Analysts' Coverage Allocation Decisions

and

Corporate Bankruptcy Prediction.

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Abstract

This study examines different methods used for bankruptcy prediction purposes. Results provide evidence on inconsistencies in financial ratios evaluation of corporate performance and low accuracy of bankruptcy forecasting using financial predictive models. Meanwhile, a positive and significant relation is captured between analysts' tendency to drop coverage and companies' propensity for bankruptcy filing. These findings suggest that the number of analysts covering a particular stock might be a better proxy for corporate failure prediction. In general, all three methods studied show similar patterns during the last years of the companies' life and are able to predict corporate bankruptcy with different levels of accuracy.

Contents

1. Introduction

This master thesis provides evidence on bankruptcy prediction using several techniques. The main purpose of this thesis is to provide evidence on effectiveness of financial analysis and financial predictive models to forecast bankruptcy and to evaluate whether number of analysts following the stock is a better proxy for bankruptcy prediction.

First, common methods of financial failure prediction, such as financial analysis and financial predictive models, were studied to evaluate ability of financial statement data to timely signal about corporate failure. Especially, the thesis attempts to answer the following question:

RQ1: To what level do ratio analysis and financial predictive models signal of financial failure before the corporate bankruptcy filing?

An answer to this research question is important to evaluate whether financial statements provide accurate, complete and timely information about underlying business to their stakeholders to timely assess distress of the underlying business. Results might be of interest to a wide range of stakeholders, one of which is Financial Accounting Standards Board (FASB), which was established for setting up financial accounting and reporting standards for companies that follow Generally Accepted Accounting Principles (GAAP), and the other one, namely U.S. Securities and Exchange Commission (SEC), whose main mission is "to protect investors, maintain fair, orderly, and efficient markets, and facilitate capital formation" (U.S. Securities and Exchange Commission). Till now both of the organizations implemented dozens of standards to improve quality of financial statements and achieve effective information spread between market participants.

Secondly, this thesis examines analysts coverage allocation behaviour, especially analysts' decisions to cease the coverage of a particular stock. The main focus is based on corporate failure prediction by tracking the number of analysts covering a particular stock. Especially, the thesis attempts to answer the following question:

RQ2: Can analysts' decisions to cease coverage signal of potential company's financial failure?

Answer to this question would be of high interest for investors as they demand information, which could help them in assessing company's financial strength, to come up with further investment decision.

During the last decade a considerable amount of research examined financial corporate failures, as they can cause substantial losses both to creditors and stockholders. Therefore, a lot of emphasis was put on factors that can predict corporate bankruptcy as early as possible. A lot of research is focused on financial accounting data as a main source of information that could provide ample warning for the stakeholders about corporate distress (Beaver, 1966; Altman, 1968; Ohlson, 1980). However, different points of view are present in the existing literature. While one array of the studies suggests that financial statements are valuable sources of information for investors, especially in revealing poorly performing companies and assessing chances for their bankruptcy filing (Beaver, 1966; Altman, 1968; Beaver et al., 2005), the other highlights that predictive ability of accounting data has deteriorated over more recent periods (Menon, 1987; Hopwood et al., 1989; Chen, 1992; Brennan & Tamarowski, 2000; Ball & Shivakumar, 2008). Thus, there is no obvious consensus on the accuracy of financial analysis and predictive models in corporate strength assessment.

Meanwhile, a wide stream of previous research highlights superiority of analysts' reports in bankruptcy prediction (Fried & Givoly, 1982; Moses, 1990; Jegadeesh, 2004). Several studies examined performance and behavior of sell-side analysts and found bias in analysts' coverage allocation behavior (McNichols & O'Brien, 1997). Great concern is expressed in the prior studies on analysts' self-selection of which companies to cover and what information to release due to pressure from firms they work for and arose incentives. Now, there is a gap in the existing literature as no previous research examined benefits of tracking analysts' coverage decisions.

The main sample used to examine the questions stated above in this thesis includes 97 U.S. bankruptcies sampled over the period 2000–2015. Data on each company covers the period of four fiscal years before the bankruptcy filing. For each of the companies, a set of the selected financial ratios is studied for each of the four years preceding the bankruptcy. Next, for each of the examined years financial predictive models, namely Altman Z-score model (1968) and Zmijewski probability model (1984) are built to evaluate corporate strength. To examine analysts' coverage allocation behavior data on the number of analysts on quarterly basis is retrieved for 12 quarters preceding the bankruptcy filing. The main sample is tested to assess the predicted decline in the number of analysts covering particular stock. Also, a control sample of 620367 firm-quarter observations, where 523503 and 96864 are quarterly observations for healthy and subsequent bankrupt companies accordingly, is used to control for time- and industry-fixed effects.

The remainder of the thesis is structured as followed. Section 2 provides literature review and Section 3 discusses hypothesis development. Research design, methodology and variable measurement are discussed in Section 4. Section 5 describes the data and summarizes the empirical findings. Section 6 concludes.

2. Literature Review

Investors face substantial problems when searching for a stock to buy. There are thousands of common stocks in the financial market directly available for purchase. So investors demand information, which could help them in assessing a company's financial strength, to come up with further investment decisions. The biggest issue for investors is revealing poorly performing companies, as it is not particularly profitable to invest in bankrupt companies (Clarke et al., 2006). There are many different ways to assess the financial strength of a company and predict bankruptcy timely. In the extreme, all information available in the market would be fully and immediately reflected in the security prices upon the release. This is a widely debated topic and still no consensus is reached regarding the market efficiency question. However, a wide array of studies discusses the doubt of market inefficiency with focus on the global financial crisis of 2008 when the market failed to capture distress of the economy in whole (Cooper, 2008; Ball, 2009). Given the questionable efficiency of markets, investors can not fully rely on market prices as a determinant of company's real performance. In general, information on the financial strength of a company can be derived in three key ways: by performing financial analysis, by implementing financial statistical models and from analysts' reports.

2.1. Financial Analysis for Bankruptcy Prediction

Back in the late 19th century, the accounting evolution in U.S. financial ratio analysis was developed. The ratios were originally developed for analyzing accounting statements (Horrigan, 1965). Ratio analysis, together with cash flow analysis, represents a financial analysis and is based on the information contained in the financial statements of the company (Palepu, Healy, & Peek, 2013). Horrigan (1965) examines 17 ratios that are based on numbers derived from the financial statements and highlights that generally, financial ratios are correlated with each other. This means that even a small number of ratios can capture most of the information that the ratios can provide in total. In the ratio analysis, ratios of the firms are compared over several years (a time-series comparison), with ratios of the other firms in the same industry (cross-sectional analysis) and with some absolute benchmarks (Palepuet al., 2013). While financial ratios were firstly used to assess corporate strengths, they can also be used as corporate bankruptcy predictors (Green, 1978). Beaver (1966) confirms that accounting data can be considered in terms of predictive ability. Commonly, the biggest emphasis is put on the ratios, which capture leverage, liquidity, activity and profitability of the business. Green (1978) provides an overview of studies, which support that financial ratio analysis provides valuable information and can be used for monitoring corporate health. Chen & Shimerda (1981) demonstrated the usefulness of financial ratios in evaluating financial performance of a company. Gardiner (1995) states that ratio analysis is the most powerful financial tool in assessing financial strength of a firm. A more recent study of Alireza et al. (2012) shows considerable evidence on financial ratios predictability of corporate financial crisis. While testing a group of 44 bankrupt and 56 non-bankrupt companies between 2003-2007, the authors came up with results that financial ratios are able to predict corporate financial crisis up to three years before the financial bankruptcy.

2.2. Bankruptcy Prediction Models

Number of studies suggested benefits of evaluating companies using the whole set of information contained in the financial statements, rather than specific ratios

(Beaver, 1966). Several studies were conducted to develop statistical models, which could assess the performance of a firm by simultaneously examining a set of proxies derived from the financial statements. Different statistical techniques were used to build models, which included a set of financial ratios. The most common models developed are the multivariate statistical model using discriminant analysis (Altman, 1968), logistic regression (Ohlson, 1980), the probit model (Zmijewski, 1984) and the hazard analysis model (Shumway, 2001; Hillegeist et al., 2004; Chava and Jarrow, 2004).

However, mixed results are provided on accuracy and timeliness of these models (Francis & Schipper, 1999; Beaver et al., 2005). Moses (1990) argues the drawback of using accounting information. One of the arguments provided is that accounting data is released periodically and reflects historical information. It is sensitive to implemented accounting choices, which might differ among companies and industries. Moreover, accounting information fails to provide stakeholders with a fair view of future prospects of the company and the total industry dynamics. Francis & Schipper (1999) highlight that the explanatory power of earnings levels and changes for returns dropped over time. Beaver et al. (2005) document a slight decline in the predictive power of the financial ratios over time. This is mainly attributable to the increased discretion in the financial statements. Increased discretion deteriorates the quality of the financial statements by decreasing their comparability and interpretation, making it easier for management to mislead the stakeholders. This creates needs of market participants to aid in adjusting for discretion in financial reporting (Beaver et al., 2005).

2.3. Complexity of stock analysis

An analysis of the financial position of a particular company requires time and effort. Mostly, investors lack time to thoroughly evaluate each of the stocks available in the market (Barber & Odean, 2007). While some investors trade based on superior analysis of available public information, there are still insufficiently informed investors, who add noise to the market increasing volatility of the stock prices. Odean (1998) and Barber & Odean (2007) provide evidence that individual investors are prone to buy stocks, which catch their attention first. These might be stocks discussed in the media or stock with abnormal trading volume (Barber & Odean, 2007).

