DEPARTMENT OF ACCOUNTING AND FINANCE

What is the role of capital structure and industry to the probability of committing fraud?

MASTER THESIS

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2022

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Master Thesis in Finance

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Abstract

The aim of this study is to explain the challenges that organizations face when they belong to different industry and have different capital structure. This paper examines the effect of fraud on financial leverage and how this relation is influenced by capital structure by employing a range of 150 fraud USA firms for the period 2010–2020. We find that firms with high debt to equity at the year of fraud revelation and one year before are associated with higher chances of fraud commitment. More importantly, this positive relation is attenuated by specific industries such as technology and manufacturing. Another strong finding revealed by the research is that large organizations are more vulnerable to fraud as it is very likely to face information mismatch between executives which will lead to wrong decisions. Our results lend strong support to the notions that both corporate debt and size of a firm can be served as a signal to the market to likelihood of fraud.

Keywords: Fraud, Misreporting, Capital Structure, Assets, Industry

Date: December 22, 2022

Acknowledgement

I would like to acknowledge and give my warmest thanks to my supervisor Stelios Markoulis of the Department of Accounting and Finance at the University of Cyprus who made this work possible. His guidance and advice carried me through all the stage of the project.

Secondly, I would also like to give special thanks to my caring, loving and supportive husband Harris for his encouragement when the times got difficult.

Finally, I would like to say special thanks to my parents Marios and Maria and my siblings Melina and Andreas, who always stood by me and provided strength in pursuing this project

Contents

1. Abstract

This study brings us face to face with traits of the organizations that might affect at a great scale their probability of committing fraud. The aim of this paper is to explain the challenges that organizations face when they belong to different industry and when they have different capital structure. This paper examines the effect of fraud on financial leverage and how this relation is influenced by capital structure by employing a range of 150 fraud USA firms for the period 2010–2020. We find that firms with high debt to equity at the year of fraud revelation and one year before are associated with higher chances of fraud commitment. More importantly, this positive relation is attenuated by specific industries such as technology and manufacturing. Another strong finding revealed by the research is that large organizations are more vulnerable to fraud as it is very likely to face information mismatch between executives which will lead to wrong decisions. Our results lend strong support to the notions that both corporate debt and size of a firm can be served as a signal to the market to the likelihood of fraud. After managing thoroughly any possible statistical issue and addressing various robustness tests, our main conclusions remain confirmed.

2. Introduction

Corporate fraud is a much discussed and questionable topic. Firstly, this study will examine in what extent fraud firms are affected by their capital structure. Capital structure is an important characteristic of a firm as one of the first things that will be examined by a potential investor is the debt/equity ratio because is an indicator of how risky a company is. Results from previous research on the association between debt and fraud offers controversial results. On the one hand, some studies support the positive relationship. To be more specific, debt hypothesis expects the motivations of managers to manage earnings in order to avoid debt covenant violations as breaching these contractual terms can be costly (Watts & Zimmerman, 1986). Apart from the context of debt covenants, earnings can also be misreported to achieve favourable contract terms (Rodríguez-Pérez & van Hemmen, 2010; Watts & Zimmerman, 1986) or to maintain relationship for additional debts. On the other hand, control hypothesis of Jensen (1986) mentions debt financing as an effective monitoring mechanism to reduce manager's opportunistic behaviors due to the inspection of both creditors and investors. Additionally, the contractual commitments for debt repayments leaves a low level of free cash flow available, which limit manager's discretions in sub-optimal projects (Jensen, 1986). Moreover, Michael Jensen (1986) supports that managers cannot produce the performance required to justify high stock price. Therefore, create a setting in which some mangers(agents) take actions to support firm's short-term stock price and those actions are costly to debtholders and long-term stockholders(principals). Empirical research has found a large scale of evidence supporting the "debt hypothesis" (B. H. Kim, Lisic, and Pevzner (2010); Jha (2013); Alzoubi (2017); Lazzem and Jilani (2018)). However, the controlling effect of debts to increase financial reporting quality is also suggested through other research (Ahn & Choi, 2009; Alsharairi, 2012; Jelinek, 2007; Rodríguez-Pérez & van Hemmen, 2010)

Due to the nature of manager's compensation contract which is designed to have the lowest possible agency cost and prevent the conflict between manager and shareholders. In most cases, the compensation contract is based on accounting numbers to minimize agency costs arising from the separation of ownership and control. In addition, the managers may have obligation to maintain the ratio of earnings to total debt above a determined threshold. This is called debt covenants which are set by the firm's lenders to reduce the cost of monitoring.

Main motivation of the study is to shed light on the controversial relationship between leverage and fraudulent activities as we believe that debt hypothesis is more likely to exist because high levels of debt cause frustration to organization that want to increase their capital and are obliged by debt covenants. Moreover, we would like to evaluate the specific parameter in the framework of a different industry and how the environment of the organization changes the dynamics. We would expect that more stable industries will be affected by smaller extent from debt covenant obligations rather than technological firms which have more uncertain environment. Another motivation is the strong influence that misreporting might have to the overall performance of the organization. According to Farber(2005), the firms which are involved in frauds will face significantly negative abnormal returns. Similarly, Edmans(2011) supports that the revelation of misreporting and any fraudulent activity within an organization will cause negative earnings. Therefore, it's very important for shareholders and debt holders to be cautious as regards to the fraud signals. However, it is imperative for the firm to take the necessary ex-ante actions I order to prevent misreporting.

This research contributes to the literature in several ways. First, its emphasis on the association between combination of industry and capital structure and fraudulent activities is a new addition to the literature. It highlights how the role of capital structure and environment of the firm affects managements decisions. While the literature emphasizes the role of debt and fraud, the research provides evidence that the effect changes in different industries.

There are a lot of examples that prove that being involved in fraud can lead to unpleasant consequences if not to dissolution. It is documented that firms which manipulate earnings experience significant increases in their cost of capital when manipulations are revealed(Dechow et al. , 1996). Many theories support that misreporting into an organization has serious impact on its future, since high leverage will force them to misreport financial statements in order to present a beautified image to potential investors and bank institutions (Rodríguez-Pérez & van Hemmen, 2010; Watts & Zimmerman, 1986). On the other hand, many argue that high leverage might be a signal of transparency because the bank institutions follow specific guidelines and examine thoroughly organizations before issuing new debt. The debt hypothesis is the foundation of our hypothesis 1 which states that high levered companies face more limitations when are in the process of issuing new debt and stock due to the interest debt covenants. We expect that debt to equity ratio and leverage will have positive association with the likelihood of fraud. Wang and Winton elaborate on the characteristics of specific firms and their association with fraud litigation. They find evidence that lower product market sensitivity to individual firms' information and greater use of relative performance evaluation encourage the probability of financial frauds. Due to a lot of individual firms, industry common signals and less trading of individuals' firms shares, both competitors of a specific market and investors in the capital market do not collect information of individual firms. Therefore, the lack of information of individual firms implies less effective monitoring system by competitive firms and reduces the probability of fraud detection which encourage the likelihood of committing fraud. The second hypothesis is established in the rationale that more transparent industries and more price sensitive environments will be less likely to misreport financial statements in order to mislead their potential investors and bank institutions (Wang et al., 2011). The last hypothesis (hypothesis 3) supported by the previous framework is that firms belonging to a different industry might be affected differently by the capital structure changes and this will eventually affect in a different way the probability of involvement in fraud.

Hypothesis 1: Firms with high capital structure are more likely to commit fraud.

Hypothesis 2: Companies that belong to technology and service sectors have more probabilities of being involved in fraudulent activities.

Hypothesis 3: Firms which belong to technology and service sectors with high leverage affect in larger extent the probability of committing fraud

There are a lot of research which support that good corporate governance within an organization will decrease their likelihood of fraud commitment. Especially, Farber(2005) finds that firms trying to restore investors' trust by improving their governance and in the long run after fraud detection these firms have governance characteristics like healthy firms and in some cases even improved.

3. Literature Review

There is a wide range of studies dealing with corporate fraud challenges in organizations. This research topic is important because investors review earnings information in order to take investment decision and fraudulent financial statement may affect quality of earnings information received by investors and lead them to the wrong decision. In addition, fraud firms are highly associated with corruption leading to poor performance and in many cases to the dissolution. In the context of these, the research question of this study is how the capital structure and industry of the firm affects its probability to be involved in fraud. Although there is no study discussing how capital structure of specific industries affects firms being involved in frauds, there are some studies directly or indirectly incorporating the three major variables. For example, the study of Bae et al.(2008) finds that there is negative relationship between leverage and a firm's ability to treat employees fairly. The insight of this argument is that stakeholders are unwilling to come to an agreement with high levered companies because financial difficulties will affect them. Therefore, rational stakeholders require higher remuneration in order to overcome the consequences of a possible bankruptcy. At the end, firm's costs are increasing affecting firm's value. Further to this study, Zhang et al. (2020) investigate the relationship between company's employee treatment and its likelihood of committing fraud. Results illustrate that as long as employees are treated fairly, the probability of fraud is decreasing. Firms are nothing else than individuals acting collectively. As long as the employees are treated fairly, they will act for the benefit of the organization and the organization will flourish. When the firm ceases to reward its people, they will stop taking will-intentioned actions for the organization. These studies incorporate indirectly the one of the interest variables that will be examined in this paper and enhance the argument that the higher the leverage the higher the probability of fraud which will be examined in this paper.

The other variable will be examined in this research is the capital structure and the relationship with fraud commitment. There is a wide range of research that studies fraudulent activities and capital structure in a direct way. Following to the pecking order theory by Myers and Majluf (1984), firms prioritize their sources of financing and prefer to use internal financing at the first glance, then debt is issued and finally they turn to equity issuance. The theory supports that equity issuance is translated by investors as an act of firm to sell overvalued shares, so managers will beneficiate from overvalued equities. Therefore, investors will place a lower value than expected to the new equity.

Dichev and Skinner(2002) and Efendi et al. (2007) explain that **interest coverage** is widely used in debt agreements as the ratio measures whether companies can pay their outstanding debts. According to Efendi et al. (2007) findings, misstatements are more likely for firms that are constrained by an interest coverage debt covenant and that raise new debt or equity capital. Misstatements could affect beneficially the current stockholders as new capital will be raised, and a CEO could gain with in-the-money options. The research of Kim et al. (2010) strengthens the argument that managers will take real earning management actions in order to avoid costly debt covenant violations. In addition, the positive association between leverage and earnings management is supported by the reason of financial distress theory (Jaggi and Lee, 2002 and Fung and Goodwin, 2013). Specifically, these studies show that managers use positive discretionary accruals when financially distressed firms are granted waivers for debt covenant violations, and they use negative discretionary accruals when waivers are not granted and the debt contract terms are renegotiated, especially when the problematic debts are restructured. These results suggest that managers use income-increasing discretionary accruals when in technical default due to temporary financial difficulties, but the firm is basically in good financial condition. Firms' inability to uphold a term of the agreement is recognized by creditors by granting waivers for debt covenant violations. If financial distress is severe and waivers for debt covenant violations are not granted, especially when financial distress leads to debt restructuring, the managers use negative discretionary accruals to highlight the firm's financial difficulties, which may enable them to negotiate better terms with debt contracts. Moreover, Haw et al. (2004) find that high levered companies have more income managements, in order to overcome accounting constraints in debt contracts and facilitate debt renegotiations during financial distress. The research of An et al. (2016) shows that firms with high earnings management activities are associated with high financial leverage. Moreover, the results declare that higher earnings management activities enhance the demand for debt as an external control mechanism that reduces the agency cost of free cash flows. The **agency costs of free cash flow hypothesis** is defined by Jensen(1983) declares that when managers have excess available cash there is an incentive to waste the additional cash on non-profitable investments. It’s important to mention that the positive relation is mitigated by strong corporate governance. The argument of An et al. (2016) is upheld by the fact that those who run the business(managers) tend to manipulate earnings in order to retain private control and enjoy benefits like exercise of in-the-money options. One mechanism to reduce the amount of free cash flows available to corporate managers is the leverage, issue more bonds. This practice has an effective impact when managers target to mislead shareholders about the firm’s free cash flows because managers are more willing to settle interest payment rather than discretionary dividends. (Jensen, 1986). According to Dechow et al. (2011), managers of fraud firms tend to be more sensitive to their firm’s stock price. The misstatements appear to be made with the objective of recovering from a slowdown in financial performance in order to achieve high stock market valuations.

