ACCOUNTING AND MARKET BASED RISK MEASURES AS PREDICTORS OF BANK DEFAULTS

MASTER THESIS

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Preface

Abstract

The purpose of this paper is to investigate the debate regarding the ability of market and accounting based risk measures to predict credit events such as the bankruptcy of a financial institution. Specifically, literature suggests that accounting measures include information regarding past performance of banks and don't have a predictive ability, something that makes the periodical reformulation of accounting methods necessary. On the other hand, market prices are used to predict expected cash flows and consequently can be more suitable for forecasting. Using a sample of 18 European and American banks during the period 1995-2015 the paper tries to investigate the relation between market and accounting based risk measures and their relationship with the default probability of banks. The results underline the utility of combining accounting and market based risk measures in distress prediction models for banks and that accounting based risk measures provide an important economic benefit over the market based risk measures.

Table of contents

1. Introduction

There is a debate among analysts and academics regarding the ability of accounting and market based risk measures to predict the default of an entity. The banking sector uses accounting and market based risk measures for the assessment of its financial condition. The purpose and the conditions on which the accounting or market based measure is applied, define which of the two measures is more appropriate. Specifically, if a regulator wants to evaluate the economic health of a bank, the accounting risk measures are more appropriate than market based risk measures. On the other hand, the beta of a bank, which is a market based risk measure, is the most effective measure for an investor who wants to use a bank stock in his/her portfolio. Nevertheless, the economic conditions can influence the accounting and market based risk measures in a different way and their significance isn't constant over time.

A great number of papers discovered an important relation between accounting and market based risk measures in the US. However, the managerial control, banking composition, regulation, capital requirements and market framework are different between countries. All these differences can influence the risk management of a bank and consequently the relation between market and accounting risk measures. Furthermore, the economic environment makes the estimation of default probability to be used as significant tools, in order to ensure the stability of the economy. The Basel II rules obliged regulators to make more sufficient forecasts for bankruptcy. The capital reserves of banks are estimated with the use of models that calculates the default probabilities.

The financial world is an interconnected system and in a financial crisis a shock event has the ability to transmit and have negative consequences to global financial stability, something that emphasizes the fragility of the banking sector. As we can see in the real world, the banking activity is growing and gives the chance to banks to become too big and simultaneously too vital for the financial stability.

The crisis of 2008 created new elements in the relation between systemic risk and the banking sector. The consequences of systemic risk extend at national and international level. Specifically, systemic risk can affect not only a firm because it causes financial barriers but also other financial institutions and consequently all the financial system. The financial system is sometimes characterized as flawed and the presence of systemic risk causes additional problems in the entire economy. The banking sector plays a vital role in the economy and its vulnerability can create a concern about the solvency of other banks and can prompt a systemic banking crisis. First of all, it can decrease the solvency of a bank. Consequently, the banking system loses its confidence and bank runs can occur. Moreover, systemic risk can lead to the ineffective distribution of loans to a large number of borrowers who may face problems financing their liabilities, so it is vital that banks continue finance them. Also, a decrease in investments and in asset prices can be observed, because the banking sector will increase interest rates due to systemic risk. It is very difficult to recapitalize the banking sector, something that leads to the rise of financing costs, and the vulnerability of banks can make the measures of the central bank inefficient.

Consequently, the crisis of 2008 emphasizes the lack of adequate risk management models. Specifically, the banks need to structure probability of default models with the purpose to provide them valuable information about the conditions of the corporate sector, macro environment and accessibility and accuracy of data.

One way of assessing banks' default probabilities is the Merton model. The Merton model highlights that the common stock of an entity can be considered a call option on the entity's assets. If the assets of the entity are valued less than the face value of the debt at maturity, the firm goes bankrupt. Also, shares are traded in a daily basis and an assessment model that focuses on equity prices can provide asset valuations that are more credible than the models that are based on accounting data. An assessment model based on equity may lead to more reliable default forecasts. While the market based methods are attractive, they don't give the reasoning behind managerial risk decisions. Many analysts believe that other similar market based models bring in a superior probability of bankruptcy statistic. Also, investors use more structural models similar to the Merton model of the default probability of public companies.

Although, the market based risk measures are more popular, accounting based risk measures play a significant role in the forecasting of distress. If markets are not efficient in a perfect way then the market based risk measures may not capture the information regarding the default probability. Furthermore, a lot of companies that are privately held use accounting base risk measures to calculate the probability of default. Taking into consideration the relevance of accounting based risk measures in the pricing of default risk, highlights the significance of accounting based risk measures.

Moreover, one of the most useful measures of default risk comes from the credit default swaps market, because CDS spreads are considered to be forward-looking and with which we can measure risk-neutral default probabilities. The CDS spread shows the probability of default of a firm. The counterparty risk in CDS contracts is a significant point in this analysis. First of all, in the situation where the seller of protection displays higher risk of default, a decline in the price of default insurance (CDS spreads) is observed, if the two defaults manifest a correlation. Consequently, the CDS spread shows not only the probability of default of the issuer of the bond but also the risk of joint default with the seller of protection. Moreover, the analysis indicates that an expectation of an abrupt rise in the joint default probability of Lehman Brothers and Merrill Lynch was derived from the CDS markets more than a month before the weekend that both banks eventually collapsed.

In the risk related literature, the difficulty in forecasting firm's default constitutes a constant problem. There are well known risk models. First of all, the z-score model that uses accounting based variables and financial ratios to estimate the probability of default and is based on information that is derived from the firm's financial statements. On the other hand, there is the Merton model that is a market based model which recommends that one can combine a firm's debt ratio with its asset volatility to forecast its default probability. However, there is a debate in the related literature about which of these measures, their combination or the inclusion of other measures like macroeconomic variables is better regarding their ability to forecast 'true' defaults.

The thesis will investigate the ability of the accounting based and market based risk measures to predict credit events such as the bankruptcy of a financial institution and attempt to answer the following research question:

RQ: Do market based risk measures are better predictors of bank failures than accounting based risk measures?

Providing an answer to this investigation is important because the results of the thesis should be of relevance to investors, banks and regulators who need information about individual banks and try to develop tools of monitoring bank defaults. Besides understanding the importance of the prediction of bank failures, the results of this thesis could also provide insights into the debate about the ability of accounting based and market based risk measures to predict bank default. Previous literature finds an association between the two measures but it is important to have empirical evidence on which one of the measures can predict a bank failure more effectively.

The financial world is characterized of the plethora of connections among its components something that became significantly observable in the financial crisis. Credit shocks can have the ability to influence the economic consistency of markets and institutions. For this analysis, a vital part is the banking sector because the banks play a significant role in financial intermediation and have highly leveraged operations. In the previous literature, there are several accounting and market based tools that achieve to measure and monitor systemic risk and the default of the financial institutions but not accurately predict the default of banks. This thesis aims to contribute to the literature by examining the ability of risk measures to predict bank failures and simultaneously investigating which measures (accounting or market based) present the most effective, predictive ability, something that improves the literature and is very useful for central banks and supervisory agencies.

Related literature shows some significant differences between accounting and market based risk measures. First of all, accounting variables fail to include a vital factor for the probability of default, the stock market. The market based risk measures give additional information about the default of a firm to accounting measures. Moreover, accounting based risk measures include past performance of the firms and they don’t have the ability to predict the future. Also, the accounting measures don’t have the ability to predict bankruptcy because of their formulation. Specifically, they are based on an assumption that the firm will not default. On the other hand, the market based risk measures are more accurate to predict future cash flows and consequently defaults. While the market based risk measures are more effective than accounting based risk measures, accounting measures can give additional information to market based measures and together have the capacity to describe the default probability because they are risk measures.

My sample contains 15 major US and European banks such as bank of America, Barclays and Banco Santander and 3 bankrupt banks that are Lehman Brothers, Bear Stearns and Merrill Lynch. The probability of default depends on accounting and market based risk measures. Specifically, the accounting risk measures are the profitability, leverage and earnings variability ratio and the market based risk measures are equity returns, equity volatility, market capitalization to total debt and size of the banks. I will define the probability of default similarly to Merton. In this model, the default probability of a bank can combine the asset value volatility with the debt ratio to forecast the default probability. The paper calculates the default probability as the normal distribution function of the distance to default measure. The distance to default is calculated as a function of firm asset value, asset volatility, estimated asset growth and time to maturity of a zero coupon bond issued by the firm. The results of the default probability regressions suggest that the combination of accounting and market based risk measures has the ability to improve the prediction of default probability of the banks.

