26,043.72	39,789.93	146.21	300,348.00
EBITDA (CNY, in thousands)	465	6,276.41	8,545.75	-945.20	96,098.00
Fin Debt / EBITDA	461	12.57	13.18	-82.69	127.47
Total Assets (CNY, in thousands)	461	206,863.50	285,010.30	4,188.76	1,948,365.00
Inventory (CNY, in thousands)	461	104,414.60	153,623.40	482.61	1,064,189.00
Rev /TA	461	0.16	0.94	0.01	20.19
Inv / TA	461	0.47	0.15	0.02	0.78
Inv /Rev	461	4.75	2.88	0.03	22.88
Ln (Rev) (logarithmic scale)	465	9.37	1.33	4.99	12.61
Ln (Debt) (logarithmic scale)	461	10.43	1.07	7.27	13.50

Variable	Observation	Mean	Std. Dev.	Min	Max
Ln (Assets) (logarithmic scale)	461	11.63	1.12	8.34	14.48
Current Ratio	453	1.61	0.33	0.71	3.02
TD / TA	453	30.98	7.27	11.76	59.44
Profit Margin (%)	456	20.05	23.31	-32.54	372.22
Asset Turnover (time)	445	0.30	0.91	0.01	19.35
Inventory Turnover (time)	445	0.46	1.55	0.02	32.83
Quick Ratio	453	0.31	0.17	0.02	1.42
Accounts Receivable Turnover (time)	406	130.23	370.22	4.08	4,066.81
Working Capital (CNY, in thousands)	453	51,963.28	67,801.43	-3,670.38	492,658.00
Total Current Assets (CNY, in thousands)	453	164,165.60	246,455.60	2,951.76	1,713,900.00
Total Current Liabilities (CNY, in thousands)	453	112,202.30	190,146.60	1,371.13	1,378,900.00
Retained Earnings (CNY, in thousands)	452	24,857.90	28,315.78	0.00	173,365.20
Free Cash Flow (CNY, in thousands)	348	-1,209.20	12,363.84	-88,045.00	55,357.82

Table 2 presents a summary of the observed values for each of the independent variables used in the analysis. It provides key statistical measures, including the number of observations, mean, standard deviation, and minimum and maximum values for each variable. For instance, variables related to profitability and financial performance, such as Profit Margin, Return on

Assets (ROA), and Return on Total Equity (ROE _ Total), are included in the analysis. Other variables, such as financial debt, revenue, EBITDA, and asset turnover, are also considered. Additionally, ratios and logarithmic transformations of certain variables, such as the debt-to-assets ratio and the natural revenue logarithm, are included as potential indicators.

The data presented in Table 2 reflect the selected Chinese real estate companies' financial characteristics and performance metrics. These variables serve as the independent variables in the regression analysis, allowing for an examination of their impact on the likelihood of company insolvency. It is essential to highlight that these variables are included based on their theoretical relevance and potential to provide insights into the insolvency risk faced by Chinese real estate companies. The final selection of variables for the regression analysis will be guided by rigorous statistical analysis and a consideration of their practical significance.

Time

The time selection for this study considers the dynamic nature of the Chinese economy and aims to capture the most relevant and recent data. Given the substantial changes in the Chinese economy during the 21st century, historical data from earlier years may have limited predictive value for understanding the current and future economic landscape. Furthermore, a larger dataset is desired to ensure accuracy in the regression estimates.

In order to address these concerns, this study focused primarily on the last ten years, specifically from 2010 to 2021. This time frame provides a breadth of coverage of recent developments and trends in the Chinese real estate industry. By analyzing semi-annual records, we can better understand the financial indicators and their relationship to the likelihood of company insolvency. This extended time period enhances the statistical power of the analysis and facilitates a more reliable assessment of the factors influencing company insolvency within the Chinese real estate sector.

Tools

The analysis in this study uses a panel dataset consisting of financial records from 28 Chinese real estate companies over ten years. Two essential tools are utilized to analyze and interpret the data: Microsoft Excel and STATA/SE 16.0.

Microsoft Excel is a valuable tool for data management and initial exploratory analysis. It facilitates the preparation of variables and transformations required for subsequent analysis. Furthermore, STATA is employed for more advanced statistical analysis and modeling. To analyze panel data, STATA provides a wide range of tools to investigate the relationship between the dependent variable, company insolvency, and the independent variables, financial indicators. The analysis employs regression models, including Ordinary Least Squares (OLS) and Fixed Effect (FE) models.

Several statistical measures are employed to ensure the reliability of the regression models. The Variance Inflation Factor (VIF) test assesses multicollinearity among variables. A high VIF value indicates that the variable strongly correlates with other variables in the regression model.

R-squared and adjusted R-squared measure the proportion of variance explained by the independent variable in the dependent variable. A higher value indicates a more significant proportion of the dependent variable being explained by the independent variables, indicating a more accurate model.

The P-value associated with the t-statistic indicates the significance of each variable. If the p-value is lower than 0.01, the variable is considered significant at the 0.01 level. The following tables shown in the result section will represent ***, **, and * to indicate the statistical significance level of the t-test at 1%, 5%, and 10% levels, respectively.