The agency problem is highly associated with fraudulent accounting methods. A real world’s typical example of agency problem is the bankruptcy of the energy giant Enron. The company appear to have more money than in reality because company's agents (executives) deliberately manage to hide debt in Enron's subsidiaries and overstate revenue. These misstatements allowed the company's stock price to increase when executives were selling their stock holdings. Although Enron's managers were responsible for the shareholder's best interests, the agency problem resulted in management acting in their own best interest.(Healy, Palepu, 2003)

Assets

The size of company and assets in companies involved in frauds are parameters that are strongly preoccupying researchers. Important findings came out of the study of Maureen Nichols et al. (2008) that illustrate the serious influence of investment decisions in firms that misstate their earnings. Firms are tending to over-invest in fixed assets during the misreporting period. Furthermore, right after the misreporting period, these firms no longer over-invest, showing that corrected information leads to more efficient investment levels. There are two reasons of firm's decision to over-invest. Firstly, decision makers substantiate their decision on future growth and the current reported revenues and earnings. As Richardson et al. (2002) declares firms tend to report consecutive earnings increases in order to show a better state than the real one. Therefore, overstatements of revenues and earnings misled by those unaware leading them to be over-optimistic. Secondly, investment decisions makers who are aware of the real performance of the firm will choose to over-invest in order to turn around the current state. This finding strengthens the hypothesis that the capital structure and especially debt is highly associated with the probability of fraud.

Unlike our expectations, the study of Tjen et al. (2015) shows that fraudulent financial statement is negatively but not significantly influenced by leverage. This means that many companies prefer to issue stocks to gain additional capital from investors without having to make new debt agreements that cause the company's debt burden to be greater. Even though the study doesn't support the association between frauds and leverage, it dredges up the importance of financial stability in the decision of financial misstatement. The financial stability is the company's financial condition, and the financial stability variable is proxy by using asset growth rate. Following to the same pattern, the finding of Bonini et al. (2010) provide evidence that firms involved in frauds tend to decide to issue more securities than their industry peers the period before the revelation of fraud. The year before the filing, these companies were detected to rely on equity instead of debt because debt costs and volumes are highly sensitive to corporate information. The revelation of fraud will lead to an immediate downgrade rating which will raise debt financing costs, will increase financial rigidity, and will make debt financing nonviable. Moreover, Noor et al. (2015) have documented evidence that leverage has a significant negative relationship with fraud so as long as the debt is increasing, managers have less incentive to involve in frauds or earnings management.

Industry

The other interest variable that will be examined in this study is the industry and its impact in committing frauds. The findings of Zhang et al. (2020) show that the negative relationship between employee treatment and probability of fraud is illustrious in high-tech companies and less competitive industries. Similarly, in the paper of Wang et al. (2021) is pointed out that industries such as software and programming, business services, financial services, computers, and electronics have a continuously higher likelihood of securities fraud litigation than do in industries such as food and textiles.

Corporate governance

With respect to corporate governance, Farber(2005) shows that fraud firms have poor governance relative to a control sample in the year prior to fraud revelation. Especially, firms involved in fraud have a higher percentage of CEOs who are also chairmen of the board of the directors and a smaller percentage is audited by Big 4 auditing firms. However, Farber proves that fraud firms take the relevant actions to restore investors' trust. Over the period of three years after the fraud revelation, these firms have similar or even better governance characteristics to control/not committed fraud firms. According to Klein(2002), there is a negative relation between audit committee independence, board independence and abnormal accrual (earnings management). The results of Klein's research show that a decrease in the board or audit committee independence is linked by a significant increase in abnormal accruals. These results proving that the independent boards, with more outside directors, are more effective in monitoring the corporate financial accounting process. Similarly, Aderson et al. (2004) supports that borrowers, banks and investors are interested in board of director characteristics. Their research find that cost of debt is inversely related to board independence and board size. Also, yield spreads are found to be negatively related to audit committee size and meeting frequency. Generally, results provide evidence that boards and audit committees are key factors affecting the trustworthiness of financial reporting. Moreover, research of Dechow et al. (1996) incorporates two important factors, fraudulent activities, corporate governance, and cost of debt. They illustrate that an important motivation for earnings manipulation is the desire to attract external financing at low cost. It is documented that even after controlling contracting motives, the motivation remains significant. Furthermore, firms manipulating earnings are more likely to have boards of directors with a strong influence by insiders instead of outsiders, it’s more likely to have duality, meaning that a Chief Executive Officer serves as Chairman of the Board at the same period of time, it’s more likely to have a Chief Executive Officer who is also the firm's owner, it’s less likely to have an audit committee and likelihood to have an outside blockholder is lower.

Another interesting finding came out from Zamri et al. (2013) and Ganny(2010), Return on Assets which is a measure of how efficient a company's management is in generating profit from their total assets on their balance sheet has a positive relationship with Real Earnings management. Managers’ decision to exercise operational discretion leads to a presentation of better future performance than reality and signalling.

Summarizing the important findings, Efendi et al. (2007) illustrate that firms which are constrained by an interest coverage debt covenant and which raise new debt or equity capital have higher probability of misstatement because the current stockholders will take advantage of new capital and a CEO could gain with in-the-money options. In addition, studies (Jaggi and Lee, 2002 and Fung and Goodwin, 2013) support that financial statements are misstated when debt contract terms exist. Moreover, high levered companies have more income managements in order to overcome accounting constraints in debt contracts and facilitate debt renegotiations during financial distress (Haw et al., 2004). The size of company and assets proved by previous literature to have positive relationship with probability of fraud as the managers tend to over-invest during misreporting period. An important aspect analysed is that corporate governance and transparency has negative influence on the chance of committing fraud. Last but not least, recent literature describes that those industries such as technology, service, finance have a continuously higher likelihood of securities fraud litigation than do in industries such as food and textile- manufacturing.

This study aims to shed new light on the relationship between the capital structure and industry and the probability of committing fraud, and we expect to find that the more depended is a company on debt the more likely to commit fraud.

4. Data and Methodology

4.1 Sample construction

The sample of corporate frauds consists of U.S. firms against which a securities class action lawsuit has been filed under the provisions of the Federal 1933/1934 Exchange Acts (Dyck et al., 2010) for the period 2010 to 2020 for North America. Securities Class Action Clearinghouse

(SCAC) platform is used which provides detailed information regarding the prosecution, defence, and settlement of federal class action securities fraud litigation. According to previous studies (Choi et al., 2008), it is highly unlikely that a fraud emerge without a subsequent class action suit being filed. By using data from SCAC platform, it is unlikely to miss important frauds because all cases are file, but the challenge is that to exclude the less important cases. In order to address this concern some filters applied. First, we restrict our sample to large domestic firms, as these firms have sufficient assets and insurance to motivate law firms to initiate suits. Practically, the sample is restricted based on the size of firms with at least $20 million in assets in the year prior to the end of the class period because firms reduce dramatically in size during the revelation of fraud. Secondly, all cases dismissed during the judicial review process are excluded. Finally, when a firm has multiple convictions in different year, the earliest one is included in the sample(Wang et al. , 2010).

The selection of the control sample has been done precisely taking into consideration a lot of aspects to be comparable and not randomly. As a start, a sample of all firms with assets over $20 million was collected from COMPUTSTAT database for the period 2010-2020. Then, firms which were detected to be involved in fraud were excluded from the sample in order to ensure that control sample consists only non-fraud firms. Then, methodology of Beasley(1996) is followed to construct a 1-1 matched sample with size, year and two-digit SIC code. Specifically, we matched firms with the closest asset value the year before fraud commitment and within the same industry(two-digit SIC code).

For the comparison sample, a random sample of litigation-free firms has been constructed. As a beginning, we found all firms with total asset value between $20 million less than $600 million (Compustat database) and those in fraud sample are excluded. In line with Zhang et al. (2020), a 1-1 matched sample is constructed based on size of the firm, fraud year and the industry. The industry is defined by the two-digit SIC code. Table 1 and 2 represents the 1-1 matched sample of each fraud firm in year and in industry.

Fraud-1 Healthy-0	Manufacturing	Finance	Technology	Services	Retail	Transportation	Health Care	Construction	Wholesale	Mining
0	46	30	21	21	11	8	5	3	3	2
1	46	30	21	21	11	8	5	3	3	2
Grand Total	**92**	**60**	**42**	**42**	**22**	**16**	**10**	**6**	**6**	**4**

Table 1: Fraud and Control Firms breakdown by industry

Fraud-1 Healthy-0	Year 2020	Year 2019	Year 2018	Year 2017	Year 2016	Year 2015	Year 2014	Year 2013	Year 2012	Year 2011	Year 2010
0	4	13	16	16	25	9	19	14	13	10	11
1	4	13	16	16	25	9	19	14	13	10	11
Grand Total	**8**	**26**	**32**	**32**	**50**	**18**	**38**	**28**	**26**	**20**	**22**

Table 2: Fraud and Control Firms breakdown by year

4.2 Independent variables

The values of the independent variables size of firms, interest coverage, market to book value, debt to equity and ROA are obtained from the Computstat database. In case that CEO of the firm is also the president of the Board of Directors the variable of duality is equal to 1, otherwise 0. The data of CEO title is acquired from Execucomp database. Institutional ownership data is retrieved from Refitiv Thomson-Reuters Institutional Holdings Database. The industry of each firm is categorized based on its SIC code shown in the Computstat database. The table 3 represents the number of firms belonging to total ten industries. As we observe, most companies belong to manufacturing, finance, technology, and services segment. This is prima facie evidence that firms belong to these sectors are more likely to commit fraud as they have higher participation mix % in the sample. In addition, the fact that we have sufficient sample of these firms will help us examine the research question. Unfortunately, there is no large sample of firms in the other industries (retail, transportation, health care, construction, wholesale and mining) but we won't remove them from our sample as each of these firms can give us insights regarding the Hypothesis 1 – Capital Structure and Fraud Commitment.

Total Companies	Manufacturing	Finance	Technology	Services	Retail	Transportation	Health Care	Construction	Wholesale	Mining
300	92	60	42	42	22	16	10	6	6	4
100%	31%	20%	14%	14%	7%	5%	3%	2%	2%	1%

Table 3: Total Firms breakdown by industry

In table 2, data presented show how many fraud cases filed in each year. In order to avoid having biased results due to the filing year, we apply in our logistic regression year fixed effects. By using year fixed effects, we can remove the effect of the time-invariant characteristics so we can assess the net effect of the predictors on the outcome variable. For example, if for a certain year issuing debt has become easier, this would affect the debt ratio of the firms. However, year fixed effects will eliminate the impact of debt-to-equity to the probability of fraud as the impact of year will be reflected in year fixed effects.

As a beginning, we started evaluating the data extracted from the different datasources by creating descriptive statistics table (table 4).

The results from the descriptive statistics show very strange figures which if followed or not re-evaluated will lead us to wrong conclusions. For example, it shows that Debt to Equity ratio from year t to t-2 has increased by **31468%**. Another example is the Market to Book value at t-1 which seems to have a maximum value of **122.27**. Generally, Market to Book value must be around 1 and a high market to book value is preferred by investors as it means that the company is a value stock. However, that amount is extremely high. Finally, the interest coverage ratio at t-1 which has as a minimum value the value of **-544.66** and maximum of **707.86.** Based on analysts, an interest coverage is acceptable at minimum 2.

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
Initial Debt to Equity t	300	0.00	155.66	1.67	9.39
Initial Debt to Equity t-1	300	0.00	27.00	1.01	2.23
Initial Debt to Equity t-2	300	0.00	29.40	1.09	2.95
Initial Change in Debt to Equity t vs t-1	300	-1.00	296.43	4.22	28.91
Initial Change in Debt to Equity t-1 vs t-2	300	-1.00	103.21	0.60	6.15
Initial Change in Debt to Equity t vs t-2	300	-1.00	314.68	3.97	28.56
Initial Market to Book Value t-1	300	0.12	122.27	3.80	8.95
Initial Interest Coverage Ratio t-1	300	-544.66	707.86	15.91	70.65

Table 4: Description statistics of the initial variables(before winsorizing method)

4.3 Winsorizing

To tackle this issue, we run several boxplots of these problematic variables to examine it further. (Appendix 1) We understand that the mean is skewed by several extreme values either too high or too low. Because the sample of fraud companies is very important for the results of the study, we will try to avoid removing completely the problematic companies from the sample. Therefore, we winsorize all extreme variables to take less extreme values. According to Anginer et al. (2014), we started to winsorize Debt to Equity t, Debt to Equity t-1 , Debt to Equity t-2, Interest Coverage Ratio t-1 and Market to Book Value t-1 at the 1th and 99th percentile levels to reduce the influence of outliers. But the results are not corrected and we winsorize at the 5th and 95th percentile levels. With this method, the variables finally follow normal distribution and there are no outliers.(Appendix 2)

Table 5 represents the descriptive statistics of the variables used in the model after winsorizing method and we draw several conclusions. The sample consists of 150 fraud firms and 150 non-fraud firms. The mean value of mining is 0.01 which means that we have only 4 cases in the total samples meaning that there are only a few companies operating in the mining sector and it is the reason that mining industry has been set as the base level.