The rest of the paper is organized as follows. Section 2 discusses the literature review about the predictability of market and accounting based risk measures and the hypothesis development. Next, section 3 discusses the methodology that will be implemented and section 4 mentions the data sources required to compute the default probabilities and the market and accounting risk measures. Section 5 shows the statistical characteristics of the sample. Section 6 presents and discusses the results and section 7 discusses any possible limitations or shortcomings related to the implementation and the expected results. Finally, section 8 concludes.

2. Literature review and hypothesis development

There are three basic credit risk models: *Altman's (1968)* z-score model and *Ohlson (1980)* o-score which are accounting based models and *Merton's (1974)* that is a market based model. The first model uses accounting based information to define the relation between the probability of default and a number of financial ratios. Specifically, the z-score for a bank is estimated with the following equation:

$$Z= 1,2x_1 + 1,4x_2 + 3,3x_3 + 0,6x_4 + 1,0x_5$$

The variable X_1 is the working capital/total asset, the variable X_2 is the retained earnings/total assets, the variable X_3 is the earnings before interest and taxes/total assets, the variable X_4 is the market value of equity/total assets and the variable X_5 is the sales/ total assets.

This equation changes separate values of the variables to a single z value. The financial institutions that use the z-score may alter the values of the weights of the ratios in the equation contrary to the bankruptcies of their portfolios because they want to achieve a better score. For example, the best approach for the banks to alter the weights of the ratios is the maximization of the difference between the average score of bankrupt and not bankrupt borrowers. *Altman's* model demonstrates that it can be accurate in the forecasting bankruptcy in 94% of cases, failure can be predicted two years prior to the actual event and the accuracy decreases after the second year.

Ohlson (1980) provides four fundamental determinants that have the ability to influence the probability of default. These factors are: the size of the firm, a variable of the financial structure, a variable of performance and a variable of current liquidity. The Ohlson o-score model is derived from a nine factor linear combination of weighted ratios.

$$T= -1,32 -0,407\log (TA_t/GNP) +6,03 (TL_t/TA_t) -1,43(WC_t/TA_t) +0,0757(CL_t/CA_t) -1,72X -2,37(NI_t/TA_t) -1,83(FFO_t/TL_t) +0,285Y -0,521 (NI_t - NI_{t-1})/ (|NI_t| + |NI_{t-1}|)$$

Where: TA is the total assets, GNP is the Gross National Product price index level, TL is the total liabilities, WC is the working capital, CL is the current liabilities, CA is the current assets, X is 1 if TL> TA, 0 otherwise, NI is the net income, FFO is the funds from operations and Y is 1 if there is a net loss for the last 2 years, 0 otherwise.

Merton's model (1974) provides a dissimilar approach. This approach can combine the asset value volatility with the debt ratio to forecast the default probability. This model constitutes the basis of most credit risk models. Specifically, Merton's model considers equity as a call option on the assets of the firm with a strike price equal to the face value of the firm's liabilities. The probability of failure is the probability that the call option will expire worthless, or that the worth of the firm's assets is less than the face value of the firm's debt at the end of the holding period. The paper calculates the default probability as the normal distribution function of the negative value of distance to default measure. The distance to default is calculated as a function of firm asset value, asset volatility, estimated asset growth and time to maturity of a zero coupon bond issued by the firm. The value of equity is related to the market value of the entity and the equity volatility is related to historical equity volatility or implied volatility from equity options.

Agusman, Monroe, Gasbarro, Zumwalt (2008) display that the decision for the risk evaluation between market and accounting measures is based on the conditions and on its objective. Specifically, if a well-diversified investor includes a bank stock in his portfolio, the most suitable risk measure is the beta, while when a bank modulator wants to evaluate the financial stability of a bank, accounting measures are more appropriate for this assessment. Also, the impact of these measures can be dissimilar because of the economic environment and their significance can change over time. The connections between accounting and market based risk measures are assessed for Asian banks by *Agusman, Monroe, Gasbarro, Zumwalt* and show that the standard deviation of the pretax return on assets and the loan loss reserves to gross loans ratio are significantly connected with total return risk. Furthermore, the loan loss reserves to gross loans ratio and the gross loans to total assets ratio are related with idiosyncratic risk. The output displays that the enterprise risk is more significant than systematic risk for the Asian banks and that the accounting measures describe an essential part of capital market risk.

Beaver, Kettler and Scholes (1970), show that accounting based measures use the volatility of earnings in order to substitute for variability of returns. Accounting measures include systematic and individualistic risk components. If these components have positive correlation, the accounting measures can be used as substitutes for measuring systemic risk. Additionally, the accounting risk measures are enclosed in the market-price based risk measures and can be used to decision-settings when the market based risk measures are not accessible. Moreover, accounting numbers can be effective predictors for enterprises with either very high or very low systemic risk while the connection between accounting numbers and beta can vary depending on the level of risk. The analysis of *Beaver, Kettler and Scholes (1970)* contradicts the implication that systemic risk is not positively associated with growth variables. In other words, accounting based growth variables can be representative for a number of omitted economic variables that are related to systemic risk.

Gonedes (1973) displays that the market for stock, bonds and other securities can be characterized as efficient because new information is incorporated into market prices quickly and consequently market prices provide all the additional information. The question is if these information are incorporated in accounting variables as well. Specifically, if a part of regulation has economic impact, the consequences that are derived from this part might be incorporated into market prices. On the other hand these consequences cannot be impounded in accounting measures because of the backward looking characteristic of accounting numbers. Nevertheless, there is a continuous interaction between financial events, impounded in market prices and accounting variables. Also, there may be a connection between the information reflected in market prices and that reflected in accounting measures. The accounting numbers are regarded to be informative about market conditions if we consider markets to be efficient. The author however concludes that the information reflected in security prices isn't incorporated in accounting variables. This contradicts the results of the *Beaver, Kettler and Scholes* paper basically due to a different estimation sample.

Das, Hanouna and Sarin (2009) find with the use of CDS spreads that a model of default with the use of accounting numbers is as effective as market based models. Credit Default swaps are derivatives that can provide security in firms that are not capable to repay their debt. CDS can be used as an effective measure of risk of failure because they can be used as hedging instruments with which investors can withstand risk. Moreover, a model that uses accounting and market based variables is more effective than the models that use accounting and market based variables separately. Both models are supplementary in default. Although, the market based risk models are famous, accounting variables play a significant role in forecasting default. Specifically, Enron underlines the hazards that have to do with market information**.** The market based model showed that when the stock price of Enron started to drop, the probability of default of the market based model raised while the downgrading of the Enron's debt took place some days later. Nevertheless, when the stock price of Enron was high, the probability of default given by the market based model was lower than the estimations of credit rating agencies. Furthermore, several companies are privately held and consequently the use of accounting numbers in the calculation of the probability of default is essential. CDS spreads play a key role in this analysis because they give the opportunity to have both cross-sectional and time-series credit quality information. Also, CDS spreads have the ability to show how markets perceive failure and include not only the default but also the recovery rate perspectives of a company's distressed debt. Finally, CDS spreads aren't as sensitive to tax and liquidity as corporate bond spreads. CDS spreads give a credible measure of default risk because they are the repayment that market participants require for taking that risk.

The paper concludes that models of distress that use accounting numbers have the ability to predict better default with the use of CDS spreads and have similar illustrative power to market based numbers. Additionally, a model that combines accounting and market based variables can predict default more effectively. *Das, Hanouna and Sarin* (2009) conclude that accounting variables have a benefit over market variables because they can be used to express the quantity of credit risks for entities that do not have traded. Also, rather than considering accounting and market based numbers as substitutes, they should be considered as supplementary in the forecasting of credit spreads.

Tinoco and Wilson (2013) show that we can measure market volatility directly with the use of market based variables that play a vital role in the prediction of default risk, something that isn't included in financial statements. Moreover, the authors display that the use of data that vary over time that reflects macro-economic changes is significant and give a progressive aspect in this procedure. *Hosmer and Lemeshow (1980)* find that a model that includes market, accounting and macroeconomic variables is a sufficient model in relation to the accounting model or accounting model with macroeconomic variables.