The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) measure the model's goodness of fit. Lower values of AIC and BIC indicate better model fit and performance.

The initial phase involved the generation of two Ordinary Least Squares (OLS) regression models, which included all available independent variables. Nevertheless, it was observed that the majority of the variables were not statistically significant. In order to enhance the model, the stepwise regression technique was utilized. A forward selection approach was utilized, starting with the significant variables identified from the initial OLS models. In this process, different independent variables were added iteratively, and the p-value of each variable was compared.

The test of Breusch Pagan can determine the presence of heteroscedasticity in the regression. The results indicate the presence of panel data characteristics, leading to the utilization of FE regression models.

The significant independent variable combinations identified in the OLS regression are employed in the FE regression model. However, not all variables remain statistically significant in the FE model. The stepwise regression technique is applied iteratively to refine the FE regression model further. Independent variables are added or removed based on their significance.

The model's accuracy and goodness of fit are evaluated using AIC and BIC. The best-performing FE regression model is ultimately identified for further analysis and interpretation.

Furthermore, it is interesting to investigate the impact of lag variables on the FE regression model. A modified dataset is created for the t-1 model to explore the impact of lag variables. Records of every company in 2010 are deleted, and the remaining records are shifted one year later. The FE regression model is then run using the independent variables previously identified. Similarly, the t-2 and t-3 models follow a similar approach, enabling an examination of the effects of lag variables on the model.

This analysis provides insights into the role of lag variables in predicting company insolvency within the Chinese real estate sector. By considering the temporal dynamics and incorporating lagged information, the model can capture potential delays in the manifestation of financial indicators and their impact on insolvency risk.

Results

Ordinary Least Squares Model

Following the methodology described in the above section, the initial regression is presented the following:

$$Insolvency = \beta_0 + \beta_1 Current\ Ratio + \beta_2 \frac{TD}{TA} + \beta_3 Inventory + \beta_4 \frac{ROA}{ROE_T} + \beta_5 Working\ Capital + \beta_6 ROA + \varepsilon$$

Table 3: OLS regression output summary, source: own elaboration

Source	SS	df	MS			
				Number of obs	=	603
Model	1082.1684	6	180.3614	F (6, 596)	=	40.62

Residual	2646.07372	596	4.43972102	Prob > F	=	0
Total	3728.24212	602	6.19309323	R-squared	=	0.2903
				Adj R-squared	=	0.2831
				Root MSE	=	2.1071

Insolvency	Coefficient	Std. Err.	t	P>t	[95% Conf.	Interval]
Current Ratio	-2.377	0.314	-7.570	0.000***	-2.994	-1.761
TD / TA	0.147	0.013	11.190	0.000***	0.122	0.173
Inventory Turnover	-0.524	0.114	-4.600	0.000***	-0.748	-0.300
ROA/ROE_T	0.218	0.033	6.540	0.000***	0.153	0.283
Working Capital	0.000	0.000	-5.210	0.000***	0.000	0.000
ROA	0.165	0.042	3.900	0.000***	0.082	0.248
_cons	3.519	0.598	5.880	0.000***	2.344	4.694

Table 3 shows that all six independent variables exhibit statistical significance at the 0.01 level, with a p-value of 0.000, indicating their strong influence on the dependent variable. These variables include the current ratio, total debt to total assets ratio, inventory turnover, return on assets to return on total equity ratio, working capital, and return on assets. The R-squared value is 0.2903, which means that 29.03% of the variance in the dependent variable can be explained by the independent variables.

Table 4:Variable VIF analysis, source: own elaboration

Variable	VIF	1/VIF
ROA	3.37	0.297

Variable	VIF	1/VIF
Inventory Turnover	3.12	0.320
ROA/ROE_T	1.61	0.623
Current Ratio	1.43	0.699
Working Capital	1.32	0.757
TD / TA	1.22	0.821
Mean VIF	2.01	

Furthermore, a variance inflation factor analysis was conducted to assess the presence of multicollinearity among the independent variables. The VIF values for all variables were smaller than 5, suggesting a low level of correlation between them (Table 4).

Table 5: Model fit statistics, source: own elaboration

Model	N	ll(null)	ll(model)	df	AIC	BIC
.	603	-1404.885	-1301.513	7	2617.026	2647.839

However, the high value of the Akaike Information Criterion (AIC) suggests that the model is not a perfect fit, indicating the presence of unexplained variation. The AIC value obtained is 2617.026 (Table 5).