However, the abnormal trading volume might not always be an evidence for the superior performance of the stocks. Some investors who can not fully evaluate the stocks sometimes rely on the behaviour of the other investors. With development of online-brokerage, some platforms provide investors with an opportunity to see how others are investing. Thus, insufficiently informed investors can just copy the actions of the other investors. One example of such a platform is GetStocks[1], which is a licensed online brokerage. It allows investors to buy and sell stocks worldwide. However, copying actions of the other investors may add noise to the stock market by increasing trade volumes of a particular stock. High trade on a particular stock will increase its price, which sometimes may cause its overvaluation. Thus uninformed investors will buy high and sell low and lose more money relative to rational investors (De Long et al., 1987). To avoid losses some investors prefer to use analysts' reports on which to base their investment decisions. The two major types of financial analysts are buy-side and sell-side analysts. While buy-side investors work for investment firms and their reports are available only within the firm they work for, sell-side analysts mainly work for brokerage houses and their reports are used to sell shares to the clients of the brokerage firm. Clients of the brokerage firm can be both managers of investment funds, and individual investors (Palepu et al., 2013).

2.4. Sell-side analysts' reports

The role of analysts as information producers has been examined extensively over the last decades. A wide range of prior literature suggests that information from analysts' forecasts and recommendations is widely used and recognized as beneficial by investors in making decisions on investment into a particular company (Fried and Givoly, 1982; Moses, 1990; Schipper, 1991; Jegadeesh et al., 2004). Givoly and Lakonishok (1979) highlight that financial analysts' reports have information content. Fried & Givoly (1982) further examine this topic, specifying that analysts' reports are more accurate predictors for companies' future performance than forecasts based on past time-series of earnings. Das et al. (1998) and Brown et al. (1987) came up with similar results, noting that predictive accuracy of past information is low. Moreover, Das et al. (1998) argue that for companies whose financial situation is difficult to

[1] https://www.getstocks.com

predict accurately there is a higher demand for analysts' reports. The idea behind that is that investors expect analysts to be able to gain access to non-public information which might be beneficial for companies' future performance forecasting. Analysts are considered an important link in capital market as they influence the informational efficiency, namely reduce information asymmetry between companies and their stakeholders (Elgers et al., 2001). Concerns about asymmetric spread of information among investors add to the demand for comprehensive analysts' analysis (Merton, 1987). Prior research provides evidence that there is a positive effect of analysts' coverage on the speed with which prices reflect public information (Elgers et al., 2001).

Investors consider analysts' reports accurate and truly reflecting market returns and risk as they are based on a wide range of information (Moses, 1990; Jegadeesh et al., 2004). Number of studies provide evidence that analysts' earnings forecasts are considered the most important information for investors (Chang & Most, 1980). Investors use analysts's forecasts to capitalize on the profit opportunity. Especially, while being insufficiently informed, investors add noise to the market increasing volatility of the stock prices, which, in turn, creates opportunity for informed investors to earn more profit (Frankel et al., 2006).

Another stream of the literature examines particular circumstances in which analysts' reports are of the most interest for the stakeholders. Lehavy et al. (2011) find that investors place greater reliance on the analyst reports issued for firms with less readable annual reports. Moreover, authors highlight the positive and significant association between readability of the company's annual report and the number of analysts following the company. Frankel et al. (2006) document a positive relation between informativeness of the analyst reports and potential brokerage profits, such as high trading volume, high volatility, and high institutional ownership. Furthermore, authors provide evidence that the informativeness of analyst research and the informativeness of financial statements are complementary.

However, there is mixed evidence on whether analysts' reports on poorly performing companies could be beneficial for investors (Moses, 1990). On one hand, analysts' reports are forward looking, and reflect a wide array of information. The main benefit is that analysts provide revised reports in a timely manner. On the other hand, forecast errors tend to be larger for failing firms as bankruptcy approached (Moses, 1990; McNichols & O'Brien, 1997). One of the possible explanations is that forecast errors are related to uncertainty. As a company falls into financial distress, uncertainty about the future of the company becomes higher. Low accuracy of the analyst reports may be attributable to the fact that failing firms may withhold announcing bad news. Thus, as analysts have high dependence on the information issued by management of the company regarding its financial situation, analysts may lack information on which to base their report. In the circumstances where analysts are unable to obtain pervasive information that fully reflects the condition of the underlying business, reports might be more biased (Moses, 1990).

2.4.1. Analyst report bias

In recent years, stakeholders raised more concerns regarding possible overoptimistic bias of analyst reports with incentive to maintain investment banking ties between analysts' employers and the companies that they follow (McNichols et al., 2006). Jegadeesh et al. (2004) provide evidence that bias in the analyst recommendations have relation with economic incentives faced by sell-side analysts. Number of researchers examined perceived quality of reports issued by analysts who are employed by the lead bank underwriting seasoned equity offerings and by the co-underwriter bank (affiliated analysts). Taking into account that underwriting business requires substantial investments to liaise relations with issuing companies, Lin & McNichols (1998, p.102) argue that investment bankers do not endorse negative reports by analysts who work for the research department. Several studies find that analysts whose employers serve as lead or co-underwriter of an equity offering tend to positively bias their forecasts and issue more favourable recommendations for the company (Dugar and Nathan, 1995; Lin and McNichols, 1998; Michaely and Womack, 1999; Dechow et al., 2000). Lin & McNichols (1998) further investigated this topic, comparing quality of the affiliated analysts' reports with the quality of reports made by analysts at investment banks that have not served as a lead or co-underwriter for the firm (unaffiliated analysts). The authors provide evidence that affiliated analysts' forecasts and recommendations are significantly more favourable than those made by unaffiliated analysts.

Das et al. (1998) examine whether analysts' strategic behaviour is affected by the presence of alternative thorough forecasts. Authors provide evidence that if market participants can form relatively accurate expectations independent of analysts' forecasts, analysts tend to issue more accurate forecasts, which are biased to a lesser extent. These results suggest that the market situation could affect analysts' strategic behavior. While analysts' reports are viewed as a more reliable source of information in comparison with forecasts based on past information, some authors argue prevalence of forecast optimism (Klein, 1990; Butler & Lang 1991). Klein (1990) reports that analysts remain overly optimistic, particularly for firms reporting recent losses. The results support scenario-induced optimism that affects analysts decision towards issuance more optimistic forecasts. More recent study of Clarke et al. (2006) in this issue provides contradicting evidence, suggesting that there are no overoptimistic biases in analyst recommendations. Their research sample consists of analyst recommendations for firms that file for bankruptcy during 1995–2001. O'Brien (1988) examines analysts forecasts' accuracy and finds that in general analysts prefer optimistic predictions and positive recommendations. Even some authors refer this fact to analysts' incentive to maintain good relations with management, O'Brien rebuts this hypothesis, highlighting that the median analyst forecast appears to be unbiased and statistically indistinguishable from forecasts based on time-series of earnings, for which management relations motives can not be attributable.

McNichols & O'Brien (1997) suggest that accuracy of analysts' report mainly depends on their true views of covered stock's future performance. Analysts put less effort in gathering information and preparing reports for companies with unfavourable future prospects. This idea is supported by evidence that there is a lower frequency of analyst reports for stocks prior to coverage abandonment. Study of Rao et al. (2001) further examines choices of securities analysts to initiate and abandon coverage of firms. Authors provide evidence on analysts to begin covering stock looking to the actions of the other analysts. However, mostly analysts are prone to overestimate the future of these companies and subsequently abandon coverage in the wake of disappointment.

2.4.2. Analysts Coverage Allocation Behaviour

By studying analysts' coverage allocation decisions, this thesis relates to prior research examining the performance of companies, which are followed by analysts. Prior studies suggest that analysts prefer not to release reports on companies whose future prospects they view as unfavourable (McNichols & O'Brien, 1997; Baik, 2006). McNichols & O'Brien (1997) highlight that there is a relationship between analyst coverage decisions and fundamental information about the stocks. In the study, the authors find that analysts tend to add stocks whose future prospects they view most favourable. Moreover the study highlights that analysts preferably cease coverage of the stocks with lower ratings than those whose coverage continues. This conclusion is based on the evidence that "realized performance, as reflected in subsequent return on equity, is significantly more favourable for stocks that analysts add than for stocks that analysts have covered in the past, or for stocks that analysts subsequently drop" (p.169). The earlier literature provides supporting evidence indicating that there is a lower number of forecasts for poorly performing companies in contrast to healthy companies (Moses, 1990). Tendency of analyst to follow stocks with specific characteristics that predict future returns was further studied by Jegadeesh et al. (2004). They came up with results indicating that the majority of the firms preferred to be followed by analysts are growing firms with high trading volume and positive accruals. O'Brien & Bhushan (1990) highlight that analysts prefer firms whose return volatility has declined over time. Das et al. (2006) suggest that analysts provide greater coverage to initial public offering firms with superior prospects. Especially, authors conclude that analysts have better predictive ability of companies' future performance and self-select to follow companies for which they hold favourable views. These results were further supported by tests examining long-run operating performance. More recent study of Lee & So (2016) examines the implications of analysts' coverage incentives and does not focus on specific contexts, such as an initial public offering. Study is based on a sample of 1,661,511 firm-months spread during 33-year period from 1982 through 2014. The study compliments main results of McNichols & O'Brien (1997) providing evidence that analysts' coverage decisions have strong predictive power for firms' expected returns. Results of the study of Lee & So (2016) suggest that analysts self-select to follow firms with better operating performance.

Peixinho & Taffler (2011) also studied the presumption that analysts possess the ability to predict the future performance of the company. Authors examined security analysts' behavior on covering companies for which a going-concern modified audit report was issued. The sample consisted of 924 non-finance, non-utility, industry firm-year observations for which going-concern modified audit reports were published for the first-time between 1994 and 2005. The authors came up with evidence that analysts show tendency to cease coverage of companies over the one-year period before the going-concern issue of the underlying company is publicly announced through the audit report. First, these results are in line with the theory that analysts are likely to avoid issuing negative recommendations, such as "underperform" or "sell", which investors interpret as unfavorable (McNichols & O'Brien, 1997; Baik, 2006; Peixinho & Taffler, 2011). Second, this evidence supports that analysts are able to anticipate future difficulties regarding the viability of a company (Peixinho & Taffler, 2011).