Descriptive Statistics					
Variables	**N**	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
Fraud	300	0.00	1.00	0.50	0.50
Duality	300	0.00	1.00	0.59	0.49
Institutuinal Ownership t-1	300	0.00	1.00	0.70	0.30
Log_assets t-1	300	1.34	6.36	3.52	0.87
Interest Coverage t-1	300	7.88	23.94	11.49	5.93
Market to Book t-1	300	0.12	4.82	2.42	1.46
Debt to Equity t	300	0.61	2.74	0.99	0.68
Debt to Equity t-1	300	0.76	1.26	0.89	0.21
Debt to Equity t-2	300	0.76	1.43	0.90	0.26
Change in Debt to Equity t vs t-1	300	-0.52	2.62	0.06	0.55
Change in Debt to Equity t vs t-2	300	-0.58	2.63	0.06	0.57
Change in Debt to Equity t-1 vs t-2	300	-0.47	0.67	0.00	0.16
Manufacturing	300	0.00	1.00	0.31	0.46
Mining	300	0.00	1.00	0.01	0.11
Retail	300	0.00	1.00	0.07	0.26
Services	300	0.00	1.00	0.14	0.35
Transportation	300	0.00	1.00	0.05	0.23
Wholesale	300	0.00	1.00	0.02	0.14
Finance	300	0.00	1.00	0.20	0.40
Construction	300	0.00	1.00	0.02	0.14
Health Care	300	0.00	1.00	0.03	0.18
Technology	300	0.00	1.00	0.14	0.35

Table 5: Descriptive Statistics of the final variables (after winsorizing method)

We use the stepwise regression which is a method that examines the statistical significance of each independent variable. Specifically, we use backward elimination method which means that we start running the model with all independent variables and then removes one variable to test its importance relative to the overall results. In our model, all variables model is presented in Table 6 where we used a number of corporate governance metrics(Institutional Ownership % and Duality), some characteristics variables(ROA, Interest coverage, Assets), interest variables(Debt to Equity at t, Debt to Equity at t-1, Debt to Equity at t-2, Change in Debt to Equity in different years) and interactions (Technology * Debt to Equity in all years, Manufacturing * Debt to Equity in all years, Services * Debt to Equity in all years, Finance * Debt to Equity in all years). The appendix 2 presents the statical data of the full model which show that our model reached the 64.7% of correctness and the Null Hypothesis is rejected because the significance level is at 0.98. Even though, the statistics metrics are very good, we would proceed with removing the variable with the highest p-value.

Variables in the Equation				
	B	S.E.	Sig.	Exp(B)
Institutional Ownership t-1	-0.685	0.463	0.139	0.504
Log_assets t-1	0.529	0.185	0.004	1.697
Duality	0.018	0.284	0.950	1.018
Interest Coverage t-1	-0.050	0.028	0.079	0.951
Market to Book t-1	-0.177	0.107	0.099	0.838
Debt to Equity t	0.900	1.374	0.512	2.461
Debt to Equity t-1	1.646	6.644	0.804	5.189
Debt to Equity t-2	-4.616	5.570	0.407	0.010
Change in Debt to Equity t vs t-1	1.678	2.174	0.440	5.357
Change in Debt to Equity t vs t-2	-1.920	1.818	0.291	0.147
Change in Debt to Equity t-1 vs t-2	-3.560	5.007	0.477	0.028
ROA t-1	2.187	1.856	0.239	8.907
Technology * Debt to Equity t	0.215	1.097	0.845	1.240
Technology * Debt to Equity t-1	-0.860	3.871	0.824	0.423
Technology * Debt to Equity t-2	-0.063	3.452	0.986	0.939
Services * Debt to Equity t-2	-5.670	4.016	0.158	0.003
Services * Debt to Equity t-1	9.728	5.133	0.058	16780.881
Services * Debt to Equity t	-1.163	0.864	0.178	0.312
Manufacturing * Debt to Equity t	-0.726	0.717	0.312	0.484
Manufacturing * Debt to Equity t-1	6.951	3.967	0.080	1044.557
Manufacturing * Debt to Equity t-2	-1.318	3.092	0.670	0.268
Finance * Debt to Equity t-2	-3.019	3.368	0.370	0.049
Finance * Debt to Equity t-1	4.054	4.441	0.361	57.633
Finance * Debt to Equity t	0.354	0.887	0.690	1.425
Manufacturing	-3.188	2.040	0.118	0.041
Retail	1.033	1.213	0.394	2.810
Services	-1.202	2.177	0.581	0.301
Transportation	0.677	1.235	0.583	1.968
Wholesale	0.927	1.401	0.508	2.527
Finance	-0.785	2.155	0.716	0.456
Construction	0.882	1.392	0.526	2.416
Health Care	0.736	1.280	0.566	2.087
Technology	1.645	1.773	0.353	5.184
Constant	0.504	1.718	0.769	1.656
Year Fixed Effects				

Table 6: Initial Model with all variables

Using the stepwise method, we ended up to the Model 1 where most variables are statistically significant, and statistics of the model prove that the model is accurate.

$$Z = \log\left(\frac{p}{1-p}\right) = a + \boldsymbol{\beta_1} * instituitional\ ownership\ \% + \boldsymbol{\beta_2} * \log assets + \boldsymbol{\beta_3} * interest\ coverage_{t-1} + \boldsymbol{\beta_4} * market\ to\ book_{t-1} + \boldsymbol{\beta_5} * debt\ to\ equity_t + \boldsymbol{\beta_6} * debt\ to\ equity_{t-1} + \boldsymbol{\beta_7} * debt\ to\ equity_{t-2} + \boldsymbol{\beta_8} * change\ in\ debt\ to\ equity\ t\ vs\ t-2 + \boldsymbol{\beta_9} * technology * debt\ to\ equity_{t-1} + \boldsymbol{\beta_{10}} * manufacturing * debt\ to\ equity_{t-1} + \boldsymbol{\beta_{11}} * technology + \boldsymbol{\beta_{12}} * manufacturing + \boldsymbol{\beta_{13}} * services + \boldsymbol{\beta_{14}} * finance + \boldsymbol{\beta_{15}} * retail + \boldsymbol{\beta_{16}} * transportation + \boldsymbol{\beta_{17}} * wholesale + \boldsymbol{\beta_{18}} * construction + \boldsymbol{\beta_{19}} * health\ care$$

Model 1: Final logistic regression model which measure the probability of committing fraud

4.4 Correlation Matrix

Another important table extracted from SPSS is the Correlation Matrix(Table 7). From Table 7 , we find that firm size is positive and statistically significant to the Debt-to-Equity ratio in t , t-1 and t-2. This means that the higher the firm the more this firm relies on leverage instead of equity. Also, another important outcome of the Table 7 is that interest coverage at the year before filing year has negative statistically significant relationship at level 5% with Debt-to-Equity ratio in t, t-1 and t-2. This means that high levered firms are more likely to won't be able to service their debt obligations. Also, interest coverage at t-1 has negative statistically significant relationship with Change in Debt to Equity at t vs t-2 this means that the higher the increase in leverage from year t vs t-2 the lower the ability to serve their debt obligations. Another outcome of the Correlation matrix is that Debt to Equity in years t, t-1 and t-2 have positive significant relationship between them. Finally, the relationship between debt-to-equity in all years is positively statistically significant with the change in debt-to-equity from year t to year t-2.

Indepedent Variables	Institutional Ownership t-1	Log_assets t-1	Interest Coverage t-1	Market to Book t-1	Debt to Equity t	Debt to Equity t-1	Debt to Equity t-2	Change in Debt to Equity t vs t-2
Institutional Ownership t-1	1	0.021	-0.035	-0.068	0.052	0.053	-0.022	0.105
Log_assets		1	0.025	-0.189	.139*	.166**	.186**	0.069
Interest Coverage t-1			1	.174**	-.218**	-.285**	-.295**	-.123*
Market to Book t-1				1	0.095	0.039	-0.031	0.104
Debt to Equity t					1	.703**	.633**	.870**
Debt to Equity t-1						1	.794**	.429**
Debt to Equity t-2							1	.229**
Change in Debt to Equity t vs t-2								1

*, ** significant at the 0.1 and 0.05 levels respectively

<u>Table 7: Correlation Matrix of independent variables</u>

4.5 Multicollinearity

In order to verify that there is no multicollinearity issue between the variables we run the collinearity statistic test through SPSS (Table 8). Multicollinearity occurs when several independent variables correlated resulting to less reliable statistical inferences. As the VIF test in all independent variables is less than 5, we conclude that there is no multicollinearity problem and all variables are independent.

	Collinearity Statistics	
Independent Variables	**Tolerance**	**VIF**
(Constant)		
Institutional Ownership t-1	0.966	1.035
Log_assets t-1	0.912	1.096
Interest Coverage t-1	0.858	1.165
Market to Book t-1	0.886	1.128
Debt to Equity t	0.240	4.159
Debt to Equity t-1	0.296	3.374
Debt to Equity t-2	0.235	4.247
Change in Debt to Equity t vs t-2	0.224	4.461

Table 8: Collinearity tests of independent variables

Table 9 presents summary statistics on the difference between fraud and non-fraud firms. Most notably, fraud firms have higher debt to equity ratio in all years(t, t-1, t-2) than non-fraud firms. It enhances our argument that firms that rely on leverage are more likely to commit fraud. Also, increase in leverage proves to be higher in the case of fraud firms than non-fraud firms. On the other hand, institutional ownership, interest coverage and market to book ratio are increasing in the case of non-fraud firms. Finally, log of assets is lower in non-fraud firms than in fraud firms. The results of the Table 9 follow the same logic which our research question and model has been developed.

4.6 Mean Differences

Table 10 shows the T-test between the mean difference of the two types of firms. Our attention is given to variables that are proved to have statistically significant difference. One of these variables is Log_Assets at t-1 which shows that there is a statistically significant difference at 1% between the two categories. This means that firms which committed fraud are larger in size than non-fraud firms at a significant level of 1%. Another important outcome from this test is that non-fraud firms have higher market-to-book value ratio than the firms which committed fraud at significant level of 10%. This means that companies with a lot of growth opportunities are less prone to committing fraud. Last but not least, Debt to Equity ratio at time t (one of the interest variables) proves to have significant difference between the two groups at the level of 10%. The mean of non-fraud firms is equal to 0.927 whereas of fraud firms is equal to 1.047. Meaning that the difference between the two groups is negative and statistically significant at 10%.

Group Statistics					
	Fraud	N	Mean	Std. Deviation	Std. Error Mean
Log_assets	0	150	3.401	0.880	0.072
	1	150	3.649	0.840	0.069
Institutional Ownership t-1	0	150	0.715	0.284	0.023
	1	150	0.682	0.313	0.026
Interest Coverage t-1	0	150	11.828	6.110	0.499
	1	150	11.159	5.741	0.469
Market to Book t-1	0	150	2.539	1.489	0.122
	1	150	2.296	1.420	0.116
Debt to Equity t	0	150	0.927	0.624	0.051
	1	150	1.047	0.738	0.060
Debt to Equity t-1	0	150	0.877	0.203	0.017
	1	150	0.896	0.212	0.017
Debt to Equity t-2	0	150	0.899	0.259	0.021
	1	150	0.906	0.259	0.021
Change in Debt to Equity t vs t-2	0	150	0.010	0.546	0.045
	1	150	0.101	0.596	0.049

Table 9: Compare the mean difference between the mean value in fraud and non-fraud firms

Independent Samples Test							
Variables		t-test for Equality of Means					
	F	t	Sign.	Mean Diff	Std. Error Diff	95% CI of the Difference	
						Lower	Upper
Log_assets t-1	0.71	-2.49	0.01***	-0.25	0.10	-0.44	-0.05
Institutional Ownership t-1	3.83	0.95	0.17	0.03	0.03	-0.04	0.10
Interest Coverage t-1	3.01	0.98	0.16	0.67	0.68	-0.68	2.02
Market to Book t-1	1.79	1.44	0.07*	0.24	0.17	-0.09	0.57
Debt to Equity t	5.26	-1.52	0.07*	-0.12	0.08	-0.27	0.04
Debt to Equity t-1	1.68	-0.82	0.21	-0.02	0.02	-0.07	0.03
Debt to Equity t-2	0.01	-0.25	0.40	-0.01	0.03	-0.07	0.05
Change in Debt to Equity t vs t-2	2.06	-1.37	0.09	-0.09	0.07	-0.22	0.04

*, **, *** significant at the 0.1, 0.05 and 0.01 levels respectively

Table 10: Independent Sample Test of Means Difference

To verify that there is no multicollinearity between the Debt to Equity in the three year and the change of Debt to Equity , we checked the VIF value which was lower than 4 in all tests. This means that independent variables(Debt to Equity t, Debt to Equity t-1, Debt to Equity t-2) in the model are not correlated.