Figure 2: Residuals vs. predicted plot, source: own elaboration

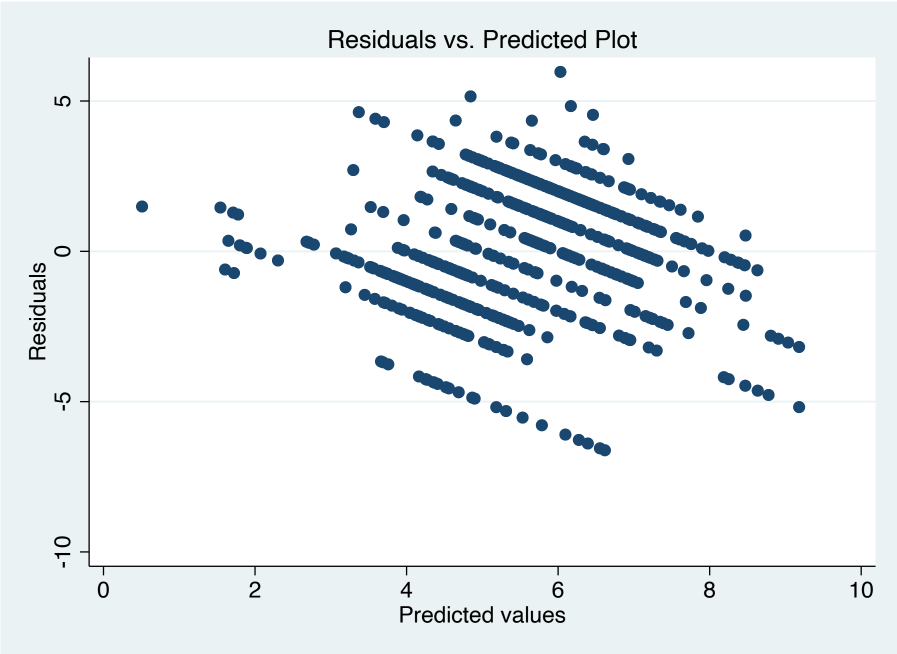


Figure 3: Breusch-Pagan Test, source: own elaboration

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Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: currentratio totaldebttototalassets inventoryturnover gear2
                    workingcapital roa