Given the incentives of analysts to allocate coverage, the relative speed with which good versus bad news is reflected in prices may be influenced, as the allocation of investors' coverage will affect information asymmetry (Lee & So, 2016). Thus, it is possible to hypothesize that bad news travels slowly (Lee & So, 2016).

3. Hypotheses Development

Even trading in a bankrupt firm's securities is common, as investors tend to have unreasonably high expectations about companies' future prospects, no abnormal returns appear to be available (Morse and Shaw, 1988). It is commonly justified that investments in bankrupt companies are irrational, as they will yield poor returns (Hubbard & Stephenson, 1997).

First, it is highly important to define what corporate financial failure means. In the existing literature, definitions of bankruptcy, financial failure and financial distress are generally used interchangeably. Best-known bankruptcy prediction studies defined business failure as the act of filing for bankruptcy (Altman, 1968; Ohlson, 1980; Zmijewski, 1984). More recent studies on corporate financial failure focus both on the firms that filed for bankruptcy and companies that have been liquidated (Chava & Jarrow, 2004; Boritz et al., 2007). Generally, the difference between liquidation and bankruptcy is in voluntary nature of liquidation, and forced ground for bankruptcy filing. Corbae & D'Erasmo (2014) in their study consider both of the bankruptcy variants, namely: Chapter 7 and Chapter 11 of the U.S. Bankruptcy Code. Chapter 7 and Chapter 11, according to the US law, are the two options available for companies to file for bankruptcy. First, when firm files a petition for reorganization bankruptcy under Chapter 11, bankruptcy law provides the firm with an opportunity to reorganize its debt under supervision of a trustee. So the company continues to operate with newly structured debt (United States Courts, a). Second, if a company files for bankruptcy under Chapter 7, it repays debts to the absolute priority with the money collected from liquidation of corporate assets. Under the absolute priority rule creditors are repaid first before shareholders. A trustee is appointed to supervise the process of creditors repayment (United States Courts, b).

The ability to correctly evaluate the financial position of a business is very important. While many organizations may appear successful in first sight, they can experience deep structural problems and bear hidden financial problems within the organization.

3.1. Theoretical Basis of the Traditional Ratio Analysis

In financial accounting literature, a lot of emphasis is made on financial analysis of a company for making forecasts of corporate future performance. Financial analysis itself is a process of selecting, evaluating, and interpreting financial data in order to assess a firm's present financial condition and to make a forecast of future financial performance (Palepu et al., 2013). Still, in the existing literature no consensus is reached as to which ratios are most useful, especially for corporate failure prediction (Barnes, 1987). Generally, in financial analysis the most significant indicators of corporate financial performance are ratios measuring profitability, liquidity, and solvency. The most widely used ratios in financial analysis are profitability ratios, which reflect how capable the company is managed. More specifically, profitability ratios capture the company's ability to earn an adequate return. Next, liquidity ratios measure a firm's ability to meet its short-term obligations. Meanwhile, solvency ratios reflect whether the company's cash flow is sufficient to meet its longer-term financial commitments. Traditionally, firm's ratios are compared with a standard benchmark for predictive purposes. DuPont Corporation suggested one methodology or ratio analysis for performance measurement in the early 1920s. This analysis involved measures of profitability ratio, which captures companies operating efficiency; activity ratio, which reflects efficiency of assets use; and financial leverage. The main purpose of the measurement is to assess company's ability to generate value for its shareholders. Several studies provide conclusive evidence, indicating that ratio analysis can be useful in the prediction of failure for five years prior to failure (Beaver, 1966). Although recent studies came up with apparently contradictory evidence on predictive ability of ratios, that are based on financial statement data (Francis & Schipper, 1999; Beaver et al., 2005). Taking into account the fact that financial ratio analysis is still widely implemented in evaluation of corporate performance, I hypothesize, that:

H1: Financial ratios predict corporate financial failure before the firm files for bankruptcy

3.2. Theoretical Evaluation of the Bankruptcy Prediction Models

Altman (2000) states that ratio analysis presented in this traditional way could be potentially confusing due to difficulties in interpretations. Altman (2000) highlights that if a company experiences profitability and/or solvency difficulties, this might be offset by firm's above average liquidity. In this case, even outcome of the solvency and profitability ratios signals potential bankruptcy, the situation may not be considered serious. Thus, interpretation of the ratios separately may cause misleading conclusions about the corporate financial performance (Altman, 1968; Altman 2000).

In the financial theory, number of predictive financial models were developed in order to timely predict financial distress of a company. The primary focus of these models is on the underlying predictive ability of the financial statements themselves, rather than specific ratios (Beaver, 1966). These models represent financial ratio analysis used for detection of company's operating and financial difficulties, while the ratios are examined in aggregate. The ratios used are calculated based on the information contained in financial reports of the company. The predictive models mainly focus on three factors: profitability, cash flow generation, and leverage (Beaver et al., 2005). Several statistical techniques were used to build the models.

Altman (1968) presented benefits of the multivariate discriminant analysis (MDA) approach for investigating corporate performance. This approach is based on simultaneous examination of a set of financial ratios - multivariate statistical model. Discriminant function is of the form:

$$Z=\sum_{i=1}^{n} ViXi = V_1X_1 + V_2X_2 + ... + V_nX_n, \qquad \text{Eq.(1)}$$

where the individual variable is transformed into a single discriminant score or Z value, which is then used to classify an object where V_1, V_2 ... V_n are discriminant coefficients and X_1, X_2 ... X_n are independent variables.

The sample used in the study of Altman (1968) consists of 33 U.S. manufacturing firms, which filed for bankruptcy between 1946 and 1965, and 33 non-bankrupt firms. Altman (1968) tested a list of 22 variables (ratios) for evaluation. The variables reflect liquidity, profitability, leverage, solvency, and activity. The final model includes five ratios that all together perform the best in the prediction of corporate bankruptcy. First variable represents liquidity (WC/TA), and provides insight to the liquidity of the company, representing the percentage of remaining liquid assets relative to the total capitalization. Second variable, RE/TA, measures profitability over time as a proportion of total assets. In addition, the RE/TA ratio measures the leverage of a firm. Companies with value of the ratio greater than 1 have financed their assets through retention of profits and do not rely heavily on debt. The third ratio, EBIT/TA, measures true productivity of the firm's assets. Fourth ratio, MKVALT/TL, reflects how much the firm's assets can decline in value before the liabilities surpass the assets, which indicates company's insolvency. The fifth independent variable is capital-turnover ratio, which is calculated as S/TA, and is a standard financial ratio reflecting ability to generate sales of the firm's assets. The final model is:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.999X_5 \,, \qquad \text{Eq. (2)}$$

where X_1 = *Working Capital/Total Assets*

X_2 = *Retained Earnings/Total Assets*

X_3 = *Earnings Before Interest & Tax/Total Assets*

X_4 = *Market Value of Equity/Total Liabilities*

X_5 = *Sales/Total Assets*

Z = *Overall Index*

Firms with a Z-score value ≥ 2.99 are considered healthy and are in "the safe zone"; firms with a Z-score between 1.81 and 2.99 are in "grey area", thus, undefined; and companies with a Z-score lower than 1.81 are in financial distress and are predicted to go bankrupt. The main idea of the model is that this combined application of ratios will result in more statistically significant outcomes, than sequential ratio comparisons. Nevertheless, in a more recent study Wu et al. (2010) authors tested the model of Altman (1968) using a sample of U.S. listed firms during the period from 1980 to 2006. One of the conclusions was that the "MDA model of Altman (1968) performs poorly relative to other models in the literature" (p.10).

Another statistical method was used by Zmijewski (1984) to capture the financial distress of a company. Zmijewski built a probit model based on a sample of 40 bankrupt and 800 non-bankrupt industrial firms from the 1972 to 1978 time period. The outcome of the probit model maps the value to a probability bounded between 0 and 1. Thus, in comparison with the MDA model, the probit model's output is easy to interpret. The final model of Zijewski includes 3 independent variables:

$$X = -4.3 - 4.5X_1 + 5.7X_2 + O.OO4X_3 \ , \qquad \text{Eq.(3)}$$

where *X_1= Net Income/Total Assets,*
X_2= Total Debt/Total Assets,
X_3=Current Assets/Current Liabilities,
X = Overall Index.

Score is used to find a bankruptcy probability applying a logistic regression formula, in this case:

$$P = P\ (X_0 = 1) = \frac{1}{(1+\exp(-X))} \qquad \text{Eq.(4)}$$

The P score determines the probability of a company's belonging to the bankrupt group based on a cumulative normal probability function. Companies with P>=0.5 are defined as bankrupt, and with P<0.5 as non-bankrupt.

The first ratio (X_1) used in the model captures firms' return on assets (ROA), which shows how efficiently a company can manage its assets to produce profits during a period, and gives an indication of the capital intensity of the company (Palepu, Healy, & Peek, 2013). It is the key profitability ratio, which helps stakeholders see how well the company can convert its investments in assets into profits. The second ratio (X_2) reflects company's financial leverage. Financial leverage indicates the reliability of a business on its debts in order to operate. If the company is highly leveraged it is considered to be in risk of failure. The third independent variable (X_3) is a measure of liquidity, which reflects firm's ability to repay its current liabilities.

Meanwhile, in study of Wu et al. (2010) authors highlight that accounting-based model of Zmijewski (1984) performs adequately during the 1970 but their performance has deteriorated over more recent periods (p.10). However, the other stream of literature argues that traditional financial reports are unable to adequately reflect underlying business systems because there are strategies, plans, commitments, personnel policies, competitive threats, and managerial succession problems that affects companies performance but could not be directly reflected in the corporate reports (Brennan & Tamarowski, 2000). Moreover, Ball & Shivakumar (2008) highlight that accounting reports are primarily backward looking and of low frequency, which undermines their ability to serve as a timely source of information. Theory suggests that existing factors used to predict companies' movement towards bankruptcy most of the time fail to timely assess going-concern issues of underlying business (Menon, 1987; Hopwood et al., 1989; Chen, 1992; Brennan & Tamarowski, 2000). So, as there are deficiencies in these models, I hypothesize that:

H2: Bankruptcy predictive models lack accuracy in forecasting eventual corporate financial failure before the company files for bankruptcy.