5. Empirical Results

One of the first tables which examined is the Descriptive Statistics tables(Table 11) of the continuous independent variables except the Interactions. The table 11 represents key statistics information of each variable. The sample consists of 150 fraud firms and 150 of non-fraud firms. The variable of institutional ownership at t-1 represents the percentage of company's available shares owned by mutual funds, pension funds, insurance companies, investment firms, private foundations, endowments or other large entities that manage funds on behalf of others. This means that the range of this variables is from 0% to 100%. Firms which are fully owned by mutual funds and insurance companies have institutional ownership equal to 100%. Similarly to Edamns, we use in our model the logarithm of assets because the distribution is more likely to behave like normal distribution hence provide better regression analysis.. The interest coverage ratio determines how easily a company can pay interest on its outstanding debt. The minimum value of interest coverage is 7.9 at a very healthy level because we generally think that a good interest coverage ratio is over 2. Furthermore, the variable Market to Book Value Ratio measures the growth opportunities of the organization. The values less than 1 implies that a company can be bough for less than the value of its assets which means that has lower growth opportunities. Whereas a market to book ratio above 1 means that the company's stock is overvalued. The Debt to Equity ratio in all years are similar between them. The last variables is the change of debt to equity ratio from the year t-2 to year t. This variable shows that there are firms which decrease their debt to equity(-0.6) in the two-year period but there are also firms which increase the debt to equity(2.6) in the same period.

Our expected signs of each variable are presented in the table 12. Our assumption is that if the institutional ownership increases, the probability of fraud decreases because such organizations are dominated by corporate governance and transparency. In the same pattern, we expect that organizations with high interest coverage will be less likely to commit fraud. On the other hand, we expect that the ability of an organization to repay its debt obligations will have a negative relationship on the probability of committing fraud. Our assumption is that Debt to Equity in all years will have positive association on the probability of fraud. We predict that the increase in Debt to Equity over the period of the 2 years, will increase the likelihood of fraud commitment.

Descriptive Statistics					
Independent variables	**N**	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
Institutional Ownership t-1	300	0.0	1.0	0.7	0.3
Log_assets t-1	300	1.3	6.4	3.5	0.9
Interest Coverage t-1	300	7.9	23.9	11.5	5.9
Market to Book t-1	300	0.1	4.8	2.4	1.5
Debt to Equity t	300	0.6	2.7	1.0	0.7
Debt to Equity t-1	300	0.8	1.3	0.9	0.2
Debt to Equity t-2	300	0.8	1.4	0.9	0.3
Change in Debt to Equity t vs t-2	300	-0.6	2.6	0.1	0.6

Table 11: Descriptive Statistics of the Final Model independent variables

Independent variables	Expected Sign	Type of variable
Institutional Ownership t-1	-	continuous
Log_assets t-1	+	continuous
Interest Coverage t-1	-	continuous
Market to Book t-1	-	continuous
Debt to Equity t	+	continuous
Debt to Equity t-1	+	continuous
Debt to Equity t-2	+	continuous
Change in Debt to Equity t vs t-2	+	continuous
Technology * Debt to Equity t-1	+	continuous
Manufacturing * Debt to Equity t-1	-	continuous
Technology	+	binary
Manufacturing	-	binary
Retail	?	binary
Services	+	binary
Transportation	?	binary
Wholesale	?	binary
Finance	+	binary
Construction	?	binary
Health Care	?	binary

Table 12: Expected sign of independent variables

Some results of the logistic regression are as expected but others are very surprising. (Table 13) Consistent with the research of McNichols and Stubben(2008), we find that the size of the firm is positively statistically significant at 1% to the likelihood of fraud commitment. We believe that the positive relationship between probability of fraud and size of the firm is one of the major findings of this project. Another important finding of this project is that Market to Book Value is negatively statistically significant at 10% with the probability of fraud. This is consistent with our prediction, that the firms with a lot of growth opportunities will be less likely to be involved to fraud. Consistent with the prediction and previous studies(Efeendi et al, 2007), the interest variable of the model, Debt to Equity at t, is statistically significant at 10% with positive association with the likelihood of committing fraud. On the other hand, it’s inconsistent with our expectations the debt to equity at time t-2. Our model proves that Debt to Equity at t-2 is negatively associated with the probability of fraud. Two explanations are given for the opposite sign. The first explanation is that the variable refers to two years before the disclosure of the fraud, which means that the financial statements might not be misreported. The second explanation is that the financial statements are already misreported in order to increase the debt. The other interest variable is the interaction between capital structure and Technology. Consistent with our expectation, high leverage on technological firms influences positively the probability of fraud. At the first glance, we find that the sign is negative but we have to calculate all the coefficients influenced by this interaction. (Debt to Equity t-1 + Tech*Debt to Equity t-1 + Technology -> -0.347 -1.849 + 2.197= +0.008). Finally, the interaction of manufacturing*debt to equity t-1 is positively statistically significant. This means that manufacturing companies with high leverage are positively related to the likelihood of fraud commitment. We have to calculate again the actual impact of the interaction on the z value : Debt to Equity t-1 + Man * Debt to Equity t-1 + Manufacturing -> -0.347 +2.974 – 1.9= +0.726. Despite the expectations and previous studies(Farber et al., 2005), we find that institutional ownership is non-statistically significant but the sign is as per our prediction. Meaning that, we expected that there will be negative association between the institutional ownership – metric of good corporate governance and the probability of fraud. Similarly, we find that interest coverage at t-1 is negative as per our expectation but not statistically significant.

Final Model	Expected sign	B	Sig.	Exp(B)
Institutional Ownership t-1	-	-0.608	0.157	0.544
Log_assets	+	0.478	0.005***	1.613
Interest Coverage t-1	-	-0.029	0.217	0.971
Market to Book t-1	-	-0.169	0.091*	0.844
Debt to Equity t	+	1.686	0.074*	5.397
Debt to Equity t-1	+	-0.347	0.788	0.707
Debt to Equity t-2	+	-2.572	0.063*	0.076
Change in Debt to Equity t t vs t-2	+	-1.209	0.166	0.298
Technology * Debt to Equity t-1	+	-1.849	0.097*	0.157
Manufacturing * Debt to Equity t-1	-	2.974	0.044**	19.567
Technology	+	2.197	0.139	8.998
Manufacturing	-	-1.900	0.264	0.149
Services	+	0.657	0.562	1.929
Finance	+	-0.037	0.973	0.963
Retail	?	0.738	0.537	2.092
Transportation	?	0.285	0.812	1.330
Wholesale	?	0.602	0.663	1.825
Construction	?	0.650	0.637	1.915
Health Care	?	0.517	0.684	1.676
Constant		0.070	0.962	1.073
Year Fixed Effects				

*, **, *** significant at the 0.1, 0.05 and 0.01 levels respectively

Table 13: Final Model

The classification matrix represents the predictions of the model and the actual observations.(Table 14) From the classification matrix, we observe that the sensitivity of the model is 66% which means that we classify correctly the 66% of the cases which didn't commit fraud. Furthermore, the specificity of the model is 60.7% which means that the model predicts correctly the 6 cases out of 10. The Area under the Curve of our model is presented in the table 15. From table 15, area under the curve is 0.675 which tells the degree of model capability of distinguishing between classes 0 and 1. The higher the AUC(closer to 1) , the better the model is at distinguishing between the fraud and non-fraud firms. We also do various checks in order to ensure that the model is reliable and there are no outliers which screw the model.

Observed		Predicted		
		Fraud		Percentage Correct
		0	1	
Fraud	0	99	51	66.0
	1	59	91	60.7
Overall Percentage				63.3

Table 14: Classification Model of the Final Model

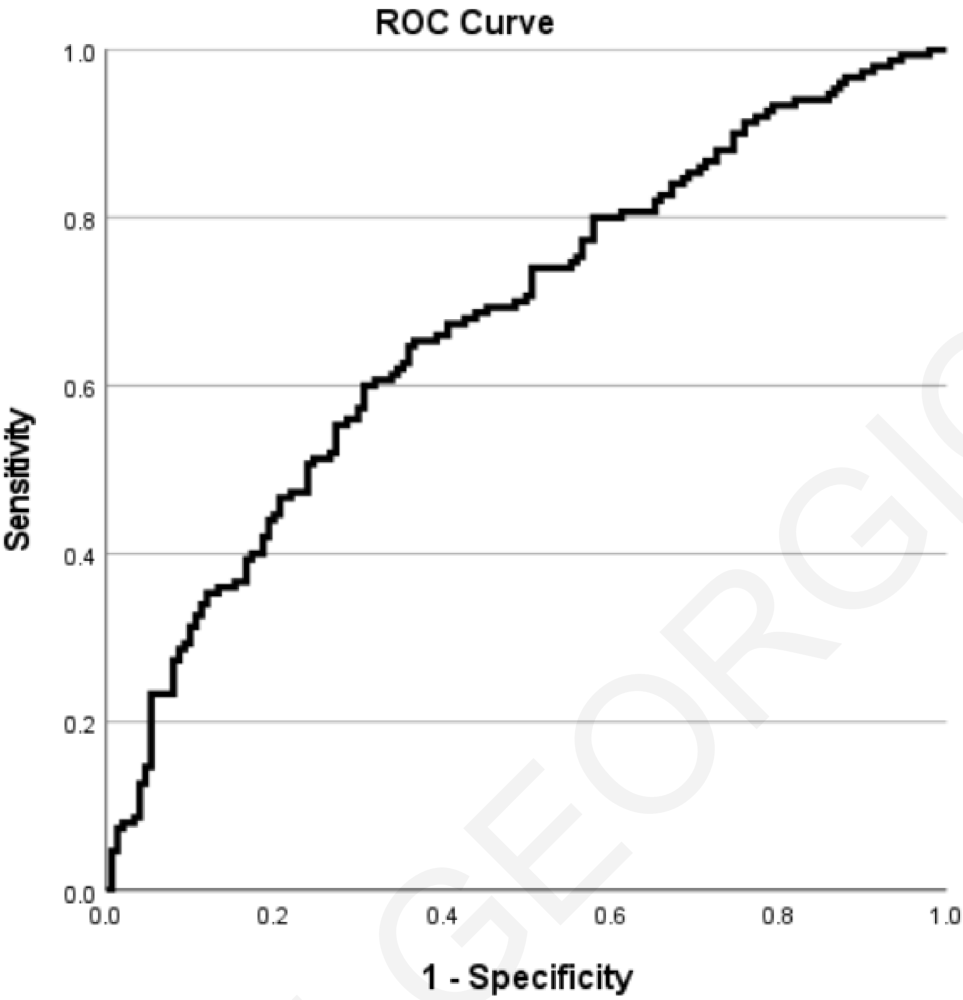

Table 15: ROC Curve

The objective of our model is to classify correctly all the observations but mostly the fraud firms. Type Error I is the most crucial error as the cost of categorizing firms as healthy if they are involved in frauds is higher than if misclassifying healthy firms as fraudulent. In order to check different scenarios, we try different cut-off values in order to minimize the type error I. In the scenario of cut off value 40%, the type error I improves to 16.7% from 39.3%(cut-off value 50%). However, the overall percentage of correctness decreases from 63.3% to 58%. This means that we gain from the aspect of specificity but we lose from sensitivity point of view(higher Type Error II). In the scenario of cut off value 60%, Type Error I deteriorates from 39.3% to 66% whereas Type Error II improves from 34% to 10.7%. We come across a tradeoff between the good prediction of non-fraud firms(sensitivity) and the good prediction of fraud firms(specificity). We will choose to gain specificity against sensitivity, and we will select the scenario with cut off value 40%.