         chi2(6)      =    27.95
         Prob > chi2  =   0.0001
```

From Figure 2, the residual and predicted value plot shows a clear pattern, indicating a lack of random dispersion of residuals across the value. This observation suggests the presence of heteroscedasticity. To confirm this finding, a Breusch Pagan test was conducted, yielding a significant probability at the 0.01 level (Figure 3). Consequently, the null hypothesis of homoscedasticity is rejected, further confirming the presence of heteroscedasticity in the data. Considering the temporal effects and the panel nature of the data, it becomes imperative to employ fixed effects regressions, which account for the individual-specific characteristics and control for time-invariant factors.

Fixed Effect Models

Upon conducting the fixed effects regression analysis using the same set of variables as the OLS model, only the current ratio and working capital demonstrate statistical significance. And variables such as TD/TA, inventory turnover, ROA/ROE_T, and ROA do not demonstrate statistical significance in this model (Table 6)

Table 6: FE regression output summary, source: own elaboration

Fixed effects (within) regression	Number of obs = 603
Group variable: id	Number of groups = 28
R-sq:	Obs per group:
within = 0.0781	min = 3
between = 0.0396	avg = 21.5
overall = 0.0432	max = 24
corr (u_i, Xb) = 0.0763	F (6,569) = 8.03
	Prob > F = 0.0000

Table 7: FE regression output summary, source: own elaboration

Insolvency	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
Current Ratio	-0.593	0.174	-3.400	0.001***	-0.935	-0.251
TD / TA	0.005	0.008	0.600	0.550	-0.010	0.019
Inventory Turnover	0.015	0.050	0.300	0.765	-0.083	0.113

Insolvency	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
ROA/ROE_T	-0.047	0.019	-2.510	0.012**	-0.084	-0.010
Working Capital	-2.42×10^{-6}	0.000	-3.480	0.001***	0.000	0.000
ROA	-0.035	0.019	-1.810	0.071*	-0.073	0.003
_cons	6.869	0.333	20.620	0.000	6.215	7.524
sigma_u	2.305					
sigma_e	0.778					
rho	0.898	(Fraction of variance due to u_i)				
F test that all u_i=0: F (27, 569) = 140.68			Prob > F = 0.0000			

The stepwise regression technique was applied once more to enhance the accuracy and effectiveness of the FE regression model. The final improved FE regression is presented in the following equation:

$$Insolvency = \beta_0 + \beta_1 Current\ Ratio + \beta_2 \text{ROA} + \beta_3 \frac{ROA}{ROE_T} + \beta_4 \text{LT Debt} + \beta_5 Working\ Capital + \beta_6 Quick\ Ratio + \beta_7 Retained\ Earnings + \varepsilon$$

Table 8: Improved FE regression output summary, source: own elaboration

Fixed effects (within) regression	Number of obs = 603
Group variable: id	Number of groups = 28
R-sq:	Obs per group:
within = 0.1156	min = 3
between = 0.0854	avg = 21.5
overall = 0.0801	max = 24

corr (u_i, Xb) = 0.1288	F (6,568)	=	10.61
	Prob > F	=	0.0000

Table 9: Improved FE regression output summary, source: own elaboration

Insolvency	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
Current Ratio	-0.525	0.178	-2.950	0.003***	-0.875	-0.175
ROA	-0.029	0.009	-3.060	0.002***	-0.048	-0.010
ROA/ROE_T	-0.078	0.020	-3.850	0.000***	-0.118	-0.038
LT Debt	5.19×10^{-6}	0.000	2.450	0.015**	0.000	0.000
Working Capital	-3.24×10^{-6}	0.000	-1.870	0.062*	0.000	0.000
Quick Ratio	-0.609	0.285	-2.140	0.033**	-1.168	-0.050
Retained Earnings	-7.74×10^{-6}	0.000	-4.090	0.000***	0.000	0.000