Xin Huang, Hao Zhou and Haibin Zhu (2009) illustrate that an important difference between accounting and market based measures is that the accounting tools are based on the balance sheet or accounting information that may be accessible on a quarterly or longer time horizon, something that causes considerable lag in the reports while the market based measures are based on information that are available in a daily basis. Also, the market based measures do not include information related to past performance as the accounting based measures do. Consequently, market based measures may be more preferable in estimating a firm's or an institution's default probability.

Pieter Elgers (1980) shows that financial accounting numbers have two advantages: the recognition of overvalued or undervalued securities and the forecast of beta. As a result, the analyst has the opportunity to beat the market and gain abnormal returns. Consequently, the investor has the chance to review or retain the risk of her/his portfolio. A significant part of the research shows that financial accounting data don't have the ability to help investors gain high abnormal returns and the securities market is efficient, meaning that public information is rapidly reflected in securities prices. On the contrary, another part of research suggests that financial accounting numbers can be used for the forecast of beta. This prediction has the ability to assist investors restrict the adjustment costs of their portfolio in their attempt to attain a target level of portfolio risk. The beta is defined by the features of the company and their connection with the economy. If accounting numbers can be used to depict the features of enterprises that influence systemic risk and the each company's systemic risk contribution is considered to be stable, then it is comprehensible that forecasts of beta that relied on accounting numbers will be more reliable to forecasts that based on market data. The investors with the use of accounting numbers as considerable factors of beta can perceive errors in the calculation of beta. *Elgers (1980)* suggests that accounting numbers can't be considered a more reliable predictor for risk than market data. The connection of accounting variables and beta is dissimilar among different firms and time periods.

Agarwal and Taffler (2008) show that accounting based measures are built with the use of accounting ratios. The weighting of the ratios is based on the number of bankrupt and non-bankrupt firms in the sample. Also, the accounting statements that are the basis of these models show some drawbacks: first of all the accounting statements indicate the firm's past performance and might not be instructive in the prediction of the future. Additionally, a difference between the true asset values and the recorded book values may exist because of conservatism and historical cost. The management can misstate the accounting numbers and finally, while the accounting statements are produced on a continuous basis, they don't have the benefit to forecast a bankruptcy. On the other hand, market based models can give a more accurate approach and many papers use these models for the prediction of bank and firm failures.

The difference between the accounting and market based models is that the latter give a theoretical model for failure of enterprises and banks. Furthermore, stock prices can incorporate all the information that are included or not in the accounting statements, and the accounting strategy of individual banks and firms cannot impact the market variables. Also, market prices are used to predict expected cash flows and consequently can be more suitable for forecasting. Last but not least, the output of market based models is independent from time and sample. Moreover, *Agarwal and Taffler (2008)* conclude that whilst the z-score approach (accounting based model) is marginally more precise, the difference between the accounting and market based risk models is not statistically significant. In addition, when a financial institution uses the z-score approach, will perceive remarkably higher risk adapted earnings, gains, return on capital and return on risk adjusted capital than a bank that uses a market based model. The two different approaches can include vital information about bankruptcy but neither approach comprise the other. These results can prove that the accounting risk model isn't subordinate to the market based model for credit risk appreciation.

Bildersee (1975) shows that beta may be a preferable measure of risk and specifically a measure of asset risk when the asset belongs in a portfolio of a number of assets. Beta can be characterized as a measure of systematic risk. Also, it includes information regarding securities and incorporates the systematic risk related with the security. Furthermore, beta is an effective and alternative market based method to measure risk comprising corporate accounting data. Consequently, the accounting numbers are regarded a combination of events and decisions of the firm. These numbers include all the essential information about the total risk related to the company and to securities associated with the company. As a result, with this method there is a relation between the beta and the accounting numbers.

Although, the accounting numbers can be constituted as a significant source of information about the asset risk and the consequences of the choices of the company's management, they are not the only source of this information. The management choices and the effects of these choices are important determinants of firm's risk. Furthermore, the data that result from firm's decisions that include a prediction of the future of the company and economy are capable to add to the method a forecasting aspect. The use of non-accounting variables in this procedure has some advantages. First of all, the use of non-accounting data helps us comprehend the effect of corporate events in different types of risk that companies try to handle, by the capacity to convert one type of performance measure to another. Furthermore, the use of market variables that have a relation with specific events gives the opportunity to include supplementary factors like management forecasting that facilitate the investment analysis. In addition to accounting variables which are used to evaluate the events related to their dollar value, it is more appropriate to adopt information systems with the use of new aspects that can entail new perspectives of information. *Bildersee (1975)* illustrates that accounting processes aren't regulative and often produce biased results while the market systems aren't affected by accounting systems and can produce prices that are derived from unbiased estimations. Specifically, conservative accounting variables can't reflect the true current situation and status of the firm. The great number of accounting approaches means that there are a lot of ways to report new information. The accounting procedure of a company displays a drawback because the accounting numbers that are published for every enterprise also comprise alternative methods to the measurement of mergers, acquisitions and capital structure changes in ways not automatically clear to the public.

Li and Miu (2010) show that market based measures are more accessible and credible for large debtors. Consequently, financial institutions give more attention to market based measures when they want to estimate the probability of a credit event of large debtors. Also, accounting measures include past performance of the banks and don't have future predictive ability, something that makes necessary the reformulation of accounting methods periodically, *(Mensah, 1984).* Moreover, accounting data are not that capable to predict default because they are structured to describe the financial position of a bank with the assumption that it will not display default, *Hillegeist et all (2004).* On the other hand, market based measures are more effective to predict future cash flows and consequently bankruptcy. *Li and Miu (2010),* illustrate that not only the market based but also the accounting risk measures can be useful and effective in the prediction of default because both can be characterized as risk measures and have the ability to describe the default probability. The level of the probability of a credit event plays a significant role in the importance and effectiveness between the market and the accounting based risk measures. The authors of the paper combine the accounting and market based risk measures to create a hybrid default prediction model and conclude that the market based models are better and more effective predictors of default in those firms that have high credit risk and they will be more precise by putting more weight on the distance to default and reducing the weight of the accounting variables.

Hillegeist et all (2004) show that the theoretical framework of option pricing constitutes the starting point of the differences between market and accounting based risk measures. Theory based on *Black and Scholes (1973) and Merton (1974)* illustrates that a call option with the same worth as the assets of the company can represent a firm's equity. The shareholders have the ability to decide when the call option can be exercised and when the enterprise is in the situation of default. When the company issues only zero coupon bonds, there is a higher probability of a default event. Specifically, when the value of the firm's assets is lower than the value of liabilities, the company isn't capable to repay its debts and the firm needs the intervention of its debtors**.** The range between the worth of the assets and the face value of the liabilities is a significant factor in the existence of the above phenomenon. Consequently, accounting variables give no additional information about the probability of default when there is volatility in the market. *Core and Schrand (1991) and Duffie and Lando (2001)* are in contrast with the above conclusion and display that accounting numbers can give additional information when markets aren't volatile. Specifically, the accounting information will be useful when the markets can't perceive the exact worth of the firm's value, the analysts can't use financial reports to estimate the assets in a perfect way and finally when debt holders have the ability to push a default only after the infringement of an accounting based debt covenant. *Duffie and Lando (2001)* show that the incremental information about the probability of default can be produced from every accounting number that has relation with the worth of assets/liabilities. On the other hand, *Core and Schrand (1991)* distinct this relation only in the association of accounting numbers with debt covenants. The above analysis concludes that market and accounting based measures might give additional insights about the probability of default.

Reisz and Perlich (2007) illustrate that accounting based risk measures are more applicable for short term default forecasts while market based risk measures are more effective for medium and long term default forecast. Also, the combination of an accounting based risk measure with a probability of default derived from a structural model can upgrade short term bankruptcy forecasts. However, the inclusion of an accounting measure to the probability of default derived from a structural model will not improve the long term bankruptcy forecasts.

Hillegeist et all (2004) deduce that there are many disadvantages that cause a lot of doubts about the effectiveness of probability of defaults that are derived from accounting variables. The probabilities of default are declarations about the possibility of situations in the future. On the other hand the financial statements are created to estimate past performance and may not be enlightening about the future of a company. Financial statements are created based on an assumption that entities will not bankrupt. Therefore, the accounting measures are not so credible and precise to estimate the probability of default because of their formulation. Furthermore, the accounting variables can cause the underestimation of asset values in relation with their market value. These characteristics of the accounting system will restrict the performance of accounting based risk measures.