Cutoff 40%		Predicted 0	Predicted 1	Percentage Correct
Observed	0	49	101	32.7
	1	25	125	83.3
				58.0

Cutoff 50%		Predicted 0	Predicted 1	Percentage Correct
Observed	0	99	51	66.0
	1	59	91	60.7
				63.3

Cutoff 60%		Predicted 0	Predicted 1	Percentage Correct
Observed	0	134	16	89.3
	1	99	51	34.0
				61.7

Table 16: Different cut of values – Whole Sample

Training-testing method

In order to check the robustness of the model, method of dividing the sample into training and testing sample has been followed. By using this method, coefficients extracted from the training sample and applied on testing sample firms. The training sample consists of 202 firms from 2010-2016 and testing sample the rest(2017-2020). Then, we compare between different cut-off values to decide the predicting ability of the model. The tradeoff is between sensitivity and specificity. (Table 17) The sensitivity of the model is better off with the cut off value: 40% at 84%. This means that the important type Error I is just 16%. On the other hand, the type Error II is 80%. As mentioned before, it is of paramount importance to have low value at type error I which is the misclassification of fraud cases. The cut of value 50% shows that overall correct percentage is 56% and type Error I increases to 35% and type error II improves to 53%. Finally examined cut off value at 60% achieves the lowest specificity of just 47% value and the highest sensitivity at 82%. However, we prefer to choose the cut off 40% as we gain in terms of specificity.

cut off 40%		Predicted		Percentage Correct
		0	1	
Observed	0	10	39	20%
	1	8	41	84%
				52%

Cut off 50%		Predicted		Percentage Correct
		0	1	
Observed	0	23	26	47%
	1	17	32	65%
				56%

cutoff 60%		Predicted		Percentage Correct
		0	1	
Observed	0	40	9	82%
	1	26	23	47%
				64%

Table 17: Different cut off values – Training vs Testing sample

Having in mind the two methods, we compare both results and we decide that cut off value 40% gives the best results in terms of specificity in both methods. Even though, the training vs testing sample method seems to give the highest specificity(84%) the overall correctness is just 52%. Therefore, we do believe that it’s better to follow the first method when the whole sample has been used in order to get specificity at 83% and overall correctness 58%.

6. Conclusion

Consistent with hypothesis and previous studies(McNichols and Stubben, 2008), the research presented enough evidence that larger firms are more likely to be involved in frauds. Furthermore, Market to Book value is statistically significant in a positive way to the probability of fraud. We expected the association because the firms with high market to book value ratio have a lot of growth opportunities and it's less likely to commit fraud. Similarly, this research found that debt to equity at the time of fraud revelation has positive statistically significant association with the probability of fraud. This means that high levered companies are more prone to commit fraud because of the frustrations they face because of interest debt covenants when they want to issue new debt or equity (Efeendi, Sristava, Swanson, 2007). However, debt to equity two years before the fraud revelation has negatively statistically significant relationship with the likelihood of being involved in frauds. This is opposite to our hypothesis but can be explained by the fact that fraud might take place after the that period and therefore the firm's leverage is at healthy levels. Another explanation is that reports have been already misreported at that time in order to gain additional debt or equity.

The manufacturing and technological companies and debt to equity have positive relationship with the probability of fraud. In other words, manufacturing and technological companies with high leverage have positively statistically significant relationship with the likelihood of fraud. From our model, we find that when a technological firm increases its debt by 1 unit, will rise the probability of fraud by 0.008. We expected this for technological firms as there are researches presented documents that technological and services companies have higher probability of securities fraud litigation (Wang, Winton, 2021). On the other hand, we expected that manufacturing companies will react differently to this association as the industry is more stable rather than technology. However, we found that when a manufacturing company increases its debt to equity by 1 unit, will increase the probability of fraud by 0.726. This means that both industries react positively to the probability of fraud when firm increases its debt to equity. However, manufacturing firms which change their debt-to-equity have higher sensitivity on probability of fraud.

Despite the hypothesis which was based on previous studies, the association between interest coverage and probability of fraud, this study does not prove a statistically significant relationship. Moreover, we do not find that any industry parameter has any association with the probability of fraud.

We expect that there is room for improvement to this research as it could be expanded in other countries and not only in the United States(common law-context). It would be interesting to examine the relation between the debt and fraud for European code-law country. The expansion of the research to European countries(code law countries) will lead to important results because we believe that the different legislation system will change the dynamic between capital structure and fraud commitment. As indicated by Othman and Zhegal (2006), the relation between leverage and fraud can also be explained by country differences. Because common law countries have a system which protects the minorities investors, we expect that in these countries will be less likely to commit fraud rather than in European counties. We would suggest to expand the time horizon of the research to 20 years instead of 10 in order to gain more fraud observations and have more accurate results about the industry. We are confident that this will not affect the relevance of the model as year fixed effects will be applied. Finally, we recommend the usage of human resources metrics in the model. From previous studies(Zhang, Yiang, Wang, Kong, 2020; Edams, 2011), we find that the inclusion of variables that relate to employee behavior appears to have statistical significant relationship with firm's corporate governance and performance. They presented documents which prove that within organizations with bad employee treatment the probabilities of fraud are statistically higher. Employee satisfaction aspect is examined by Alex Edmans, who finds that the Best Companies experience significantly more positive earnings surprises and announcement returns. Therefore, employee satisfaction is positively correlated with shareholder returns. Further to that, Zhang et al. (2020) prove the negative association between employee treatment and fraud. They show that propensity is more prominent when the firm is in a high-tech industry, in a less competitive industry and employees have less outside employment opportunities.

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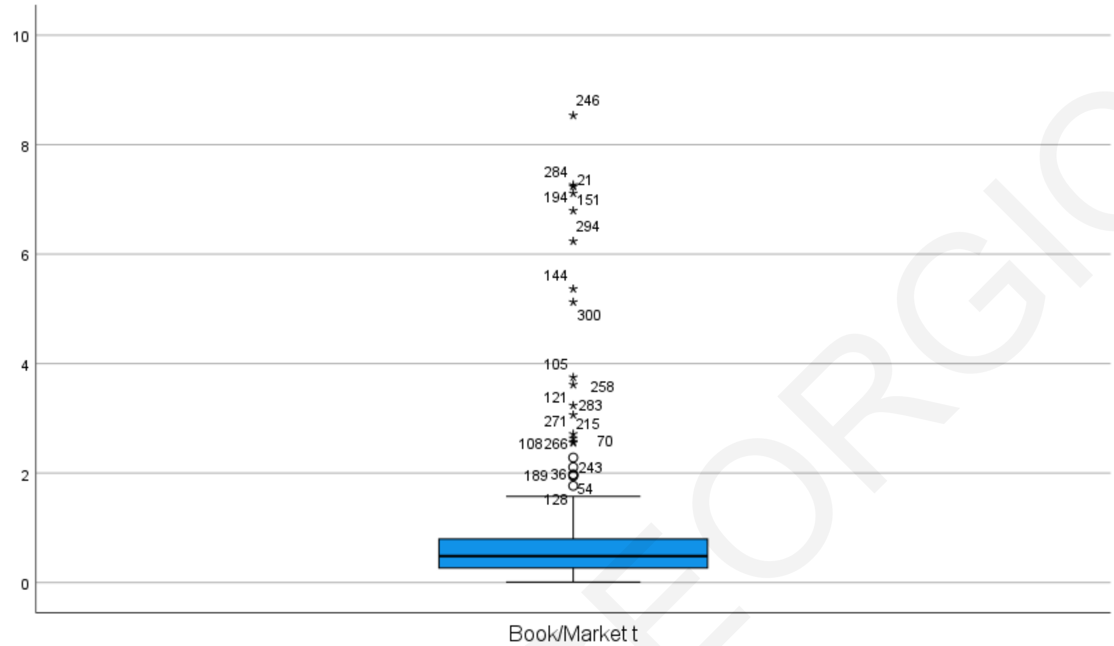
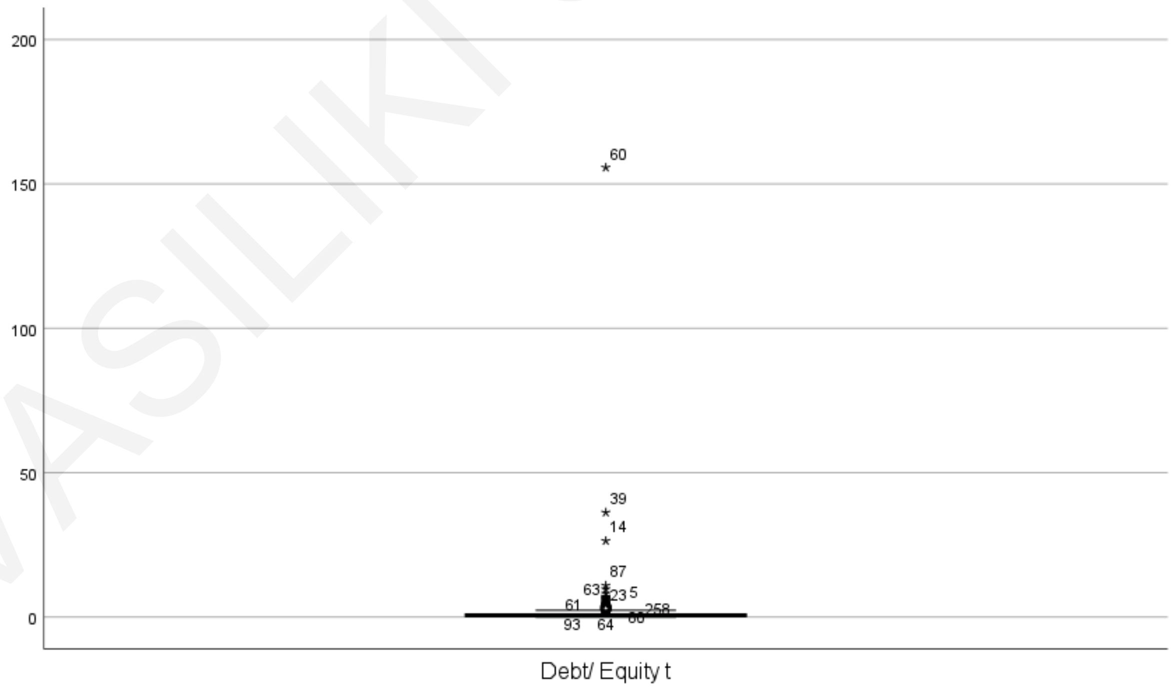
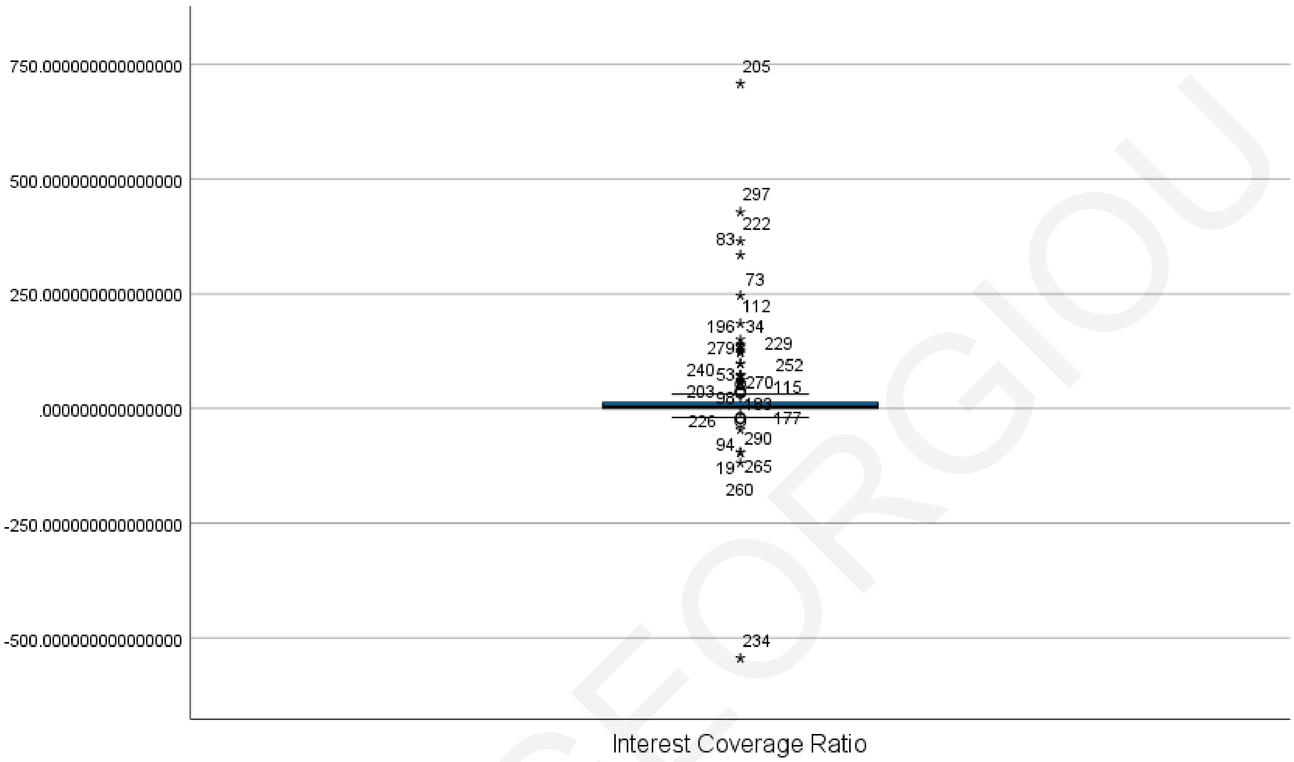
8. Appendices