_cons	7.253					
sigma_u	2.270					
sigma_e	0.763					
rho	0.899	(Fraction of variance due to u_i)				
F test that all u_i=0: F (27, 568) = 168.53				Prob > F = 0.0000		

Table 8 provides the summary statistics for the improved FE regression model, estimated using panel data with 603 observations and 28 groups. The R-squared values indicate that around 11.56% of the variation in the dependent variable, insolvency, can be explained by the within-group variation. In comparison, approximately 8.01% is explained by the overall variation.

The improved FE regression model reveals that the current ratio, ROA, ROA/ROE_T, and retained earnings are significant at the 0.01 level. In comparison, LT Debt and Quick Ratio are significant at 0.05 and Working Capital at 0.1. These variables offer meaningful implications for explaining the insolvency risk of the companies (Table 9). The interpretations of the independent variables are the following:

Current Ratio: All else equal, on average, a one-unit increase in the current ratio is associated with a decrease in the scaled insolvency risk by 0.5249 units. A higher current ratio indicates better short-term liquidity and the ability to cover the current debt, leading to a lower risk for insolvency.

ROA: All else equal, on average, a one-unit increase in ROA is associated with a decrease in the scaled insolvency risk by 0.029 units. Higher returns on assets reflect increased profitability and a lower likelihood of insolvency.

ROA/ROE_T: All else equal, on average, a one-unit increase in the ratio of ROA to ROE_T is associated with a decrease in the scaled insolvency risk by 0.0784 units. It indicates that companies with higher returns on assets than their equity tend to have lower insolvency risk.

Retained Earnings: All else equal, on average, a thousand-unit increase in retained earnings is associated with a decrease in the scaled insolvency risk by 0.00774 units. Higher retained earnings indicate better financial stability and reduce the possibility of insolvency.

LT Debt: All else equal, on average, a thousand-unit increase in long-term debt is associated with an increase in the scaled insolvency risk by 0.00519 units. Companies with higher long-term debt are more likely to face insolvency issues.

Quick Ratio: All else equal, on average, a one-unit increase in the quick ratio is associated with a decrease in the scaled insolvency risk by 0.6093 units. A higher quick ratio indicates a stronger ability to cover short-term liabilities with its most liquid assets, thus reducing the risk of insolvency.

Working Capital: In this model, the p-value 0.062 indicates that it is not statistically significant at the conventional level (p-value = 0.05). Therefore, its inclusion in the model may not provide a more meaningful interpretation.

Table 10: Model fit statistics, source: own elaboration

Model	N	ll(null)	ll(model)	df	AIC	BIC
.	603	-711.507	-674.471	8	1364.941	1400.156

Compared to the results obtained from the OLS regression model, the fixed effects regression model demonstrates a better fit, as evidenced by a lower AIC value of 1365 (Table 10). This improvement suggests that the fixed effects model captures the individual effects within the dataset more accurately, leading to a more reliable estimation of the relationship between the independent variables and insolvency.

Table 11: Summary statistics, source: own elaboration