In default forecasts, volatility is a vital measure because it includes the possibility that the value of the entity's assets will reduce in such a point that the company will not have the capacity to pay back its debt. Consequently, the probability of default is raising with volatility. Specifically, two different entities with the same leverage ratios can have dissimilar probabilities of default in relation with their asset volatilities. Thus, volatility is a significant omitted variable in the z-score model.

The stock market has the ability to give a different and more effective source of information in relation with the probabilities of default because it includes information not only from the financial statements but also from alternative sources. Although, the market based measures that give information about the probability of default are more effective, there is a problem about the extraction of the information regarding the probability of default from market prices. The option-pricing models constitute a starting approach.

The option-pricing models have advantages in default forecasts because they can give instructions about the theoretical factors of default risk and they provide the essential conditions for the extraction of information regarding default from market prices. Moreover, the market based measures make the analysts more flexible in their study because the market based measures are created independently for any publicly traded company.

Furthermore, the market based risk variables transcend the accounting variables even after their reformulation to take into account the contrasts between industries/ markets or yearly changes. Although, the market based risk measures are superior to accounting measures, accounting based risk measures provide additional information to market based measures.

Combined, these theoretical arguments lead to the following hypothesis:

H1: Market based risk measures are better predictors of default for banks than accounting based risk measures.

The corresponding null hypothesis is that the accounting based risk measures have the same predictive ability than market based risk measures.

3. <u>Methodology</u>

The purpose of this paper is to examine the ability of the accounting based and market based risk measures to predict credit events such as the bankruptcy of a financial institution. To achieve that I will use accounting and market based risk measures to compare their ability to forecast bank's failure. My sample consists of 18 US and European banks. The 15 banks that are included in the sample are Banco Santander, JP Morgan Chase, Wells Fargo, Citigroup, Bank of America, Barclays, Morgan Stanley, HSBC, Bank of New York Mellon, Capital One, Deutche Bank, ING Groep NV, PNC, Royal Bank of Canada and Toronto Dominion Bank. Also, the sample includes 3 bankrupt banks: Bear Stearns, Lehman Brothers and Merrill Lynch. I will further consider the estimation period to be from 1995 to 2015. I have chosen 1995 as the first year of my estimation, because I want to show the ability of market based risk measures to forecast a number of defaults before major financial crisis and to emphasize their difference with accounting risk measures. For these 20 years, I will calculate the default probabilities, which is the dependent variable, for each bank in the sample with the use of Merton model and I will use accounting and market based risk measures as independent variables. If the theoretical framework regarding the advantages of the market based risk measures is correct, I expect the market based risk measures to be better predictors of bank defaults than accounting based risk measures.

First of all, for the accounting risk measures I will use the profitability, the leverage and earnings variability ratio (*Beaver, Kettler, and Scholes, 1970 and Jarvela, Kozyra, and Potter, 2009*). Specifically, the profitability ratio is a measure to evaluate a firm's performance. This ratio shows the ability of a company to make a profit resulting from net income after the deduction of all costs and expenses relate to this income. The profitability ratio gives the opportunity to assess the capacity of a company to generate earnings and to compare it with other firms.

$$\text{Profitability ratio} = \text{Net Income}/\ \text{Total Assets}$$

The next accounting risk measure is the debt to equity ratio. Specifically, the debt that the company uses to fund its assets. The leverage ratio shows the capacity of a company to meet its financial obligations.

$$\text{Leverage ratio} = \text{Debt}/\ \text{Equity}$$

The earnings variability shows the volatility of the earnings per share in a given time period and is measured by the standard deviation of the price to earnings ratio

$$EV= (\sum_{t-1}^{T}(E_t/P_{t-1} – [(\bar{E}/P])^2 /T)^{1/2}$$

Where $$E_t / P_{t-1} = \frac{income\ available\ of\ common\ shareholderst}{market\ value\ of\ common\ stockt-1}$$

$$\bar{E}/P =(\sum_{i=1}^{T} \mathrm{Et} / \mathrm{Pt}-1)/T$$

As we can see, the earnings price ratio has a market term in the denominator. Consequently, this ratio can be characterized as a rate of return which consists of the income that is derived from accounting items and of the market value, something that makes the ratio to be relevant with the market rate of return.

The market based measures that I will use are equity returns, equity volatility, market capitalization to total debt ratio (MCDT) and total size. First of all, the equity volatility is measured by the standard deviation of daily returns. The banks with higher volatility are riskier. In addition, the use of equity prices is significant for the model because they incorporate information regarding financial statement data and other publicly available information contributing to the market as a more effective processor of all information than accounting numbers and thus they have the ability to increase the accuracy of the model. Moreover, it is expected that equity prices will have a strong negative relationship with the default probability because the equity prices have the ability to show the expectations of investors for future cash flows and earnings. As a result, a high value in equity prices will decrease the default probability. We expect the coefficient of equity returns to have a negative sign in the default probability regression, showing that a great value of this measure should have a negative effect on the default probability of each bank. However, I used some assumptions about equity prices include all information that is related to default probabilities. Another assumption about the equity prices is that they will contain information that is related to the financial situation and macroeconomic conditions and consequently, enhance the predictive power of the model.

Moreover, a low market capitalization to total debt ratio shows that a bank's decrease in value is near to financial distress or in the situation where the total debt overdraws the assets of the bank. Therefore, a higher market capitalization to total debt ratio should involve a lower probability of default. In contrast, a lower ratio should imply a higher probability of default. Specifically, in the situation where coefficient of this financial ratio has a negative sign in the default probability regression, this shows that when the value of this measure is high should have a negative effect on the probability of default of the bank. The last market variable is the size of the bank measured by its total assets. *Agarwal and Taffler (2008)* showed that the probability of default is the same as the probability that the call option will not be exercised in the BSM model, and the value of the assets is lower than the face value of the liabilities in the end of the exercising period. Thus, it is posited that a high value of the size measure relative to debt should involve a low probability of default. On the other hand, a small bank should have a higher probability of default, given a high level of debt. Specifically, I will expect for the coefficient of the size a negative sign in the default probability regression, indicating that a high value of this measure should involve a negative effect on the probability of bankruptcy of the bank.

In the methodology that I will follow, I have to calculate individual bank's default probabilities. *Merton (1974),* estimates the default probability as the normal distribution function of the negative distance to default measure. The distance to default is calculated as a function of firm asset value, asset volatility, estimated asset growth and time to maturity of a zero coupon bond issued by the firm. Another calculation of the default probability of the banks is that on the paper of *Avesani et al. (2006)* that estimates the default probability of a bank x_i calculated as the probability that the value of the bank's assets will fall below a certain threshold: Prob ($y_i < \bar{y}|M$) = Q (t| M), where M is a set of common factors of the institutions' default probabilities. Q_i (t) is the cumulative risk-neutral default probability, that bank i will default before time t and is expressed as follows:

$$Q_i\,(t_i \leq t) \equiv 1 - e^{-\int_0^1 \lambda i(u)du} \qquad (1)$$

Where λ_i is the default intensity function of bank i. The default intensity λ is defined as the CDS spread S over a bond's loss given default:

$$\lambda = S/ (1- R) \tag{2}$$

Where R is the bond's recovery rate in case of default.

Nevertheless, this calculation for the default probability is not feasible for the whole sample from 1995 to 2015 because the data for CDS were not available from 1995. This technique can be used only for the months that CDS are available but it is preferable to use a calculation for the entire sample. Specifically, the Merton model is more suitable for the estimation of the probabilities of default.

First of all, for the calculation of the default probabilities with the Merton model, it is necessary to identify the value of each bank and its volatility. Nevertheless, both the value of the bank and its volatility are not directly observable. Therefore, the model assumes that a bank's value and volatility can be deduced from the value of equity and the equity volatility. After, this recognition, for the estimation of the default probability, the Merton framework deduces the face value of the bank's debt from the market value of the bank and then divides this estimation by the volatility of the bank. The distance to default is used as input in a cumulative density function to estimate the probability that the bank's value will be lower than the face value of bank's debt. The market value of the bank is the value of bank's debt plus the value of bank's equity.