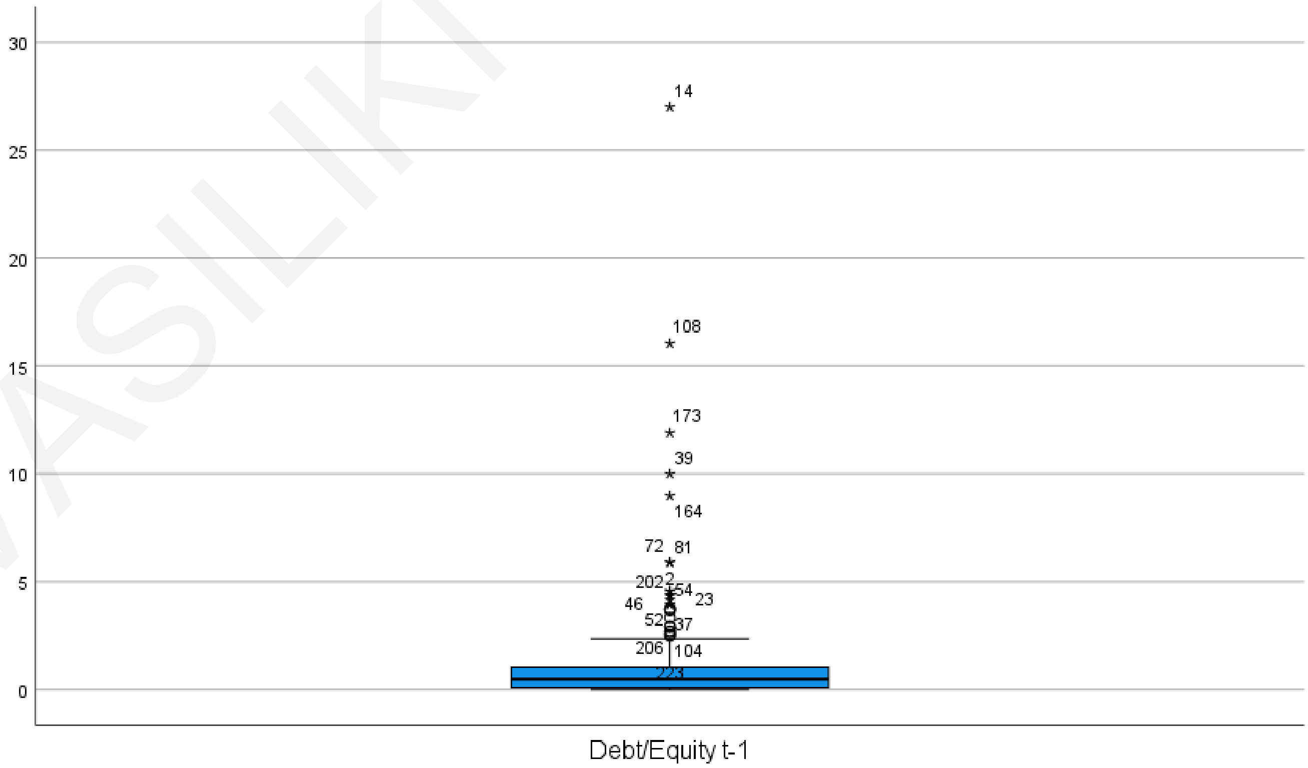
APPEDIX 1 - BOXPLOTS

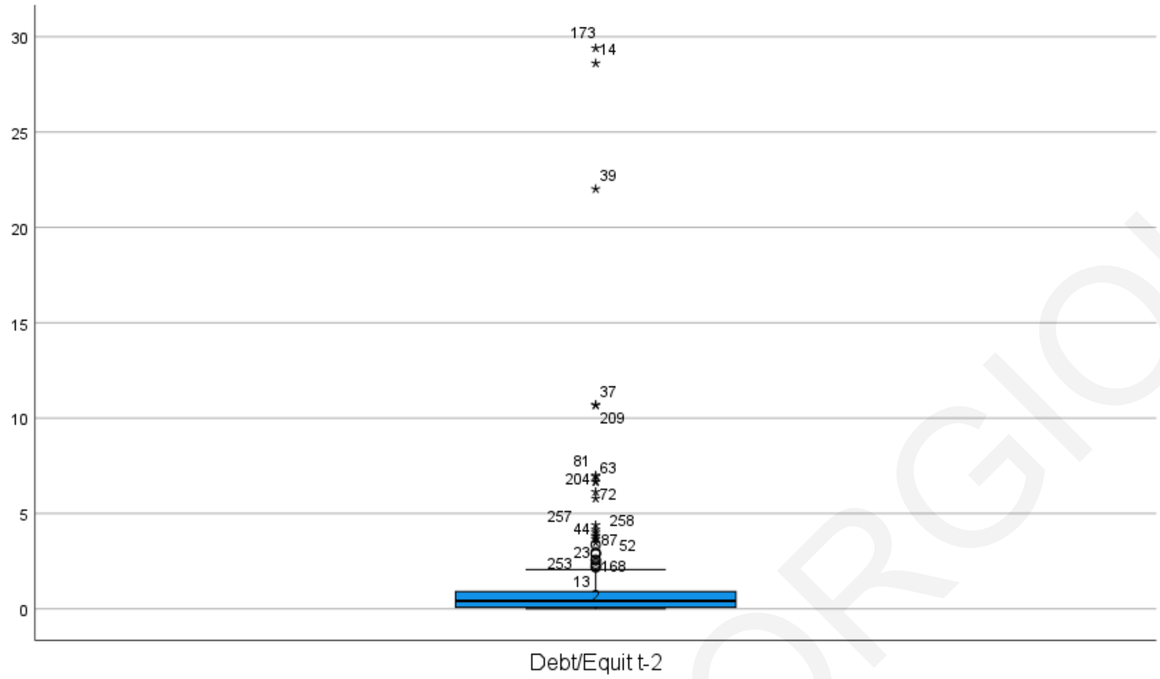
i. Independent variables before winsorizing



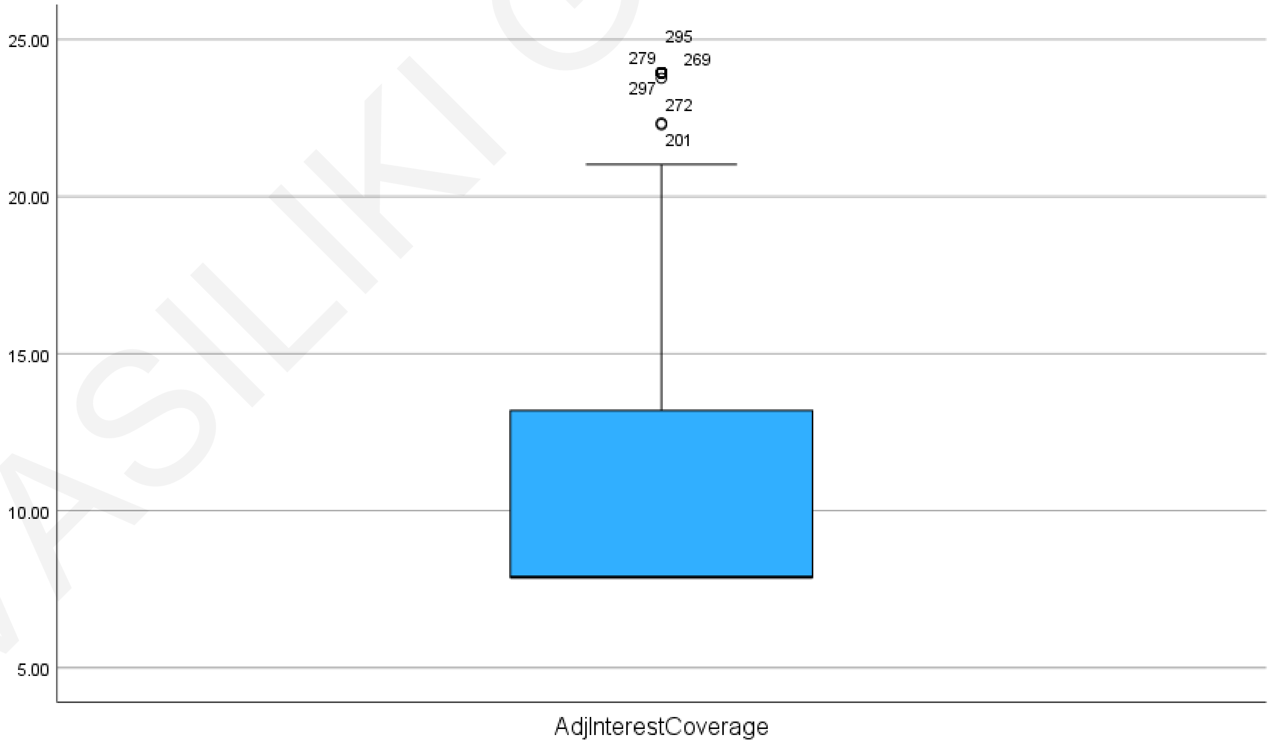


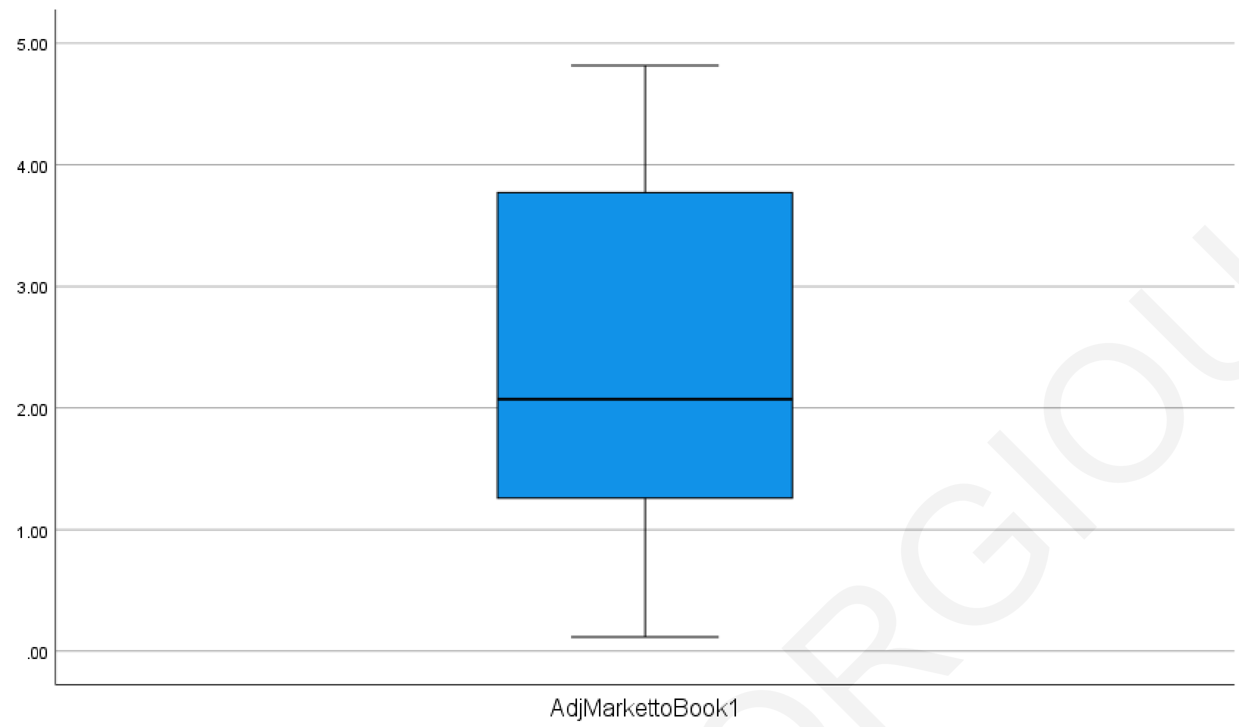

750.000000000000000
500.000000000000000
250.000000000000000
.000000000000000
-250.000000000000000
-500.000000000000000
Interest Coverage Ratio