Variable	Obs	Mean	Std. Dev.	Min	Max
Insolvency	672	5.667	2.455	0	12
Predicted Value	603	5.527	0.409	3.294	6.379

Figure 4: Yearly average of Insolvency and predicted value over time, source: own elaboration

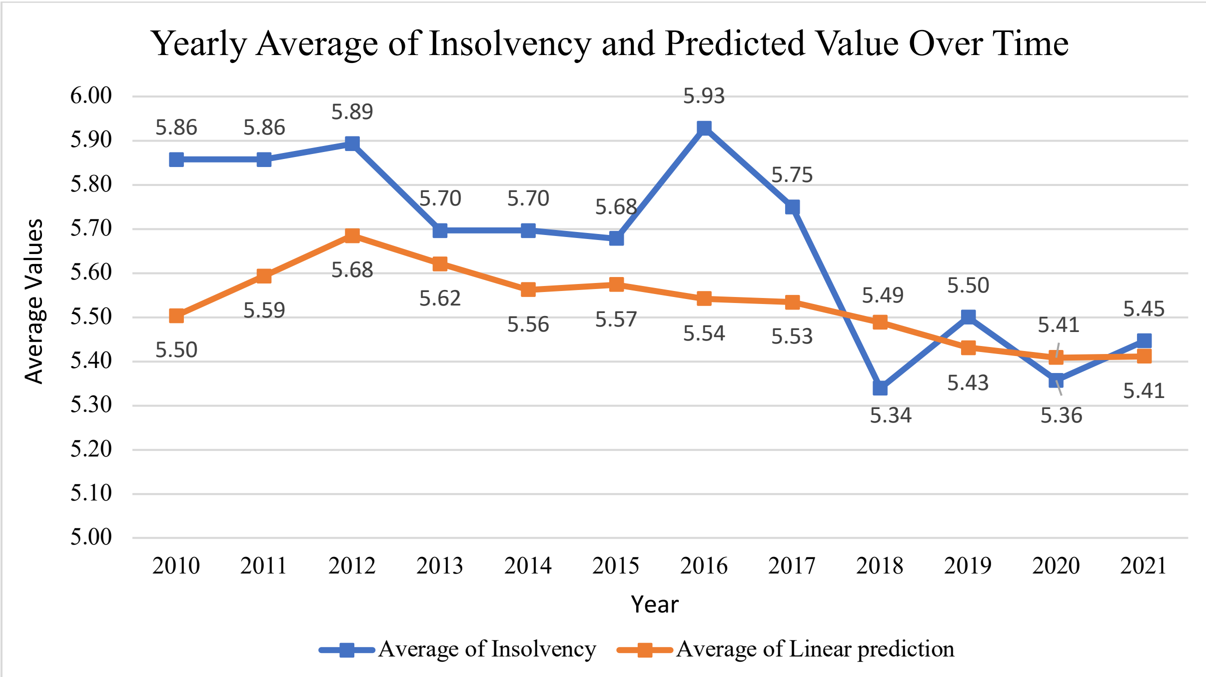


Table 11 and Figure 4 present the summary statistics and visual representation of the insolvency and predicted values from the fixed effects model. There is considerable variation in the minimum and maximum value of both the dependent variable and predicted values, ranging from 0 to 12 and 3.29 to 6.38, respectively. The average values are close, with 5.67 for insolvency and 5.53 for predicted values. Also, the predicted values followed a similar trend to the average insolvency levels, with slight variations in some years, and the predicted values were slightly lower than the average insolvency levels.

In conclusion, this study highlights the relevance of the FE regression model in understanding and assessing the risk of insolvency for companies. By considering significant variables such as liquidity ratios, profitability measures, and financial stability indicators, stakeholders can gain valuable insights into the factors influencing insolvency risk and make informed decisions to mitigate potential financial distress.

Autoregressive Models

Lastly, we employed three autoregressive models: AR (1) using t-1 data, AR (2) using t-2 data, and AR (3) with t-3 data. The result presented in Table 12 to Table 17 indicates that with each successive lag, there are fewer significant variables, and the level of significance decreases as well. However, when we examine Figures 5 to 7, it demonstrates that the yearly average of predicted value varies a little, and all three models exhibit similar patterns in their trends.

Table 12: AR (1) model output summary, source: own elaboration

Fixed effects (within) regression			Number of obs = 553
Group variable: id			Number of groups = 28
R-sq:			Obs per group:
within = 0.0865			min = 1
between = 0.0212			avg = 19.8
overall = 0.0308			max = 22
F (7,518) = 7.01			
Corr (u_i, Xb) = 0.0428	Prob > F	=	0.0000

Table 13: AR (1) model output summary, source: own elaboration

	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
Current Ratio	-0.637	0.198	-3.220	0.001***	-1.025	-0.248

	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
ROA	-0.030	0.010	-2.970	0.003***	-0.051	-0.010
ROA/ROE_T	-0.106	0.023	-4.550	0.000***	-0.152	-0.060
LT Debt	2.55×10^{-6}	0.000	1.040	0.298	0.000	0.000
Working Capital	3.82×10^{-7}	0.000	0.190	0.849	0.000	0.000
Quick Ratio	-0.408	0.317	-1.290	0.198	-1.031	0.215
Retained Earnings	-7.5×10^{-6}	0.000	-3.370	0.001***	0.000	0.000
_cons	7.377	0.346	21.330	0.000	6.698	8.057
sigma_u 2.318						
sigma_e 0.818						
Rho 0.889 (fraction of variance due to u_i)						
F test that all u_i=0: F (27, 518) = 135.33				Prob > F = 0.0000		

In the AR (1) model, the fixed effects regression was performed with 553 observations and 28 groups. The R-squared within-group values are related to low, 0.08. Among the variables, the current ratio, ROA, ROA/ROE_T, and retained earnings are significant at the 0.01 level, with a negative relationship with the dependent variable. (Table 13)

Table 14: AR (2) model output summary, source: own elaboration

Fixed effects (within) regression	Number of obs = 498
Group variable: id	Number of groups = 27
R-sq:	Obs per group:
within = 0.0587	min = 12

between = 0.0004	avg = 18.4
overall = 0.0039	max = 20
F (7,464) = 4.13	
corr (u_i, Xb) = -0.0497	Prob > F = 0.0002

Table 15: AR (2) model output summary, source: own elaboration

Insolvency	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
Current Ratio	-0.513	0.209	-2.450	0.015**	-0.924	-0.101
ROA	-0.003	0.010	-0.280	0.783	-0.023	0.018
ROA/ROE_T	-0.119	0.028	-4.320	0.000***	-0.173	-0.065
LT Debt	2.78×10^{-6}	0.000	1.000	0.318	0.000	0.000
Working Capital	2.38×10^{-6}	0.000	1.050	0.293	0.000	0.000
Quick Ratio	-0.359	0.335	-1.070	0.285	-1.018	0.300
Retained Earnings	-7.64×10^{-6}	0.000	-2.990	0.003***	0.000	0.000
_cons	6.932	0.372	18.640	0.000	6.201	7.663

sigma_u 2.396

sigma_e 0.824

rho 0.894 (fraction of variance due to u_i)

F test that all u_i=0: F (26, 464) = 124.80 Prob > F = 0.0000

In the AR (2) model, the observations are 498 and 27 groups. There is a decrease in the observations group due to a company's large amount of missing value. That company was established in recent years; it has a limited amount of earlier data available. And in this model, ROA/ROE_T and retained earnings are statistically significant at 0.01 level. Other variables do not demonstrate statistical significance. Moreover, the R-squared within-group value is lower than the previous model, 0.059. Only 5.87% of the variation in insolvency can be explained by the within-group variation. (Table 15)

Table 16: AR (3) model output summary, source: own elaboration

Fixed effects (within) regression	Number of obs = 444
Group variable: id	Number of groups = 27
R-sq:	Obs per group:
within = 0.0584	min =10
between = 0.0004	avg = 16.4
overall = 0.0031	max = 18
	F (7,410) = 3.63
corr (u_i, Xb) = -0.0497	Prob > F = 0.0008

Table 17: AR (3) model output summary, source: own elaboration

Insolvency	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
Current Ratio	-0.074	0.214	-0.350	0.730	-0.495	0.347
ROA	-0.000	0.010	-0.020	0.984	-0.020	0.020
ROA/ROE_T	-0.065	0.033	-1.970	0.049*	-0.129	0.000
LT Debt	2.03×10^{-6}	0.000	0.630	0.529	0.000	0.000
Working Capital	-4.59×10^{-6}	0.000	1.730	0.085*	0.000	0.000
Quick Ratio	-0.578	0.353	-1.640	0.102	-1.272	0.116
Retained Earnings	-0.000	0.000	-3.740	0.000***	0.000	0.000

Insolvency	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
_cons	5.949	0.394	15.110	0.000	5.175	6.723
sigma_u 2.396						
sigma_e 0.799						
rho 0.899 (fraction of variance to u_i)						
F test that all u_i=0: F (26, 410) = 117.25				Prob > F = 0.0000		

In the AR (3) model, there are 444 observations and 27 groups. R-squared performs similarly to the AR (2) model. And this time, only retained earnings are statistically significant at 0.01 level, and curiously, working capital starts having a slighter significance with the dependent variable, insolvency. (Table 17)

Figure 5: Yearly Average of Insolvency and Predicted Value Over Time (t-1), source: own elaboration

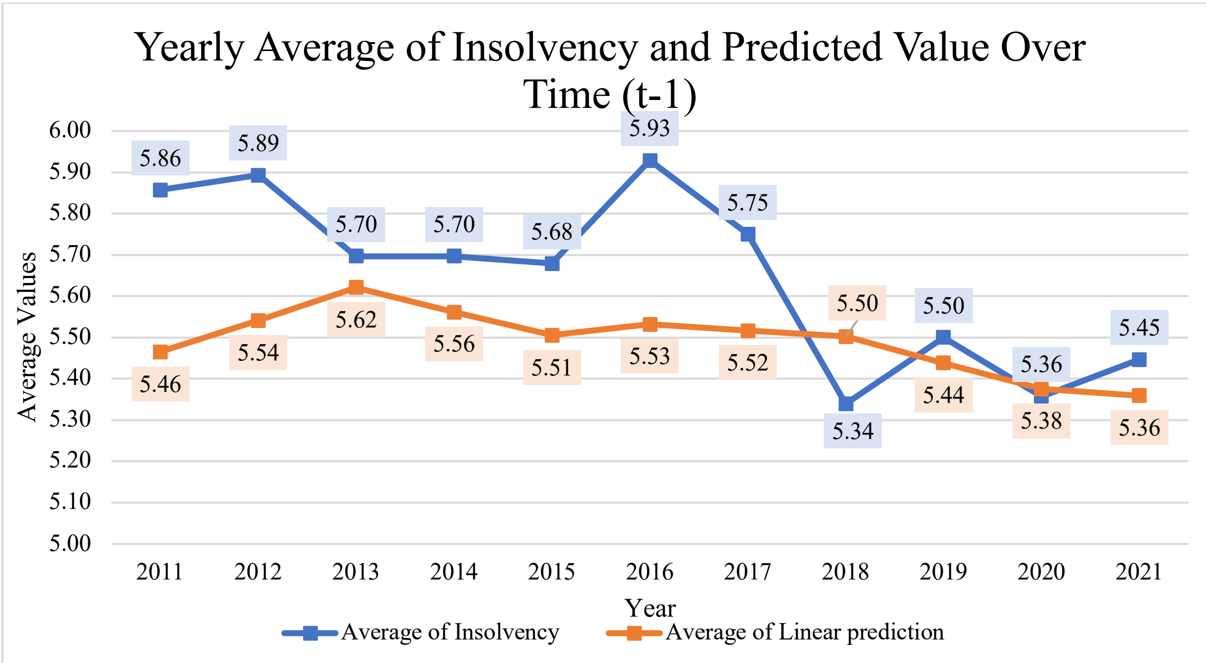


Figure 6: Yearly Average of Insolvency and Predicted Value Over Time (t-2), source: own elaboration

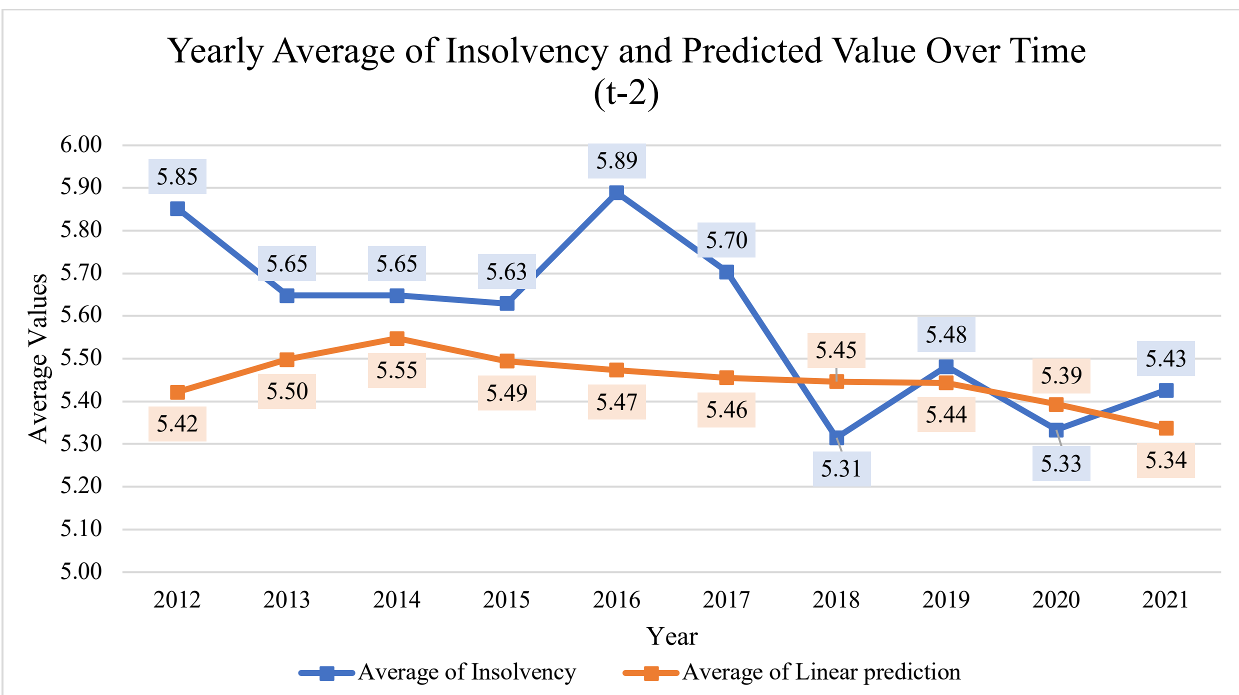
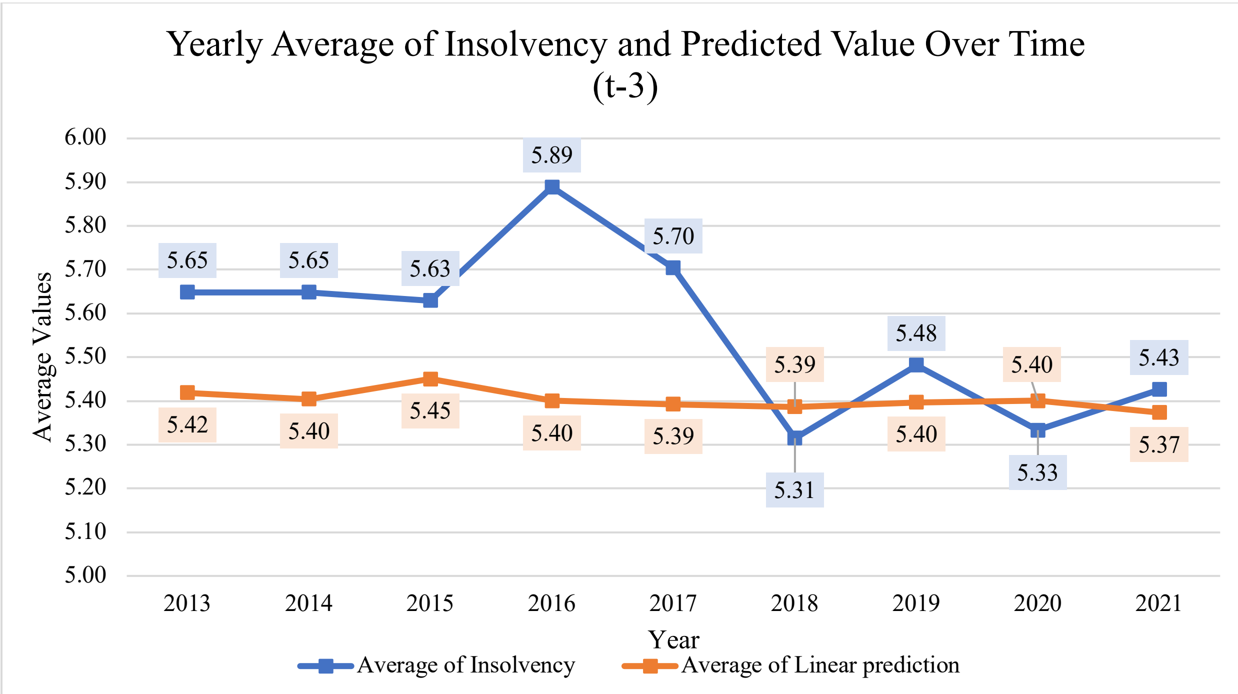


Figure 7: Yearly Average of Insolvency and Predicted Value Over Time (t-3), source: own elaboration