3.3. Trace of the Sell-side Analysts' Performance and Behavior

When it comes to the analyst forecasts and recommendations, investors hold high expectations about the reports on poorly performing companies and await analysts to downgrade their recommendations as firm moves toward bankruptcy (Morse & Shaw, 1988; Hubbard & Stephenson, 1997). The main reason why analysts are considered to have better understanding of the company's real performance is that analysts tend to specialize and cover firms in the same industry (Hong & Kubik, 2003). Results of academic research demonstrate that analysts' forecasts are more accurate than forecasts based on the outcome of financial predictive models, which might be related with a broader information set that analysts can incorporate in their analysis (Brown & Rozeff, 1978; Collins & Hopwood, 1980; Fried & Givoly, 1982). This is primarily attributable to the analysts' access to a broad information set on trading environment, company's competitive position, risks and concerns, industry-specific information and macroeconomic events (Bradshaw, 2011; Breton & Taffler, 2001; Previs et al., 1994). Also, an analyst is viewed as valuable source of information because he/she has developed an intimate knowledge of recommended firms. Thus, based on a pervasive analysis conducted, analysts are able to draw a conclusion. Moreover, analysts have the possibility to gather firm-specific information from the firm itself to answer questions about firm performance and strategy, not contained in other public information about the firm. This information can make an analyst's reports more thorough and valuable to potential investors.

However, a large body of prior research argues that analysts are reluctant to issue unfavorable opinions due to personal incentives. On one hand, issuing a nonfavorable opinion may interfere a desire to cultivate the analyst's communication with the company, and also the analyst's ability to bring in future investment banking and trading business (Das et al., 2006) The latter incentive arises as most sell-side analysts work for brokerage houses. The primary businesses of brokerage houses are investment banking, trading and research. Analysts who work for investment banking department have interest in attracting new banking clients and promoting public issues by current clients (Palepu et al., 2013). As significant attention was focused on reducing conflicts of interest generated by the relationship between sell-side analysts and investment banking departments, changes were implemented in the institutional structure of the brokerage industry. U.S. regulators placed settlement to the ten top investment firms requiring separation of the research and investment banking departments at the firms (U.S. SEC, 2003). The primary goal was reducing conflicts of interests affecting analyst research-making process, making independent research reports available to brokerage clients (Jackson, 2005). This Global Settlement hindered opportunities for sell-side analysts to generate investment-banking business (Jackson, 2005). Furthermore, while the research department itself does not generate any direct revenue (Lin & McNichols, 1998; Michaely, 1999), trading business generates a large portion of the brokerage firms' revenues. As prior to the Global Settlement, investment banking revenues were used to fund research (Cowen et al., 2006), now sell-side analysts came under pressure to help brokerage firms to generate money (Cowen et al., 2006; Jackson, 2005) and boost trading commission income (Darlin, 1983) to maintain viability of the brokerage firm itself.

Incentives of analysts to generate brokerage commissions for their employer are important because each forecast and recommendation can be considered as a potential trade generator for the analysts' employer (Irvine, 2004). This relation reveals motives that drive brokerage analysts to tilt toward high volume stocks (O'Brien & Bhushan, 1990). Moreover, Irvine (2000) highlights that the nature and structure of analysts' compensation greatly influence their behavior, as the more close ties are present between analysts' bonuses and how much trade they generate, the more biased the forecasts and recommendations can be. The author argues that while deciding which stocks to cover and which of the obtained information to release, analysts mainly take into account potential commission revenue prospects.

To hinder analysts' incentives to maintain good relations with companies' management the U.S. Securities and Exchange Commission ("SEC") adopted Regulation Fair Disclosure ("Reg FD") that was intended to stop the communication of "material" non-public information to analysts, so all private information should be equally distributed among market participants, in October 2000 (U.S. SEC, 2000). Even this regulation reduced information asymmetry between the market participants, analysts still possess the ability to gain some privileges from the management. For example, analysts are able to arrange private conversations at investor conferences behind the scenes, or, as discrimination in conference calls is present, particular analysts can be provided more opportunities by the management to raise their questions.

On the other hand, issuing overly optimistic opinions may tarnish reputation of the analyst and lead to great career issues (Das et al., 2006). Thus, mentioned above incentives are particularly offset by analysts concerns about their reputation (Cowen et al., 2006; Jackson, 2005). Analysts' decisions to get short-term gains from issuance misleading and biased overoptimistic reports come against the long-term incentives to build a good reputation by issuing the more accurate forecasts and recommendations (Jackson, 2005). The reason is that if the analyst's recommendations later turn out to be consistently unprofitable, investors will be unlikely to continue using their recommendations for making investment decisions. While high accuracy of forecasts result in promotions and "All-Star" rankings and awards for the analyst, low accuracy may be a cause of job losses (Hilary & Hsu, 2013).

In order to avoid conflicts of interests, analysts show tendency to eschew biasing forecasts and recommendations by choosing to tilt toward stocks with particular characteristics (Das et al., 2006).

Taking into account that some companies show tendency to withhold ‘bad’ news in anticipation of improvement (Penman, 1980) the information released to the public will differ, thus the information asymmetry arises resulting in overoptimistic analyst forecasts (Moses, 1990). Due to high information asymmetry analysts’ reports for companies one year before their filling for bankruptcy are highly biased and not necessarily predict subsequent corporate failure. McNichols & O'Brien (1997) provide evidence that analysts self-select to terminate following the poorly performing companies and in the last report issued on those companies analysts usually fail to reflect negative news. This is mainly attributable to the fact that analysts have ability to upgrade their recommendations. However, if analyst receives relevant information warning for subsequent “bad news”, he/she may prefer to stop following the company and not upgrade the opinion. Thus, the last report issued will fail to reflect difficulties in the underlying business.

Given the evidence that investors highly react to a decrease in the number of analysts covering a stock (Kecskés and Womack, 2008) I hypothesize that not the accuracy of the analysts’ reports but their presence could be a better sign of subsequent corporate bankruptcy:

H3*: There is a relation between analysts’ tendency to terminate following the company and propensity for corporate bankruptcy.*

Wide array of research on bankruptcy prediction emphasizes the importance of industry effects in forecasting corporate failure (Berkovitch and Israel, 1998; Chava & Jarrow, 2004, MacKay & Phillips, 2005). This topic became more substantial with the implementation of Regulation Fair Disclosure (U.S. SEC, 2000). Hutton (2005) highlights that before Regulation Fair Disclosure managers were more prone to provide detailed guidance on the actual performance of the underlying business to analysts. This is specifically essential when financial position seems uncertain and difficult to forecast, and when intangible assets constitute a large part of the total assets. Scientific results indicate higher complexity of the information regarding intangible assets in comparison with other types of corporate assets (Lev, 2003).

Thus, the difficulty of financial statement's interpretation increases with the level of intangibles (Gu & Wang, 2005). Due to the high uncertainty in the valuation of intangible assets, analyst put greater effort to issue reports for firms with greater part of intangible assets (Barth et al., 2001). As analysts tend to avoid bias in their reports, due to reputation concerns and compensation-related incentives (Jackson, 2005; Hilary & Hsu, 2013), they might hesitate to issue reports on companies with high levels of intangibles. Because once the reports turn out to be consistently biased, stakeholders may doubt the quality of all the reports issued by the analyst (Jackson, 2005). As the level of intangibles highly depends on the industry in which the company performs, analysts may allocate their coverage and flop over the companies in the other industries with lower levels of intangible assets. Moreover because of different levels of competition and different accounting conventions in each industry, the likelihood of bankruptcy can differ for firms in different industries with otherwise identical balance sheets (Gu & Wang, 2005). Thus, I hypothesize that there is an industry effect on both analysts' coverage allocation behavior and the company's propensity for bankruptcy:

> ***H4****: There is an industry fixed-effect of on the relation between analysts' tendency to terminate following the company and propensity for corporate bankruptcy.*

4. Methodology

Under the first hypothesis in this thesis for the firms, that filed for bankruptcy in fiscal years 01/2000 – 01/2015 in the U.S., under the Chapter 7 or Chapter 11 of the U.S. bankruptcy law, financial ratio analysis is conducted. Following Altman (1968) and Zmijewski (1984) several financial ratios are selected to assess corporate financial strength. Each of the selected ratios is analyzed separately under the traditional ratio analysis technique. Ratios are selected for each of the main categories of financial analysis mentioned above in this thesis in part 3.1. The interpretation of the ratios is derived mainly from Wu et al. (2010) and Palepu et al. (2013). To measure company's ability to generate profits from its operations profitability ratios are examined. Especially, business profitability is captured by the ratio of net income to total assets, (NI/TA) which is referred to as return on assets, and the ratio of retained earnings to total assets (RE/TA). Also, ratio of earnings before interest and tax to total assets (EBIT/TA) is calculated to measure a proportion between company's profitability and assets. The ratio serves as an indicator of how effectively a company is using its assets to generate earnings before repaying contractual obligations. Moreover, sales generating ability of the firm's assets is examined by the ratio of sales to total assets (S/TA). Next, the ratios of working capital to total assets (WC/TA) and current assets to current liabilities (CA/CL), which reflect corporate liquidity, are examined. To measure corporate solvency, debt-to-assets ratio is used, which is determined as total debt divided by total assets (TD/TA). The ratio of market value of equity to total liabilities (MKVALT/TL) is another proxy of corporate solvency, which indicates how much the firm's assets can decline in value before the liabilities exceed the assets and the firm becomes insolvent (Altman, 1968). The behaviour of each of the ratios is examined for the time period of 3 years preceding bankruptcy.