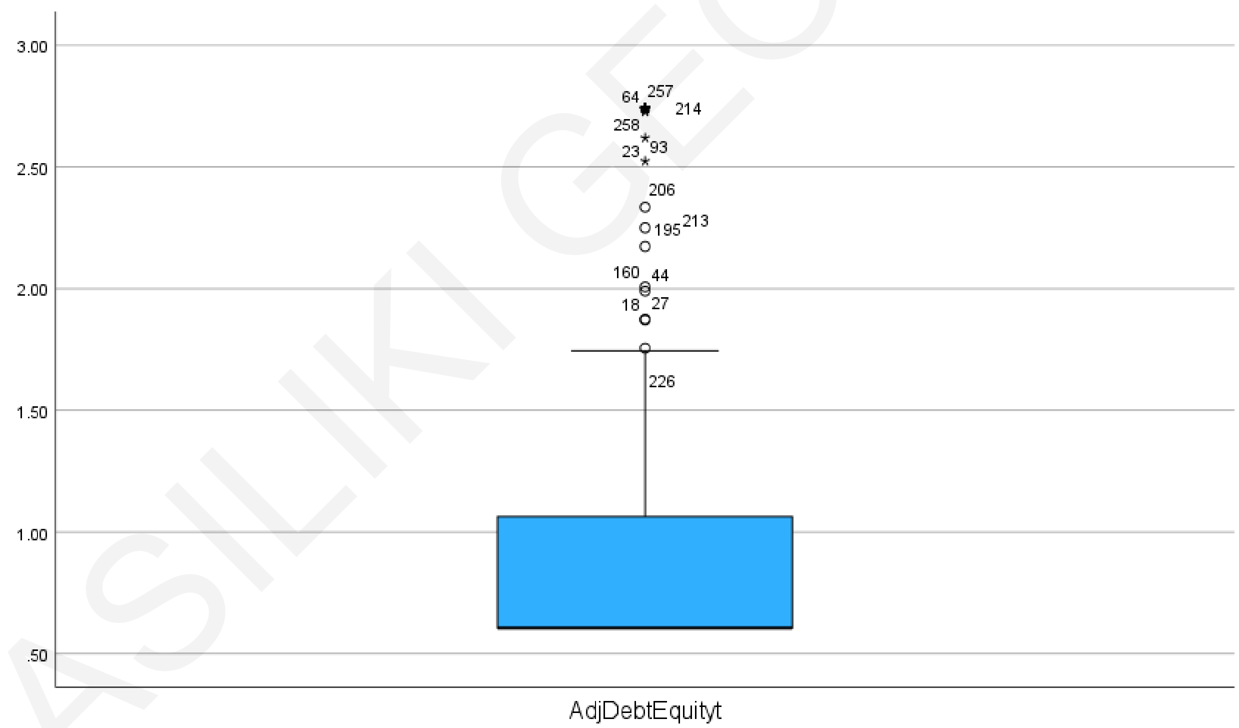

30
25
20
15
10
5
0
Debt/Equity t-1

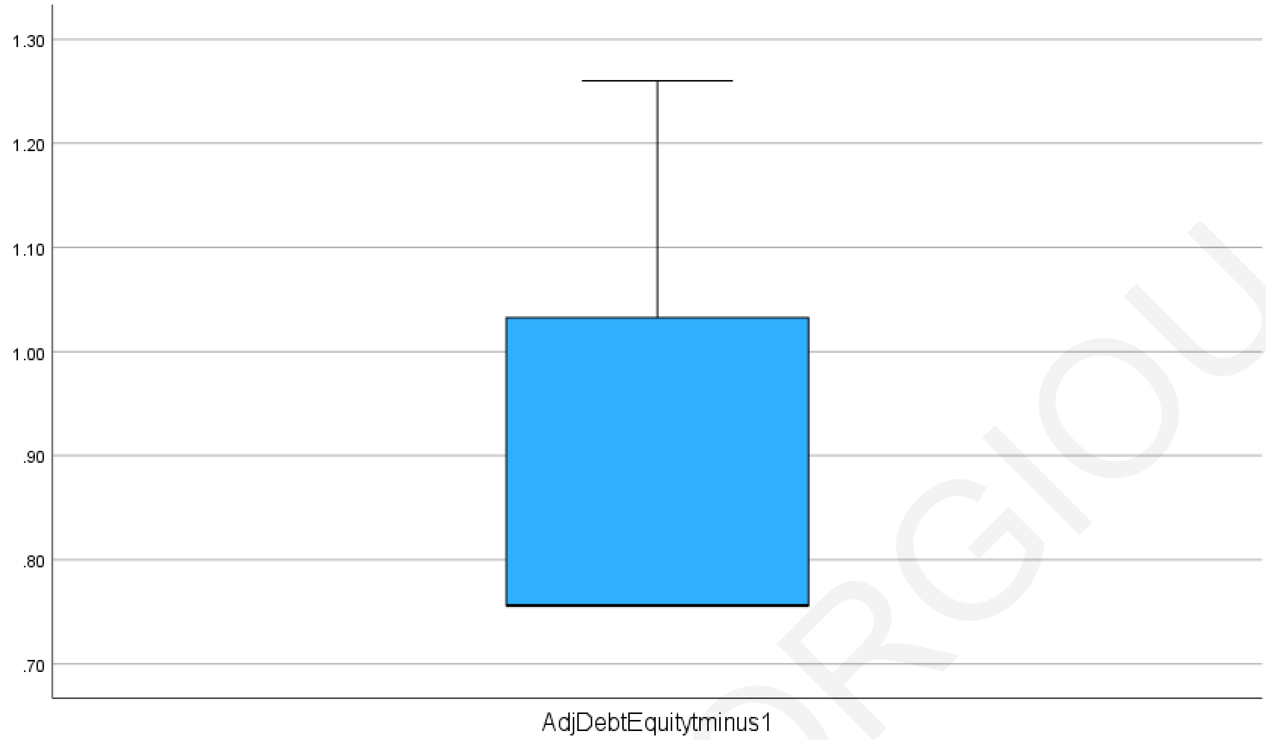


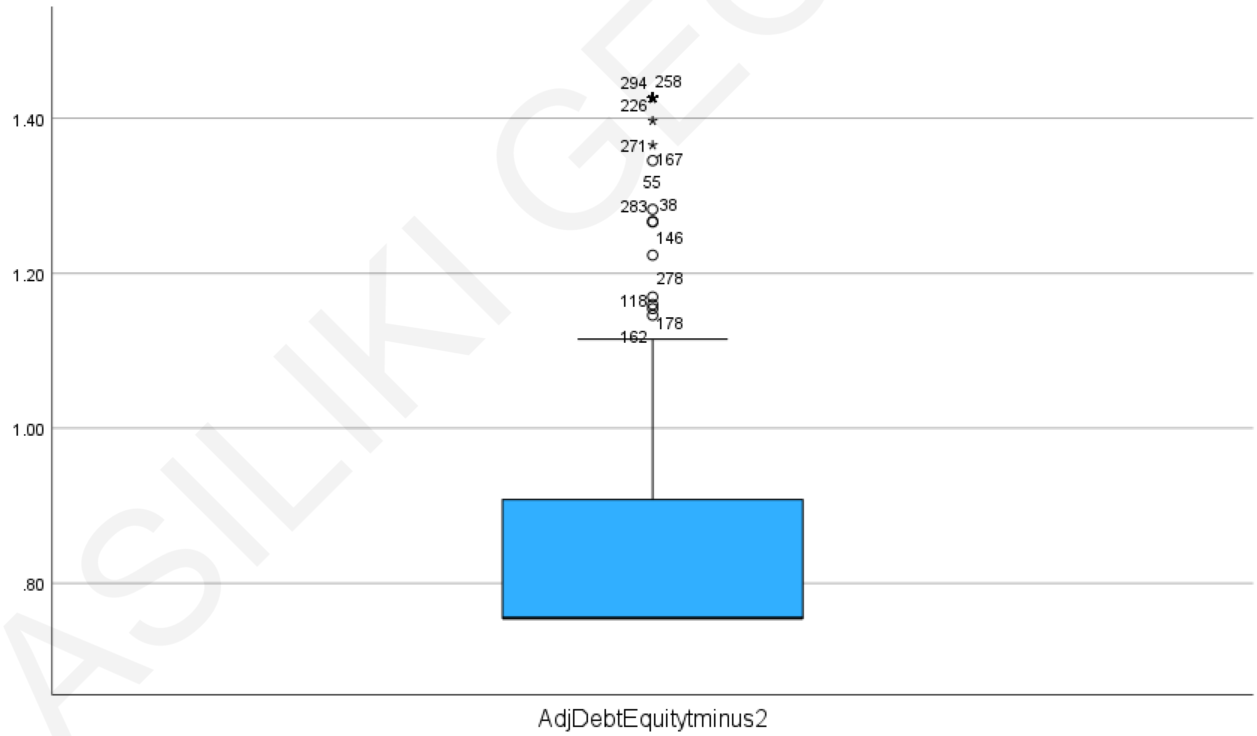
Appendix 2




5.00
4.00
3.00
2.00
1.00
.00
AdjMarkettoBook1


3.00
2.50
2.00
1.50
1.00
.50
64
257
214
258
23
93
206
195
213
160
44
18
27
226
AdjDebtEquityt


1.30
1.20
1.10
1.00
.90
.80
.70
AdjDebtEquitytminus1


294
258
226
271
167
55
283
38
146
278
118
178
162
1.40
1.20
1.00
.80
AdjDebtEquitytminus2

APPENDIX 2 – STATISTICS OF THE FULL MODEL

Classification Table[a]

Observed	Predicted 0	Predicted 1	% Correct
0	98	52	65.3
1	54	96	64.0
Overall Percentage			64.7