The Merton model is based on two significant assumptions. The first is that the banks value follows a geometric Brownian motion:

$$dV= \mu Vdt + \sigma_v VdW \tag{3}$$

Where V is the banks value, μ is the average firm growth rate, σ_v is banks value volatility and dW is a stochastic Wiener process. The other significant assumption on this model is that the financial institution provides one discount bond with maturity in T periods. With these assumptions, the bank's equity is a call option on the bank's value with a strike price equal to the face value of the debt of the bank and a time to maturity equal to T.

In the Merton model, the equity value of a financial institution satisfies the following equation:

$$E = VN\,(d1) - e^{-rt}\,FN\,(d2) \qquad (4)$$

Where E is the value of the entity's equity, F is the face value of the company's debt, r is the risk-free rate, and N (d1) is the cumulative standard normal distribution function, d1 derived from the equation:

$$d1 = ln\,(V/F) + (r + 0.5\sigma V2)\,T/\sigma_V\sqrt{T} \qquad (5)$$

And d2 = d1 - $\sigma_V\sqrt{T}$. Equation 5 is the Black-Scholes Merton equation and provides the value of an entity's equity as an equation of the value of the entity. Equation 6 includes the volatility of the value of the financial institution to the volatility of its equity. Based on Merton's assumptions and from Ito's lemma he firm's equity volatility is expressed by the following equation:

$$\sigma_E = (V/E)\,\partial E/\partial V\,\sigma_V \qquad (6)$$

Where $\partial E/\partial V = N\,(d1)$ in the Black Scholes Merton model. Consequently, the volatility and the equity of the financial institution are specified as

$$\sigma_E = (V/E)\,N(d1)\,\sigma_V \qquad (7)$$

In the Merton model, the value and the volatility of the equity of an entity are based on the equations 8 and 5. The BSM framework express the value of an option in relation with four variables: strike price, time to maturity, asset price, and the risk free rate and volatility that can be calculated. However, the market value of the asset is not directly observable, the entity's equity is regarded as an option on the firm's assets. Therefore, E is easy to calculated by the shares outstanding multiplied with the share price. Also, σ_E can be calculated but the σ_V, the volatility of the entity must be derived.

Consequently, for the calculation of the default probability the following steps are necessary. The first step is the calculation of the volatility of equity from historical equity returns or from option suggested volatility data. The next step is the selection of a forecasting horizon and a variable of the face value of the bank's debt. It is more common to use T=1 as a forecasting time horizon and total liabilities as the face value of the debt of each financial institution. The last steps is to concentrate values of the risk free rate and the market equity of the bank. Finally, the total asset value and the volatility of the asset value of each financial institution.

The distance to default can be estimated from the equation:

$$DD = [\ln (V/F) + (\mu - 0,5\sigma^2_V)\, T]/\sigma_V\sqrt{T} \qquad (8)$$

Where V is firm value, F is the face value of debt, μ is the growth rate of firm assets, σ_V is asset volatility and T is the time to maturity of a bond issued by the firm. The probability of default is then calculated as the normal cumulative density function of the distance to default:

$$N (-[(\ln (V/F) + (\mu - 0,5\sigma^2_V)\, T]/\sigma_V\sqrt{T})) = N (-DD) \qquad (9)$$

Beaver, Kettler, and Scholes, (1970) compute two separate regressions for accounting and market based risk measures to estimate the results of each of the 307 firms in the sample. Also, *Lakonishok and Shapiro, (1985)* examine the relationship between return and risk with the use of a prediction test. They estimate individual securities because of the decrease in efficiency in the case where data are grouped together, something that is supported by Litzenberger and Ramaswamy (1979). Consequently, I will run 18 regressions with the combination of market and accounting based risk measures.

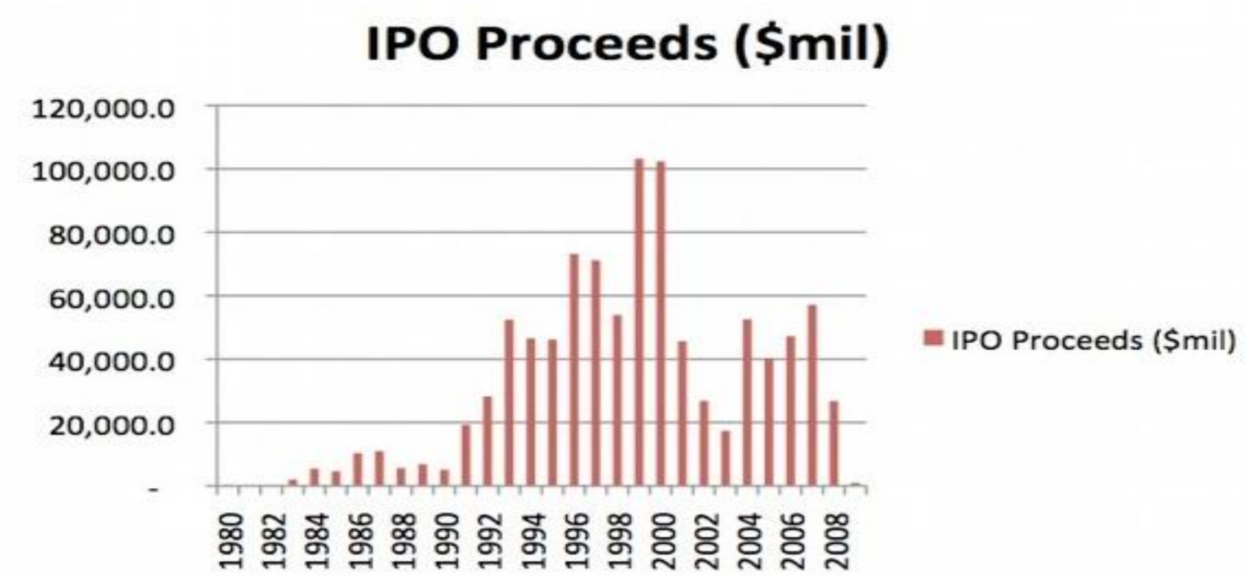
I will use the following OLS regression to estimate the results with a combination of market and accounting based risk measures in the following equation:

$$Pr_{it}(X) = \alpha + \beta_1 PR_{it} + \beta_2 L_{it} + \beta_3 EV_{it} + \beta_4 ER_{it} + \beta_5 MCTD_{it} + \beta_6 EV_{it} + \beta_7 S_{it} + \beta_8 Dcrisis_{it} + \varepsilon. \quad (10)$$

Where Pr_{it} is the probability of default of bank i in year t. $Dcrisis_{it}$ is a dummy variable that stands for the crisis years. In 1990, a rapid growth of computer and internet firms was observed. These companies became larger in a very short time period and didn't pay dividends to shareholders, something that gave the necessary mass for the capital gain tax cut to initiate the Dot com Bubble which lasted from 1999 to 2001. In figure 1 we can see the size of Initial Public

Offerings (IPOs) for every year since 1980, starting from a low level at the beginning of the 1980s to their highest level before the Dot Com Bubble:

<u>Figure 1: IPO PROCEEDS ($mil)</u>



Source: Thomson Reuters

The financial crisis of 2007-2008 is known as the Global financial crisis and one of the worse financial crisis since the Great Depression. The consequences of this crisis were among others the default of financial institutions and banks and a global decline in stock markets. The financial crisis played a vital role in the default of companies that had a key role for the economy, a decrease in the financial and economic activity that led to the 2008-2012 global recession and to the European sovereign debt crisis. A decrease in credit availability and very low investor and banking confidence had negative consequences on global stock markets with great losses from 2008 to 2009. In figure 2 we can see the percentage fall of real GDP from its pre-recession peak:

Figure 2: Real GDP, percent fall from pre-recession peak

Source: Bureau of Economic Analysis, Bureau of Labor Statistics, Federal Reserve Flow of Funds.

Consequently, the D_{crisis} will be 0 for non-crisis years and 1 for crisis years. The crisis years correspond to 1999-2001 that are related to the dot-com bubble and 2007 and 2008 that are related to the financial crisis.