To test hypothesis 2 several models developed in the financial theory are examined. First, financial strength of the sample companies is calculated using Altman Z-score model (Eq.2). At the next step I calculate companies' probability to go bankrupt using the financial model of Zmijewski (Eq.3) and find out the probability for company's bankruptcy, using Eq.4 for my sample for each year spanning the time period of 4 years preceding the bankruptcy.

Next, to test hypothesis 3, the link between analysts' coverage abandonment decisions and firms' filing for bankruptcy for the main sample is examined. First, the number of analysts issuing forecasts and recommendations for each unique firm-quarter is estimated. The notation I is used to index firms, and q to refer to the calendar quarter in which the number of analysts' following a company is estimated. In the first test one proxy for analyst coverage is examined, which is measured over the 3-year period ending the quarter company filed for bankruptcy. In total, 12 quarterly proxies for each company are examined. The dependent variable for observed analyst coverage is the number of unique earnings forecasts and/or recommendations summed across all analysts at activation date, referred to as 'number of analysts following' and denoted as NAF. The proxy is set to zero for firms without analyst coverage during observed quarter. Then, the change in the number of analysts covering particular stock (ΔNAF) is calculated as percentage of analysts who dropped coverage to the total number of analysts covering in the previous quarter:

$$\Delta NAF_i = [(NAF_{i,q} - NAF_{i, q-1})/NAF_{i,q}] , \qquad \text{Eq.(5)}$$

where q is the quarter for which NAF is calculated, and q-1 is the preceding quarter.

Further, the analysis of coverage loss of the sample companies is performed for 3-years preceding corporate bankruptcy.

To test hypothesis 4, industry-fixed effect is included in the equation, which examines the relation between corporate propensity for bankruptcy filing and the number of analysts following the company. To do this, I randomly selected a sample of quarter-company observations including both bankrupt and non-bankrupt companies spanning each industry, classified by Standard Industry Classification codes. Dummy variable *bankr* is created, which equals 1 if company subsequently went bankrupt, and 0 if it is a healthy company. Moreover, as the sample period covers 16 years and includes years of the global economic crisis (2008-2009), the relation between number of analysts covering stock and corporate bankruptcy is also controlled for any time-fixed effects.

Sample Selection

The main sample examined in this thesis includes 97 U.S. bankruptcies sampled over the period 2000–2015. Initially, the sample included 147 firm failures, but 50 firms are dropped from the sample because of a lack of recommendation and forecast data available for these companies. The sample includes biggest U.S. bankruptcies: Lehman Brothers Holdings Inc. (September, 2008; with $639 billion in pre-filing assets), Washington Mutual Inc. (September, 2008; with $327.9 billion in assets), WorldCom Inc. (July 2002; with $104 billion in assets), Enron Corp (December, 2001; with $66 billion in pre-filing assets), Thornburg Mortgage (May, 2009; with $36.5 billion in assets, Conseco Inc. (December, 2002; with $61 billion in pre-filing assets), Pacific Gas & Electric Company (April, 2001; with $36 billion in pre-filing assets).

Bankrupt firms are identified from Compustat Fundamentals Annual database, by deletion year in period from 2000 to 2015. Further, data on companies' actual bankruptcy filing dates is hand-collected from the WRDS SEC Analytics Suite in 'Filings Search', querying the report of companies in which they announced

‘Item 1.03. Bankruptcy or Receivership’ under Chapter 11 of the United States Bankruptcy Code (United States Courts), or filed petition under Chapter 7 (United States Courts).

To test hypothesis 1 financial-statement data is collected on the bankrupt companies from Compustat database using company ‘official ticker’ and controlling the sample using ‘Compustat GVKEY’. These ratios calculated based on companies’ annual report information, so I extracted data on companies’ working capital (WC), total assets (TA), retained earnings (RE), earnings before interest and taxes (EBIT), market value of equity (MKVALT), total liabilities (TL), total revenues (TE), net income (NI), current assets (CA) and current liabilities (CL) for financial predictive models calculation.

To test hypothesis 2, Altman Z-score (1968) and Zmijewski probability score (1984) are examined. All the explanatory variables needed to include in the models are calculated in the previous step.

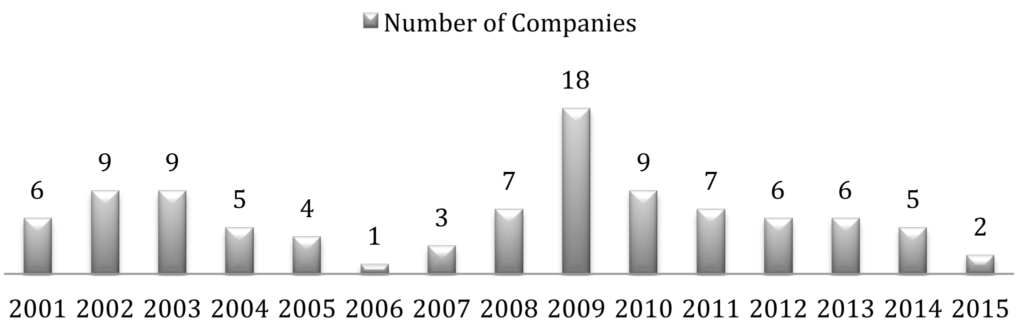
Next, bankruptcy data is manually matched with data regarding analysts’ recommendations and earnings forecast by using company name. Data on analyst coverage is obtained from the Institutional Brokers’ Estimate System (I/B/E/S) Detail History and Recommendations databases. Analyst recommendation and forecast data are extracted on a monthly basis. For the forecast data, EPS forecasts for the forthcoming fiscal year are included. Further, the quarterly number of unique analyst-firm reports is estimated. Next, I create quarter-firm observations equal to zero if no analyst report was issued during that specific period. Thus, the total of 12 quarterly observations for each firm is examined.

To test hypothesis 4, a control sample is created, where companies from each industry are selected, spanning the period from 01/1996 to 12/2015. The control sample includes data on a group of healthy companies, which is compared with the data on subsequent bankrupt companies. Information about the stocks is retrieved from Compustat Fundamentals Annual. To create a group of healthy companies I searched for firms that did not go under deletion throughout the observed period from year 1996 to 2015. To create group a of subsequent bankrupt companies, firms that filed for bankruptcy or liquidation are randomly selected. Companies, which went under Merger & Acquisition, Reverse Acquisition or changed its type from public to private company, are excluded from the total sample. This is done to avoid bias connected with these specific types of events. Further, data on the number of analysts following is collected from (I/B/E/S) Detail History and Recommendations databases. The relation between the number of analysts following and subsequent bankruptcy is also controlled for the time-fixed effects, as the sample period includes years of global financial crisis, which might have an effect on the relation.

5. Descriptive Statistics

Figure 1 presented below provides descriptive statistics of the sample companies. It shows the annual distribution of the bankruptcy cases during the years. From the table we see that there is a higher number of companies going bankrupt in years 2002 (9), 2003 (9), 2009 (18) and 2010 (9). This tendency might be attributable to a weak economy and widespread accounting irregularities in years 2002 and 2003. While the second plunge of bankruptcies might be connected with the financial crisis, which occurred in 2008.

Fig.1. Distribution of Bankrupt Companies by Year

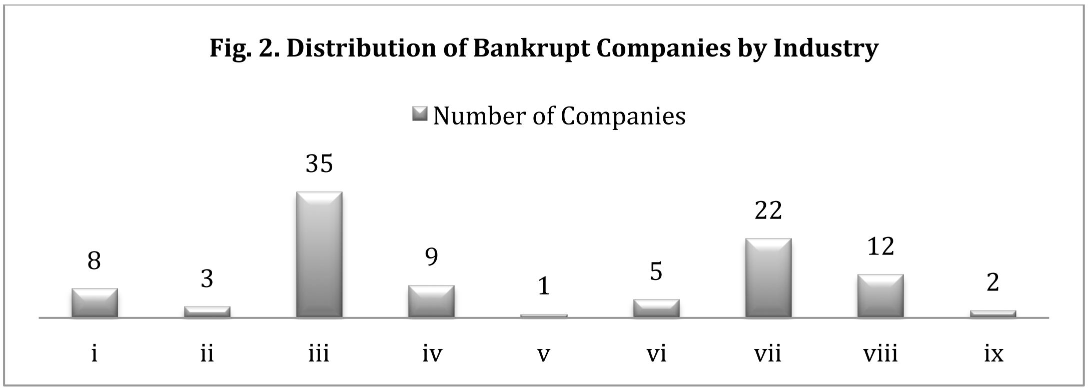


[2]

Figure 2 presents descriptive statistics for the sample of 97 company-quarter observations, which belong to 6 different industries, based on two-digit SIC codes.

Majority of the sample firms are in Manufacturing industry (35) and Finance, Insurance and Real Estate (22). The other sample companies are from Services Industry (12), Transportation and Public Utilities (9), Mining (8), Retail Trade (5), Construction (3), Public Administration (2) and Wholesale Trade (1).

[2] Distribution of bankrupt companies within sample period of 2000/01-2015/12



[3]

Figure 3 (presented in the Appendix) captures distribution of the bankruptcy filings for the sample companies divided into 4 year-quarters. According to the table 20% (19 companies) of the sample firms filed for bankruptcy during the 1st year-quarter. 28 companies, which values 29% of the main sample, filed bankruptcy petition during April-June months. 23 and 27 companies of the sample respectively conceded their bankruptcy during 3rd and 4th year quarters.

Table 1 (presented in the Appendix) provides summary statistics of the control sample for the mean number analysts following and the total number of observations separated by industry and bankruptcy factor. From the table it is possible to see that the greatest attention of analysts gathered companies in Mining (17), Manufacturing and Public Utilities (14) and Retail Trade (14) industries for healthy companies. Meanwhile, there is a greater mean number of analysts following subsequent bankrupt companies in Public Administration (11) and Wholesale Trade (10) industries. The total number of observations is 620332, where 523490 are observations for healthy companies, and 96842 are soon to bankrupt firm-quarter observations.