The above figures present the yearly average of insolvency and the corresponding predicted values based on different autoregressive models. They demonstrate that the average insolvency and predicted values have slight variations over time. The patterns in both the insolvency and predicted values remain consistent across the years, suggesting consistency between the model's predictions and the actual average insolvency levels. (Figures 5 to 7)

Discussion and Conclusions

This paper set out to determine the most impactful factors for insolvency prediction from a financial indicator perspective and predict the possibility of insolvency for Chinese real estate companies. The findings of this research confirmed the significance of the current ratio, return on asset to return on total equity ratio, and retained earnings in explaining the risk of insolvency.

Although the model's R-squared value could have been higher, indicating that the model is not a perfect fit for the data, it is important to note that there may be omitted variables that were not included in the model.

The presented study lays the groundwork for future research into Chinese real estate analysis from a financial indicators' perspective. One of the main limitations of this study was the limited sample size and data availability. Conducting a panel data analysis with a larger sample size would enhance the robustness of the findings. Additionally, further research could investigate the impact of financial indicators on the Chinese housing bubble, considering the dynamic nature of the real estate market.

Overall, this study contributes to understanding insolvency prediction in the Chinese real estate industry and highlights the importance of financial indicators in assessing the risk of insolvency. Future research should address the limitations of this study and delve deeper into the complexities of the Chinese real estate market to provide more comprehensive insights for investors, policymakers, and other stakeholders.

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Appendices (Tables & Figures)

Table 18: Company list, source: data compiled from Bloomberg and own elaboration

Ticker	Name	Market Cap (CNY in Billion)
1109 HK Equity	China Resources Land Ltd	237.46
688 HK Equity	China Overseas Land & Investment Lt	191.32
2202 HK Equity	China Vanke Co Ltd	180.52
600048 CH Equity	PRE	163.52
960 HK Equity	Longfor Group Holdings Ltd	115.29
001979 CH Equity	CMSK	101.15
2007 HK Equity	Country Garden Holdings Co Ltd	47.81
600606 CH Equity	Greenland Holdings Corp Ltd	40.76
123 HK Equity	Yuexiu Property Co Ltd	36.70
601155 CH Equity	Seazen Holdings Co Ltd	32.84
3333 HK Equity	China Evergrande Group	21.79
3900 HK Equity	Greentown China Holdings Ltd	21.12
813 HK Equity	Shimao Group Holdings Ltd	16.79
817 HK Equity	China Jinmao Holdings Group Ltd	16.64
81 HK Equity	China Overseas Grand Oceans Group Ltd	13.28
604 HK Equity	Shenzhen Investment Ltd	12.28
1030 HK Equity	Seazen Group Ltd	11.66
1918 HK Equity	Sunac China Holdings Ltd	8.17
884 HK Equity	CIFI Holdings Group Co Ltd	7.91
3383 HK Equity	Agile Group Holdings Ltd	6.72
410 HK Equity	SOHO China Ltd	6.19
3380 HK Equity	Logan Group Co Ltd	5.57
1668 HK Equity	China South City Holdings Ltd	5.55
2777 HK Equity	Guangzhou R&F Properties Co Ltd	5.22
3377 HK Equity	Sino-Ocean Group Holding Ltd	4.03
3883 HK Equity	China Aoyuan Group Ltd	3.50
1813 HK Equity	KWG Group Holdings Ltd	2.80
YLLG SP Equity	*Yanlord Land Group Ltd*	1.62
1628 HK Equity	Yuzhou Group Holdings Co Ltd	1.53
1233 HK Equity	Times China Holdings Ltd	1.45