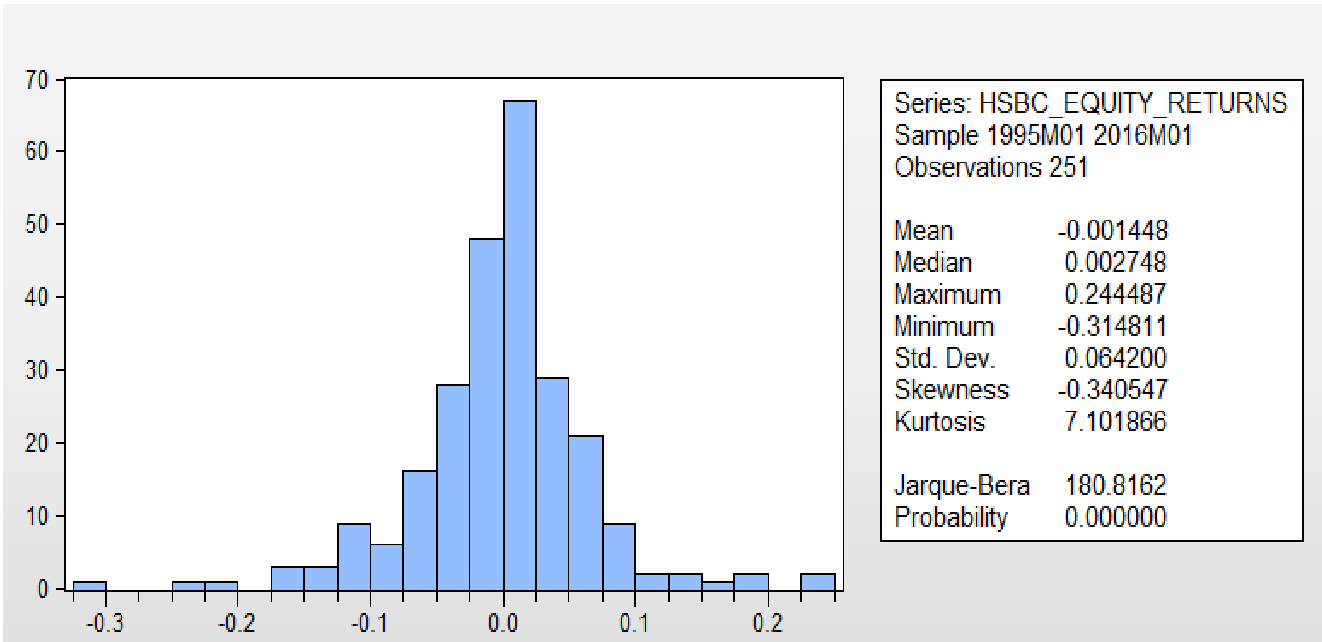
4. Data sources

Data are available through databases within the Wharton Research Data Services system to which the university library subscribes. To calculate the profitability ratio, the leverage ratio and the earnings variability ratio, I need data for debt, net income, total assets, and income available to common shareholders. These data taken from the Compustat database. For the estimation of the earnings variability ratio, I need data for the market value of common stock that consists of the share price at the end of each month multiplied by the number of shares outstanding. The market value for every bank in the sample will be derived from CRSP. Furthermore, for the estimation of equity returns and equity volatility, share prices are necessary, derived from CRSP too. In addition, for the estimation of the size variable, total assets are necessary, obtained from Compustat database. In the Merton model, the estimation of distance to default and consequently the default probability needs data for five variables: share prices, the risk free rate, the time to maturity of the debt, the face value of the debt of every bank in the sample and volatility of share prices. The share prices and the market value of equity are derived from CRSP database for every of the 18 banks in the sample. The face value of the debt on the bank obtained from Compustat database. The 3-month Treasury bill is assumed to be the risk free rate of interest, obtained from the database of the board of governors of the Federal Reserve System

5. Descriptive statistics

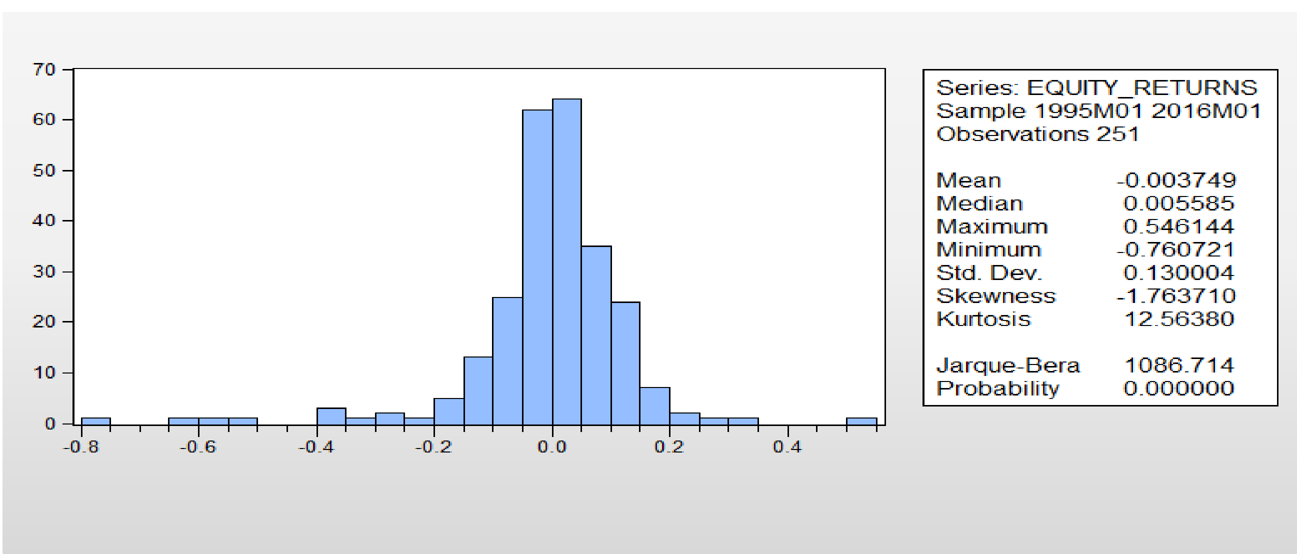
Before the analysis of the results and the comparison between accounting and market based risk measures regarding their predictability on bank defaults, I will exhibit the statistical characteristics of the18 banks in my sample. The monthly returns of the 18 banks in the sample follow a distribution that is close to normal (skewness=0, and kurtosis=3) without the inclusion of outliers. I will show the equity returns distribution of HSBC and Bank of America indicatively because all banks in my sample are in a similar economic environment and have similar characteristics which affects their equity returns distribution. Figure 3 shows HSBC's equity returns distribution. In the appendix, there are the histograms and descriptive statistics of all banks in the sample.

Figure 3: Histogram and Descriptive statistics of HSBC's stock returns



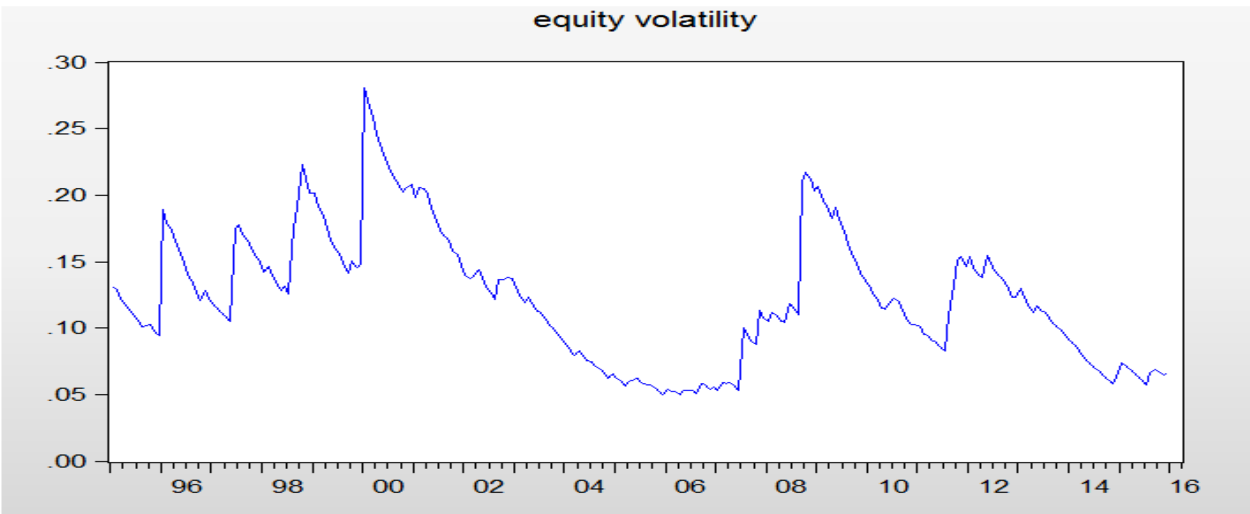
There are some exceptions that follow a distribution with kurtosis greater than 3 and skewness smaller than 0, mainly because of the outliers in each return distribution. Figure 4 shows Bank of America's equity returns distribution.