Empirical Results

Financial ratio analysis

Table 2 (provided in the Appendix) presents statistics of financial metrics for the sample companies. According to the table, during all 4 years before bankruptcy mean

[3] Distribution of companies that went bankrupt by filing petition under Chapter 11 and Chapter 7 of the United Stated Bankruptcy Code between 2000/01 and 2015/12. Industry classification is based on Standard Industrial Classification codes. Where industry i- Mining; ii- Construction; iii- Manufacturing; iv- Transportation and Public Utilities; v- Wholesale Trade; vi- Retail Trade; vii- Finance, Insurance and Real Estate; viii- Servicer and ix- Public Administration.

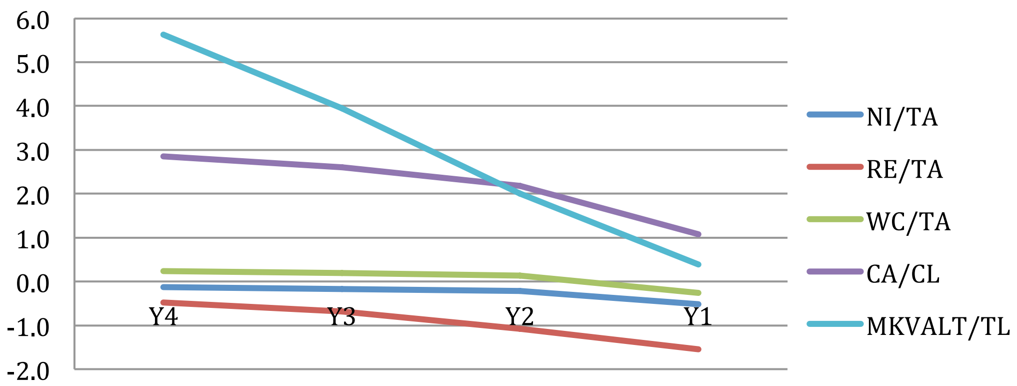
ROA (NI/TA) of the main sample was negative, reaching -0.518 during the last year before bankruptcy filing, which indicates that companies experienced a financial loss. While financial leverage ratio (TD/TA) higher than 2-to-1 is an indicator of financial distress, the mean financial leverage ratio for the sample companies during all 4 years was lower than 2-to-1. However, increasing slant is captured, as the mean value of the ratio grew from 0.635 on 4th year before bankruptcy to 1.057 one year before bankruptcy. Further, threshold for the liquidity ratio which is computed as CA/CL is 1, and values less than 1 indicate that a company's liabilities are greater than its assets, which makes the company's ability to pay off its obligations questionable if they came due at that point. However, the mean value of liquidity ratio is close, but higher than 1 for sample companies throughout examined period, namely, mean value descended from 2.849 on 4th year before bankruptcy to 1.076 the year preceding the bankruptcy. From another point of view, liquidity is also defined as WC/TA, and in this case the mean value of the ratio for the sample companies is lower than one during observed period and is negative (-0.264) during the last year before filing for bankruptcy. This tells that the operations of the business are not running efficiently to support the business' current debts. Mean value of ratio of RE/TA is negative during the observed period, declining from -0.474 on 4th year to -1.552 on 1st year before bankruptcy, which indicates that companies' business is not profitable. Also companies are not productive during the last 4 years before bankruptcy, which is captured by mean values of EBIT/TA ratio. The negative trend in the mean values of Market Value of Equity to Total Liabilities ratio is captured, plummeting from 5.638 to 0.387 throughout observed period. The mean value of the ratio during the last observed year is less than 1, which indicates that the stock is overvalued. Sales turnover ratio, calculated as S/TA is positive and even shows an upward course during the last 4 years before the bankruptcy, increasing from 0.895 to 1.087 during the last 4 years, which comes in contrast with the fact of subsequent bankruptcy. These results are in line with Altman (1968) warning of difficulties with bankruptcy

predictions using financial ratios separately. It is evident, that even some ratios signaled company's poor performance, the other ratios did not provide demonstrative evidence of corporate financial difficulties. However, thorough financial analysis includes also comparison of the firm's ratios with the ones for the preceding years, and to the industry benchmark. Thus, positive tendency of the ratios might not in fact tell that the company is doing good and improves its performance. It is worth to mention that financial analysis is complex in interpretation.

If take a closer look to the ratios that capture main corporate financial metrics, namely profitability, liquidity and solvency, it is possible to see an overall negative tendency of these ratios during the 4 years preceding corporate bankruptcy. Figure 4 presents the trend lines for ratios NI/TA and RE/TA, which reflect profitability; WC/TA and CA/CL, which capture corporate liquidity; and a measure of firm's solvency- MKVALT/TL. These trends provide evidence, that financial ratios decline as a company moves toward bankruptcy.

So, the answer to the first hypothesis is positive as the main financial ratios to some extent declined simultaneously with company's financial recession. However, in line with Chen & Shimerda (1981), these results indicate the need for thorough selection of ratios, which could be useful for bankruptcy prediction purposes.

Fig. 4. Trend Lines of Accounting Variables



[4]

Financial predictive models

Table 3 presents results for the regressions used to test hypothesis 2. The results give an overview of Altman Z-scores and Zmijewski Probability Scores for the main sample of subsequent bankrupt companies. As companies issue financial reports by the end of the fiscal year, this means that operating performance related to the 4th

[4] Slope of accounting variables during the period of 4 years preceding bankruptcy, where Y4 is the fourth year before bankruptcy and Y1- the last year of the company's operation before the bankruptcy filing.

year before bankruptcy was reported by the beginning of the 3rd year before bankruptcy.

	Y4	Y3	Y2	Y1
Altman Z-score	4.481	2.431	0.311	-2.577
Zmijewski Probability	0.424	0.478	0.609	0.831

Table 3. Estimation of Altman Z-score and Zmijewski Probability Score [5]

From the table we see, that financial statements of the companies during the 4th year before bankruptcy obtain mean value of 4.481, which means that at that point of time companies were considered healthy. During the 3rd year before bankruptcy companies move to another group, according to the score-value of the Altman Z-score model, where the value of 2.431 means that a company is in the “grey area”. By the end of the 2nd year before bankruptcy financial statements of the company give a more clear view to the financial position of the company, where the Altman Z-score model outcome obtains the mean value of 0.311 for the main sample, which predicts companies’ bankruptcy. These results concerning the business performance are reported by the end of the 2nd fiscal year before the bankruptcy, which means that the model warns stakeholders the earliest of 8 quarters before (if the company filed for bankruptcy by the 4th quarter of the fiscal year) or by the latest of 4 quarters in advance (if the company filed bankruptcy petition in the 1st quarter of the fiscal year). During the last year before bankruptcy mean Altman Z-score for the sample companies gained a negative value of -2.577, indicating companies’ high propensity to go bankrupt.

Zmijewski probability score values, presented in the Table 3, indicate that by the 4th and 3rd years before bankruptcy companies were considered healthy, as the probability score gained values of 0.424 and 0.478 respectively. As probability values higher that 0.5 indicate bankruptcy, it is possible to say that by the end of the 2nd year financial statements conducted evidence of the firms’ financial distress, as the probability score grows to 0.609. During the last year before bankruptcy, the probability score escalates to 0.831 reflecting the companies bankrupt position. These

[5] Altman Z-score and Zmijewski Probability scores are calculated for the main sample of subsequent bankrupt companies, using Eq.3 and Eq.5 accordingly. The mean numbers are presented for the period of 4 years before the bankruptcy. Y1 is the year preceding the bankruptcy, Y2 refers to the 2nd year before bankruptcy, etc.

results match with the results of the Altman Z-score model, and predict companies' bankruptcy from 7 to 4 quarters in advance before the bankruptcy filing.

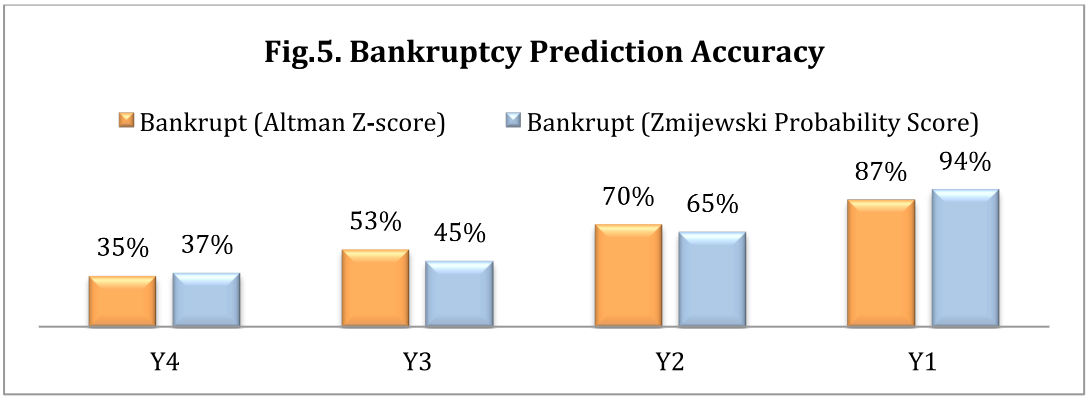
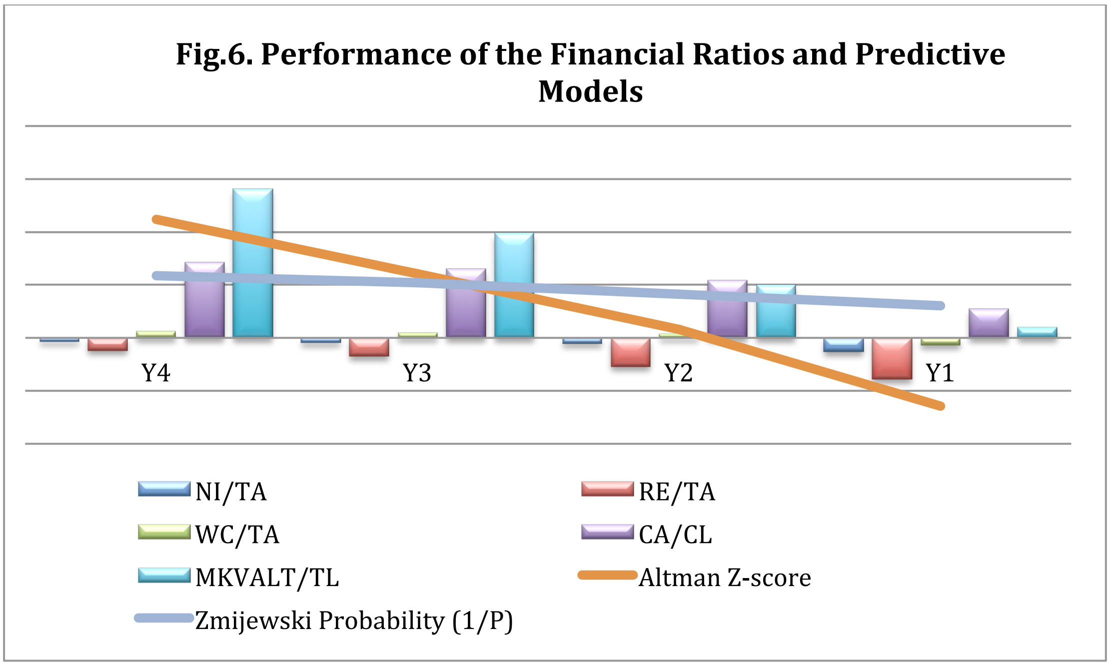