a. The cut value is .500

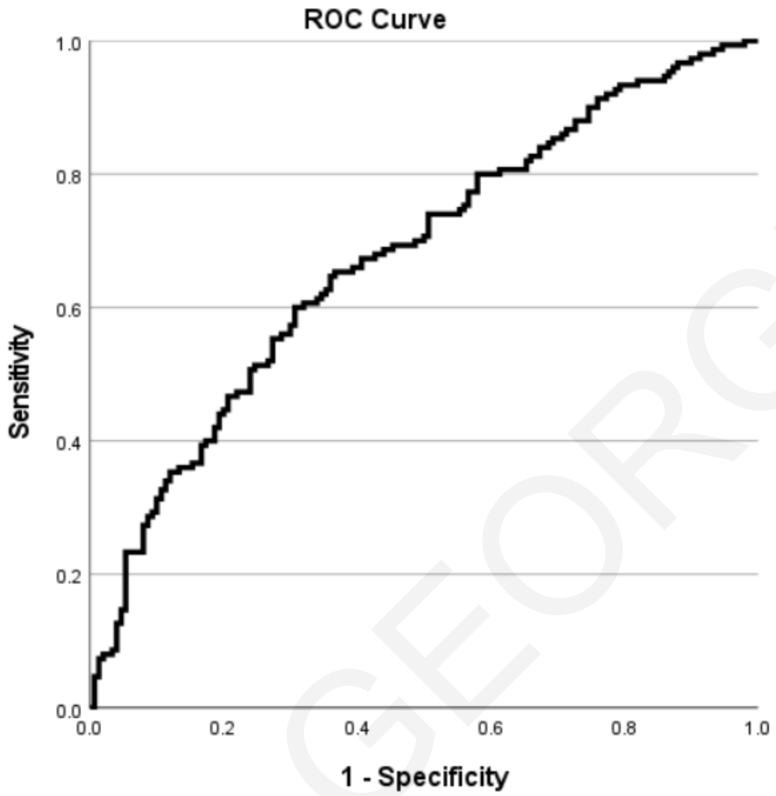
Model Summary

-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
378.297[a]	0.118	0.157

Hosmer and Lemeshow Test

Chi-square	df	Sig.
2.035	8	0.980

APPENDIX 3 – STATISTICS OF THE FINAL MODEL



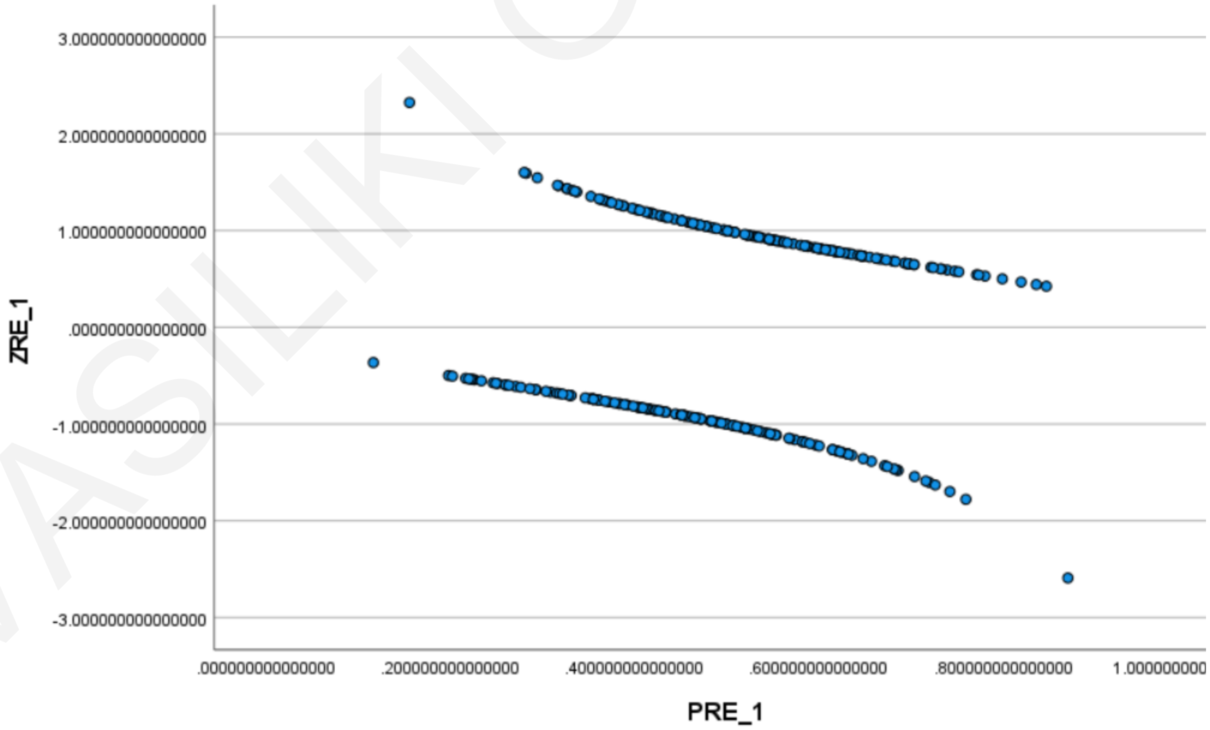
Model Summary		
-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
388.939[a]	0.086	0.115

Hosmer and Lemeshow Test		
Chi-square	df	Sig.
6.912	8	0.546

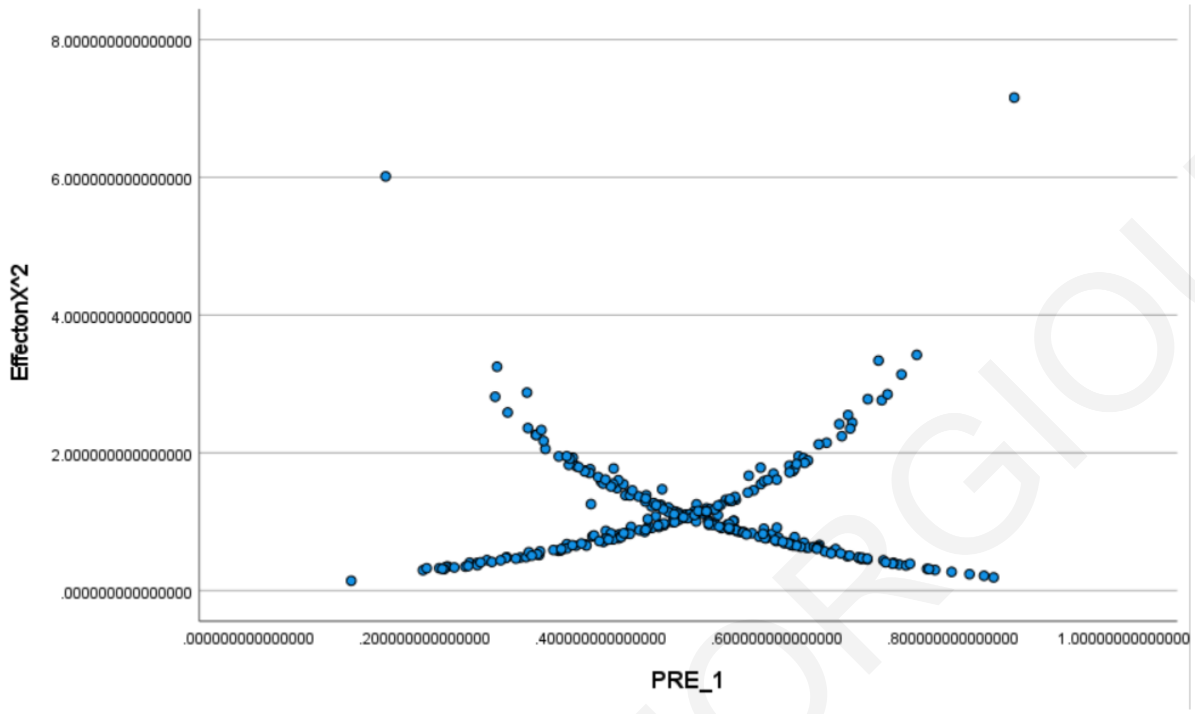
Observed		Predicted		
		Fraud		Percentage Correct
		0	1	
Fraud	0	99	51	66.0
	1	59	91	60.7
Overall Percentage				63.3

Cut off value 50%

Pearson Residuals for Fraud data

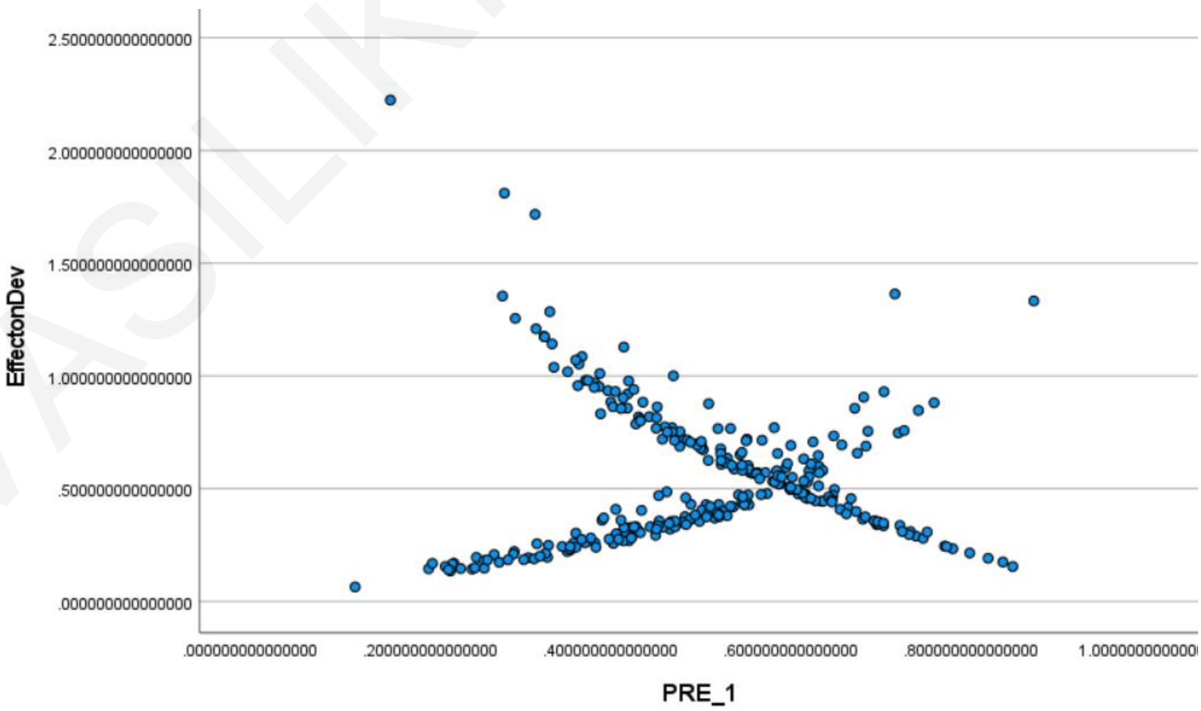


Effect on x2 data



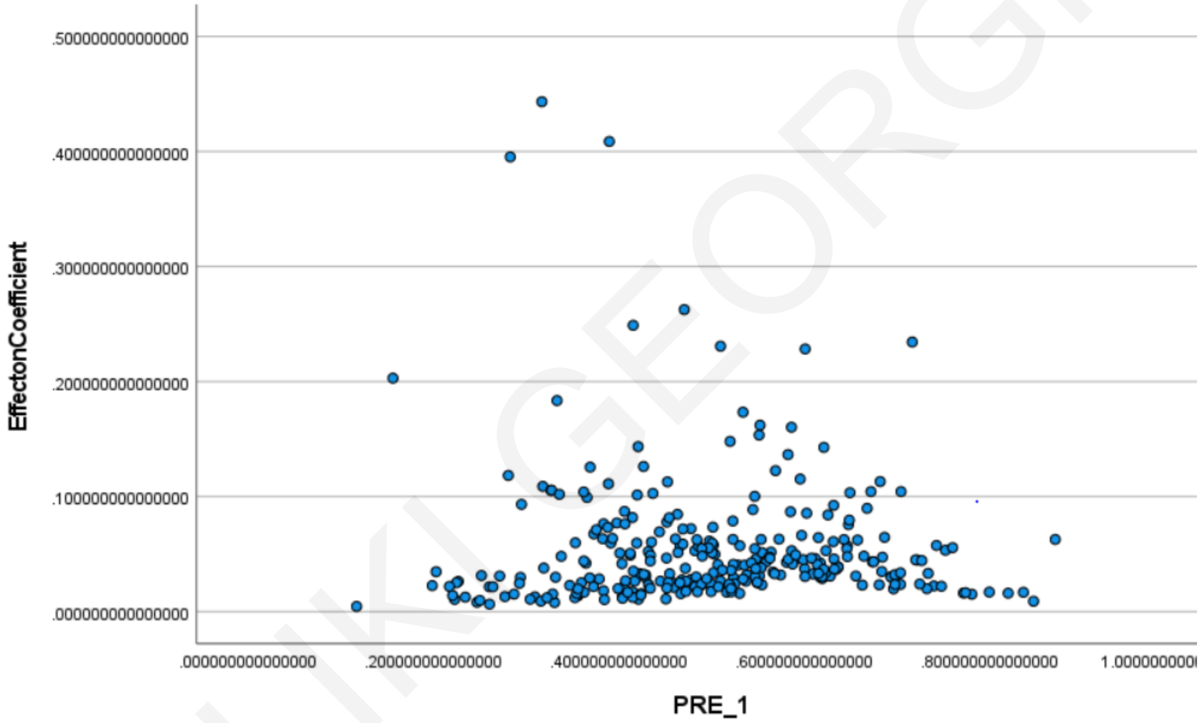
- **As expected, y=1 is expected to be decreasing and y=0 to be increasing**
- **Investigate more the two values which are above 4.**

Effect on Deviance



- Expect to be small for predicted probabilities <0.1 and >0.9, large for 0.1-0.3 or 0.7-0.9 and moderate in the center
- All the values are below 1 which means that there is no need to remove any value

Effect on coefficient



- Expect to be small for predicted probabilities <0.1 and >0.9, large for 0.1-0.3 or 0.7-0.9 and moderate in the center
- All the values are below 1 which means that there is no need to remove any value

APPENDIX 4 – DEFINITION OF VARIABLES

Variables	Definition of Variables
Fraud	1 if the firm is involved in fraud(violated rule 10b) and 0 for control firms
Institutional Ownership t-1	percentage of shares owened by pension funds, investment companies and insurance companies
Duality	1 if the CEO is also chairman of the board and 0 otherwise
Log_assets t-1	logarithm of assets of the firm
Interest Coverage t-1	Company's earnings before interest and taxes (EBIT) / interest expense during a given period.
Market to Book t-1	Closing price of the stock at t-1 / Book value per share at t-1
Debt to Equity t	Total Liabilities / Shareholders Equity at t
Debt to Equity t-1	Total Liabilities / Shareholders Equity at t-1
Debt to Equity t-2	Total Liabilities / Shareholders Equity at t-2
Change in Debt to Equity t vs t-1	Change between Total Liabilities / Shareholders Equity at t vs Total Liabilities / Shareholders Equity at t-1
Change in Debt to Equity t vs t-2	Change between Total Liabilities / Shareholders Equity at t vs Total Liabilities / Shareholders Equity at t-2
Change in Debt to Equity t-1 vs t-2	Change between Total Liabilities / Shareholders Equity at t-1 vs Total Liabilities / Shareholders Equity at t-2
ROA t-1	Net Income/Average Assets at t-1