Figure 4: Histogram and Descriptive statistics of Bank of America's stock returns



Furthermore, equity volatility for all banks seems to follow a similar route with few exceptions. Specifically, volatility is higher for all the banks in the sample throughout the period from 1998-2002 because of the dot com bubble and throughout the period of financial crisis 2007-2008. Figure 5 shows the standard deviation of returns of Morgan Stanley. The figure depicts a high standard deviation of returns for Morgan Stanley after 1996. The highest equity volatility is throughout 1999-2000 and during financial crisis.

<u>Figure 5. Morgan Stanley's standard deviation of equity returns</u>



In the following figures (figure 6 and 7), we can see the variation of market and acounting based risk measures for 3 bankrupt banks, Bear Stearns, Lehman Brothers and Merrill Lynch, and for 5 non bankrupt banks, Bank of America, Citigroup, Deutche Bank, ING, and Royal Bank of Canada from 1995 to 2015. These graphs show how the market and acounting based risk measures behave around the two crisis periods and from this analysis we could provide some evidence about which one of market and accounting based risk measures predict bankruptcy better.

Figure 6. market and accounting based risk measures for 3 bankrupt banks

As we can observe, the first three graphs show the accounting based risk measures for bankrupt banks from 1995 to 2015. The highest and the lowest values of leverage and profitability ratio respectively are throughout 1998-1999 and during the financial crisis. Although, the earnings variability ratio doesn't display a great variation throughout the years, it has the lowest values throughout the financial crisis and the dot com bubble.

Figure 6.1 Merrill Lynch, Lehman Brother and Bear Stearn's leverage ratio

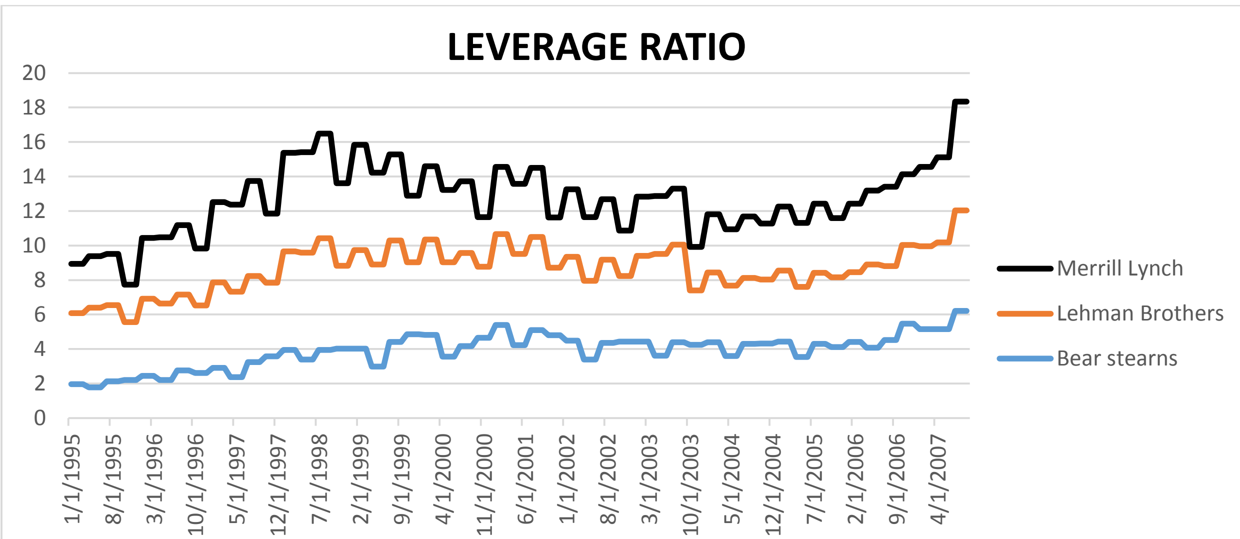
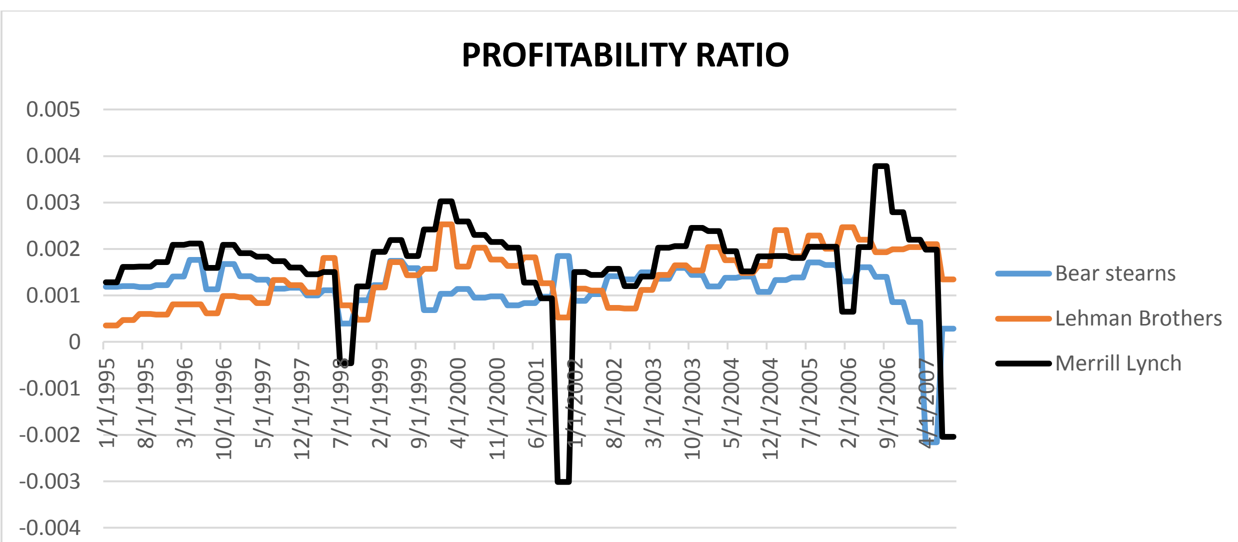
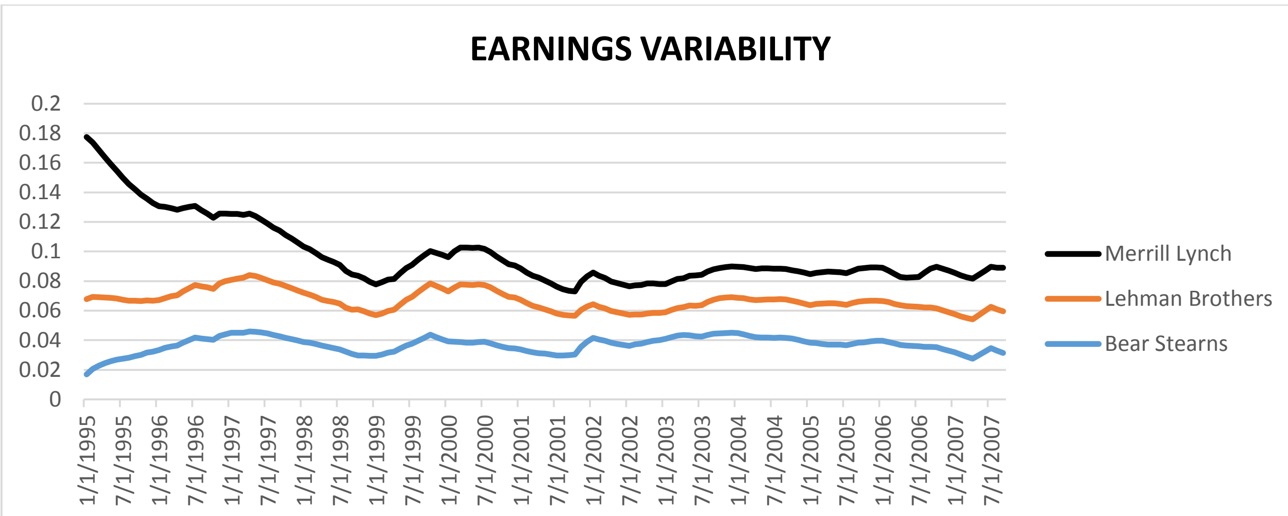


Figure 6.2 Merrill Lynch, Lehman Brother and Bear Stearn's profitability ratio



<u>Figure 6.3 Merrill Lynch, Lehman Brother and Bear Stearn's earnings variabilty</u>



The following diagrams display the market based risk measures for Bear Sterans, Lehman Brothers and Merrill Lynch. Specifically, Lehman Brother's equity volatility takes the highest values during the dot com buble and the financial crisis. Equity returns display the lowest values in the same time periods. For all 3 banks, market capitalization to total debt has the greatest value throughout 1999-2000 but after that reaches unprecedented lowes until bankrupcy. The final market based risk measure, size, displays the lowest value during the dot com buble but after that loses its representativeness during the financial crisis.