Figure 5[6] captures accuracy of the bankruptcy prediction by statistical models of Altman (1968) and Zwijewski (1984). The percentage of firms that were defined as bankrupt according to the models is measured. Results indicate that in 87% of the cases for the year preceding bankruptcy and in 70% for the cases for second year before bankruptcy statistical model of Altman predicted corporate failure. Outcomes of Zmijewski probability model show that during the first and the second years before the corporate bankruptcy in 94% and 65% cases, accordingly, the model is able to predict subsequent failure of the business. The results support hypothesis 2 and call efficiency of the models into question.

However, the overall trend of the outcomes of both models is negative, and captures a decline in the companies' operating performance. While 100% accuracy is not reached for the estimation sample, the vast majority of the companies were defined as bankrupt in accordance with the predictive models. While behaviour of each of the financial ratios included in the models was examined separately under the previous hypothesis, studied in aggregate these ratios reflect similar pattern. Figure 6 provides an overview of the drift for the main financial metrics and predictive models.

[6] Sample Analysis for MDA Model of Altman and Probit Model of Zmijewski. Percentage of the estimation sample companies that were identified as bankrupt by Altman (1968) and Zmijewski (1984) models is reported for the period of 4 years preceding the bankruptcy. The Y1 is the year preceding the bankruptcy; Y2 refers to the 2nd year before bankruptcy; etc.



While Figure 4 captured the negative trend of the financial ratios separately, it is possible to see that when examining these ratios simultaneously as suggested by Altman (1968) and Zmijewski (1984), the same trend is evident. The Z-score of the Altman model (1968) plummeted during the 4 years preceding corporate failure. Zmijewski probability score captures the same pattern of decline. These results indicate the predictive ability of the financial ratios, either examined separately or in aggregate. The financial statements reflect difficulties that companies face during their last years, however, the timeliness of the information provided by the annual reports is uncertain.

Analysts' coverage allocation

The primary test for hypothesis 3 examines the relation between analysts' coverage and corporate bankruptcy. Figure 7 reports the summary for the mean numbers of analysts following companies spanning 12 quarters prior the bankruptcy filing.

These results suggest that the mean number of analysts covering companies that subsequently went bankrupt dropped from 6 in the 10th quarter before the bankruptcy to 1.2 in the quarter of bankruptcy filing.

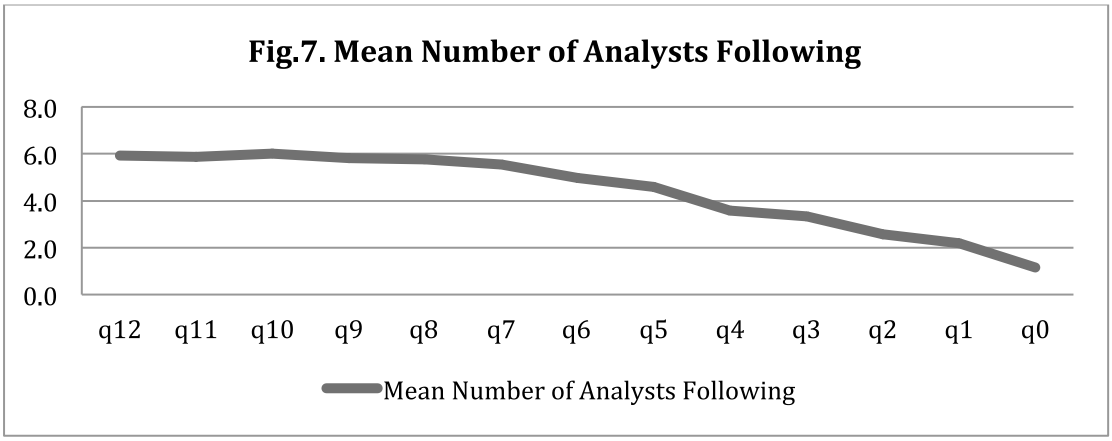
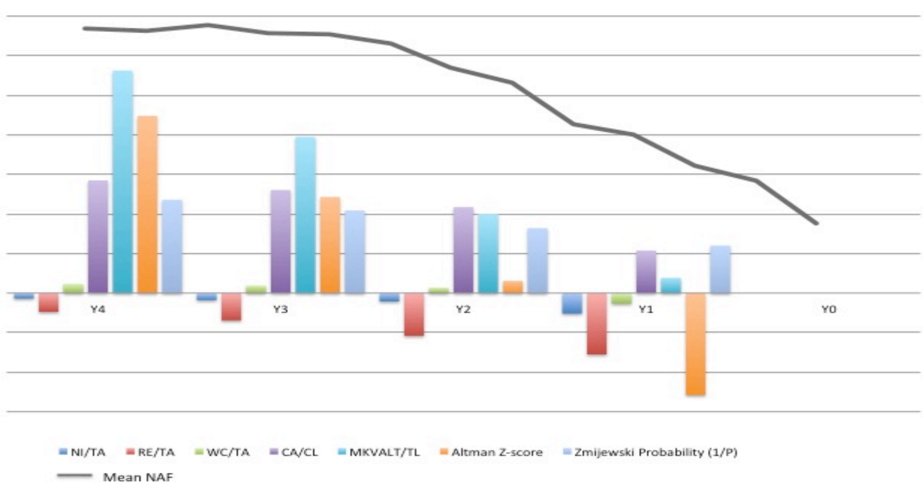


Table 4 (presented in the Appendix) provides the summary statistics for the change in the number of analysts following throughout the observed time period. The decline occurs from the 10th quarter preceding the bankruptcy. The decline between 10th and 9th quarter before bankruptcy captured 3% level. The greater decline occurred between 7th and 6th quarter, reaching 10.22%. The more sharp fall hits between 5th and 4th quarters and 3rd and 2nd quarters reaching 21.8% and 22.6% respectively. The decline to the quarter of bankruptcy filing made up 47.42%. These results support hypothesis 3, capturing steady decline in the number of analysts following, starting from 10th quarter before bankruptcy filing.

Further, the control sample of observations is used to test the relationship between number of analysts covering firms and bankruptcy with control for industry and time trends. Table 5 (provided in the Appendix) presents results for the regression when using time and industry fixed effect. These results capture a negative and significant (under 1% significance level) coefficient estimate for dummy variable *bankr*, meaning that if the company will be bankrupt, then the number of analysts following would decrease by 4.98. The regression provides no pervasive information about industry and/or time fixed effects, which declines hypothesis 4. However, the R-square of the control test is 0.1455, which indicates that the model does not fully explain the variability in the number of analysts following around its mean. Overall, this tests captures difference in the mean number of analysts following for healthy and subsequent bankrupt firms, indicating that there is a smaller number of analysts covering poorly performing stocks in comparison to healthy stocks.

While several methods of bankruptcy prediction are studied individually, Figure 8 captures the overall trend for each of the proxies used for bankruptcy prediction. It is observable that each of the methods reflects the negative drift of the companies.

Fig.8. Overall Trend of the Proxies Used for Bankruptcy Prediction



As proxies that are based on the financial statement data show decline as a company moves toward bankruptcy, the number of analysts following also drops throughout the observed period.

6. Conclusion

In this thesis the corporate bankruptcy prediction methods are studied to answer two questions: To what extent do ratio analysis and financial predictive models signal of financial failure before the corporate bankruptcy filing? Can analysts' decisions to cease coverage signal of potential companies' financial failure?

Using a sample of 97 U.S. firms that filed for bankruptcy or liquidation during the period 2000-2015, different methods are examined to estimate their accuracy for bankruptcy prediction. In general, all three methods studied, namely ratio analysis, predictive models and analysts' tendency to cease coverage, show a negative trend as a company moves toward bankruptcy. This evidence suggests that each of the methods predicts corporate failure to some extent.

Empirical results suggest that financial ratio analysis is complex in interpretation, which impedes shareholders evaluation of the corporate performance. Statistics shows inconsistencies within the ratio values. While some ratios point out to corporate distress, the other ratios indicate the company's above-average performance. Thus, the results of the analysis might be misleading. However, overall trend of the main financial ratios is negative during the observed period. This pattern coincides with the pattern of predictive models' outcomes. Meanwhile, outcomes of Zmijewski probability model (1984) and Altman Z-score model (1968) lack accuracy in corporate failure prediction. During the last year before filing for bankruptcy only 87% of firms received a value of Altman Z-score which forecasts bankruptcy. For the same sample, Zmijewski probability score correctly forecasted bankruptcy for 94% companies. Conclusions can be made that financial statements lack relevance for timely bankruptcy prediction, as both the traditional financial ratio analysis and financial predictive models fail to predict some of the bankruptcy cases. Thus, answering the first research question it is possible to mention low accuracy of the models' predictive ability.

Meanwhile, the number of analysts following performs as a better proxy signaling subsequent corporate bankruptcy. I find that the sample firms experience a gradual deterioration in the number of analysts covering them. The number of analysts covering the stock and the subsequent decision to cease coverage is highly related to the firm's performance. Namely, the decline in the number of analysts occurs 10 months before the bankruptcy, and the mean decrease from the 12th quarter before the bankruptcy and the quarter of bankruptcy points 80%. Moreover, no time- or industry-fixed effects were determined, that could potentially mediate the relation between company's bankruptcy and the number of analysts following the company. Next, the relation between the number of analysts following and corporate strength is negative and significant on 1% level. The number of analysts covering a healthy company is significantly higher relative to companies that subsequently file for bankruptcy. Thus, based on empirical evidence, the answer for the second research question is positive. The results support the inference of Mola et al. (2010) that some additional information or foresight that analysts dispose allows then to drop companies that move toward bankruptcy before their financial failure is self-evident.

These results add to the existing literature of accounting and finance research that empirically evaluates the quality of methods used for bankruptcy prediction purpose. First, it contributes to the literature on bankruptcy prediction, which examined effectiveness of financial ratio analysis (Francis & Schipper, 1999; Beaver et al., 2005), generalizability of bankruptcy prediction models (Altman et al., 2014) and creation of models based on financial statement data (Grice & Dugan, 2003). Empirical evidence of this thesis supports both low generalizability and weak efficiency of the existing bankruptcy prediction models and the low predictive ability of the financial failure by the ratio analysis. Meanwhile, no research paid particular attention on the number of analysts following the company as a proxy for bankruptcy prediction. For the long time the main attention in research on financial analysts was centered on the quality of analyst reports (Givoly & Lakonishok, 1984; McNichols & O'Brien, 1997; Agrawal & Chen, 2005; Givoly et al., 2009). Empirical results of this thesis provide evidence on benefits of tracking coverage allocation behavior of sell-side analysts, as it may perform as a more efficient predictor of corporate financial failure.

By connecting the corporate financial failure event with analyst coverage allocation behavior, this thesis provides novel evidence about how sell-side analysts react to bad news. As for practical implications, results of this study should be relevant to investors, who are interested in avoiding losses by timely assessing corporate financial failure. This thesis provides complementary evidence on the usefulness of tracing analysts' coverage choices. Moreover, this thesis provides additional interest to auditors, who need to make judgment on corporate going-concern based on financial statement data and prevent non-disclosure of pervasive information regarding possible financial distress of the company. And, finally, empirical evidence of this study might be relevant to regulators and standard setters as it adds to the existing debates on financial reporting quality and information asymmetry between a company and its stakeholders.

6.1. Limitations of The Study and Suggestions for Future Research

The reader should be aware of some important caveats when interpreting the results. Firstly, only U.S. companies are examined throughout the thesis, which may affect generalizability of the results. U.S. companies comply with GAAP accounting and the differences in the accounting standards may result in different levels of informational content of the financial statements. Thus, evidence provided solely by this thesis is insufficient to argue against general efficiency of the financial ratio analysis and predictive models.

Secondly, although financial analysts around the world could cover U.S. companies, only U.S. analysts that cover these companies are counted in this thesis. This is a drawback, as some of the big international companies might receive great analyst coverage from abroad, which might offset the decrease in the number of U.S. analysts following a particular company. Especially, the increase in the general number of international analysts following the company enhances information flow regarding these companies in the financial market. Thus, there might be less demand for the U.S. analysts' reports on these companies, which influences the number of U.S. analysts covering the stock.

Thirdly, quantitative evidence on the number of analysts covering stock might lack power to make final conclusion on analysts' tendency to cease coverage based on the companies' future performance expectations. This is because analysts face different incentives and pressures, which might affect their coverage allocation decision. As a robustness check of my results for hypothesis 3 and 4, it was planned to undertake a survey from buy-side and sell-side analysts, who hold an opinion on analysts' coverage allocation behavior, due to their professional background. However, because of a vacation period I was not able to collect answers to the survey. Providing additional evidence gathered from specialists in this field would allow making more powerful conclusions. Therefore future research may be extended by providing additional evidence on this topic.

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Appendix

Table 1. Control Sample Descriptive Statistics

	bankr		
Industry	0	1	Total
1	9	3	9
	27843	*562*	*28405*
2	17	8	15
	18180	*7314*	*25494*
3	10	3	10
	87259	*4912*	*92171*
4	12	7	11
	91401	15116	106517
5	14	5	12
	67231	*20018*	*87249*
6	12	10	12
	62486	*1637*	*64123*
7	14	6	12
	84331	*17691*	*102022*
8	8	6	8
	38872	*10045*	*48917*
9	12	7	11
	37046	*3801*	*40847*
10	6	11	9
	8841	*15746*	*24587*
Total	12	7	11
	523490	*96842*	*620332*[7]

[7] Where industry 1 is Agriculture, Forestry, Fishing; 2- Mining; 3- Construction; 4- Manufacturing; 5- Manufacturing and Public Utilities; 6- Wholesale Trade; 7- Retail Trade; 8- Finance, Insurance and Real Estate; 9- Servicer and 10- Public Administration. The first line of results represents mean number and the second line - standard deviation in the number of analysts following. The third line represents number of observations. *Bankr* is equal to 1 if company subsequently went bankrupt, and 0 otherwise.

Table 3. Statistics for the Estimation Sample

Accounting variable	Y4	Y3	Y2	Y1
WC/TA	0.236	0.195	0.139	-0.264
RE/TA	-0.474	-0.690	-1.080	-1.552
EBIT/TA	-0.079	-0.115	-0.117	-0.272
MKVALT/TL	5.628	3.950	2.002	0.387
S/TA	0.895	0.809	0.892	1.087
NI/TA	-0.135	-0.178	-0.210	-0.518
TD/TA	0.635	0.680	0.789	1.057
CA/CL	2.849	2.606	2.173	1.076[8]

[8] Descriptive statistics for the estimation sample of 97 U.S. bankruptcies reflects mean numbers for each accounting variable for time period spanning 4 years before the year when company filed for bankruptcy. Y1 is one year before the bankruptcy; Y2 is the second year before bankruptcy; etc

Table 4. Summary Statistics for the Change in the Number of Analysts Following

Quarter Before Bankruptcy	q12	q11	q10	q9	q8	q7	q6	q5	q4	q3	q2	q1	q0
Mean NAF	5.9	5.9	6.0	5.8	5.8	5.5	5.0	4.6	3.6	3.3	2.6	2.2	1.2
ΔNAF		-1%	2%	-3%	-1%	-4%	-10%	-8%	-22%	-7%	-23%	-15%	-47%[9]

[9] Mean number of analysts (NAF) following companies in the main sample, covering the time period of 12 quarters before the bankruptcy. Where q12 is the 12th quarter before the bankruptcy, and q0 is the quarter when company filed for bankruptcy. ΔNAF represents the change in the NAF from the previous quarter.

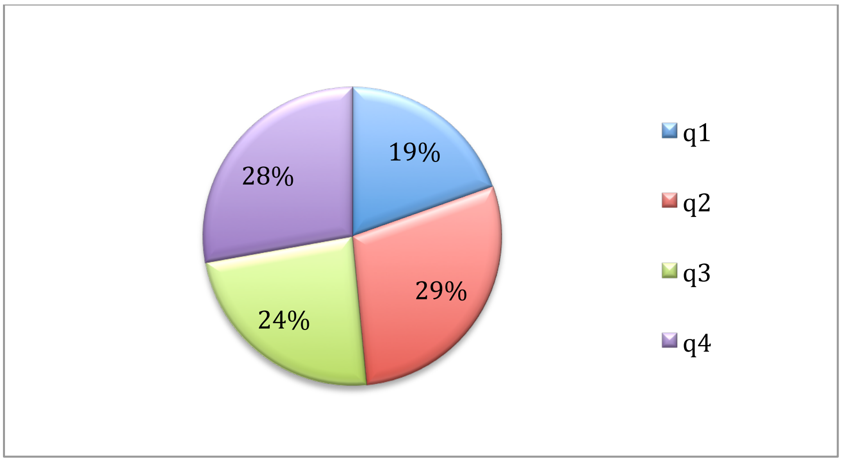
Table 5. Linear Regression for the Correlation between Number of Analysts Following and Corporate Bankruptcy

Linear regression, absorbing indicators	Number of obs	620,332
	F(81, 620241)	944.88
	Prob > F	0.000
	R-squared	0.1455
	Adj R-squared	0.1454
	Root MSE	6.9227

numb_fol	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]	
bankr	-4.983	0.026	-189.220	0.000	-5.035	-4.931[10]

[10] Linear regression for the control sample, including 620332 firm-quarter observations, with 523490 quarterly observations for healthy companies, and 96842 for soon-to-bankrupt firms. *Numb_fol* is the dependent variable, capturing the number of analysts following particular company in each quarter, and *bankr* as a dependent variable, which equals 1 is the company subsequently went bankrupt, and 0 otherwise. Descriptive statistic of the sample used is described by Table 2

Figure 3. Descriptive Statistics for the Distribution of Bankruptcy Filings Across the Fiscal-Year Quarters



[11]

[11] Frequency of the bankruptcy filing for the main sample, divided into 4 year-quarters. Where Jan-Mar is the first quarter (q1), Apr-Jun the second (q2), Jul-Sep the third (q3) and Oct-Dec the 4th year- quarter (q4).