Figure 6.4 Merrill Lynch, Lehman Brother and Bear Stearn's equity returns

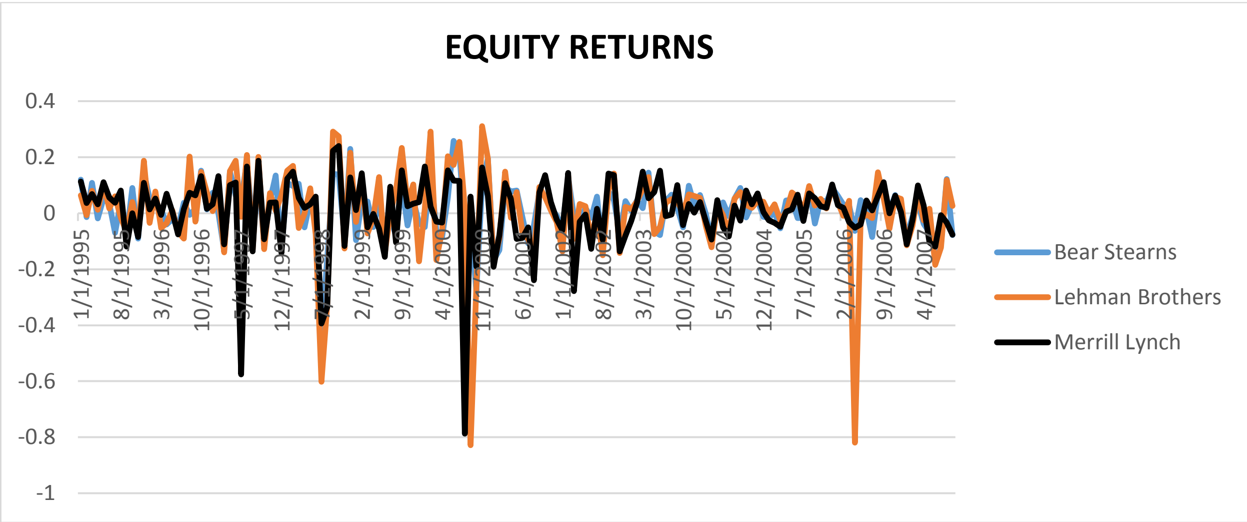
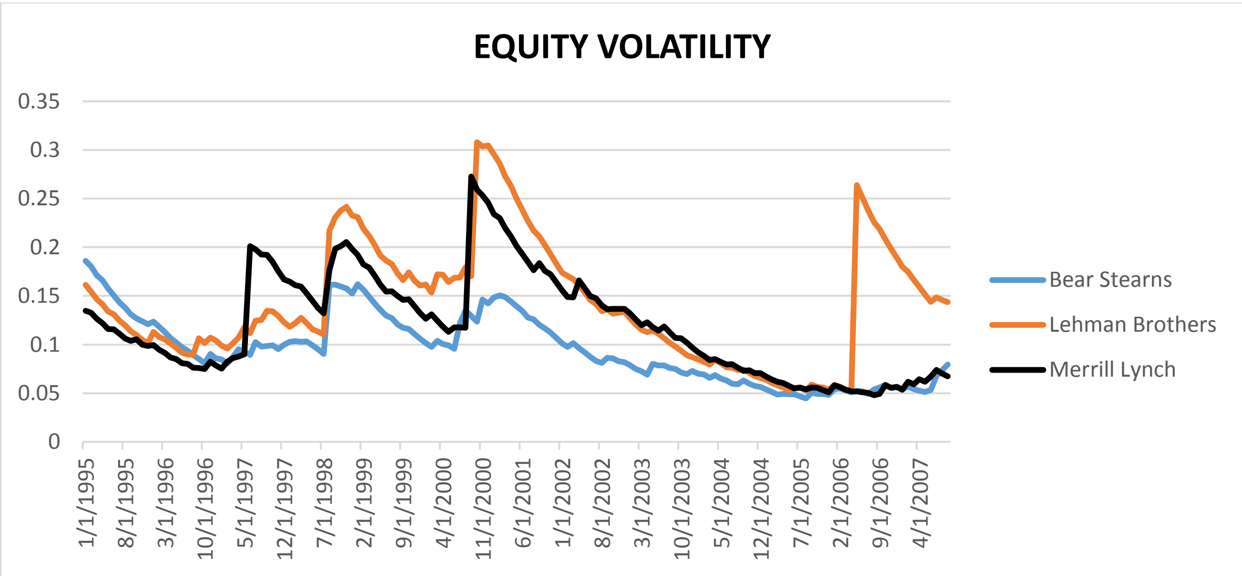
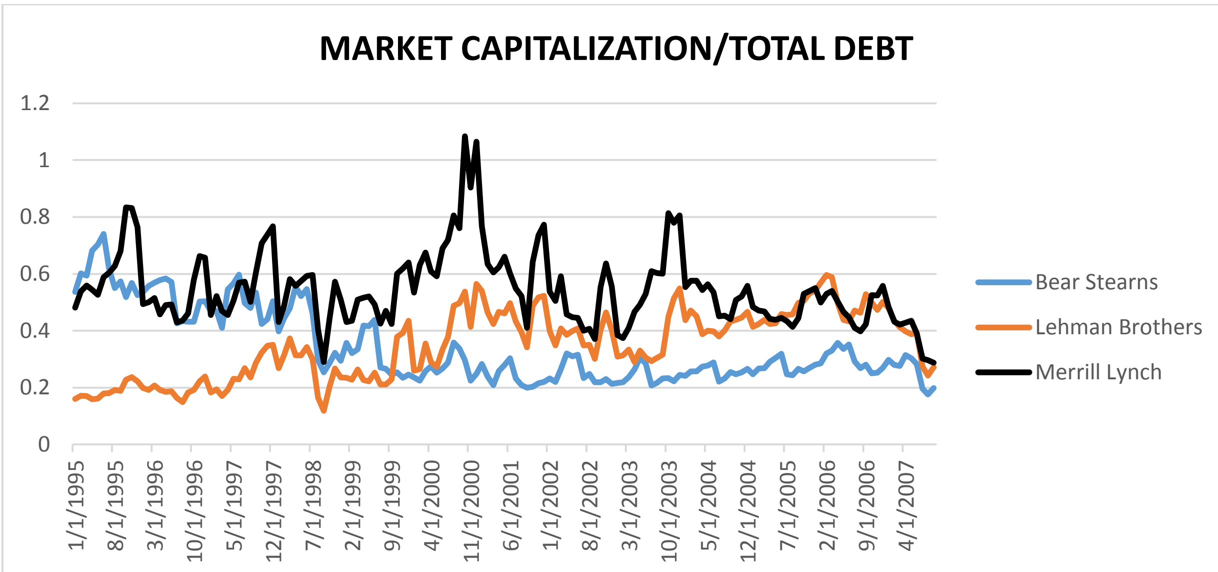


Figure 6.5 Merrill Lynch, Lehman Brother and Bear Stearn's equity volatility



<u>Figure 6.6 Merrill Lynch, Lehman Brother and Bear Stearn's market capitalization/total debt ratio</u>



<u>Figure 6.7 Merrill Lynch, Lehman Brother and Bear Stearn's size</u>

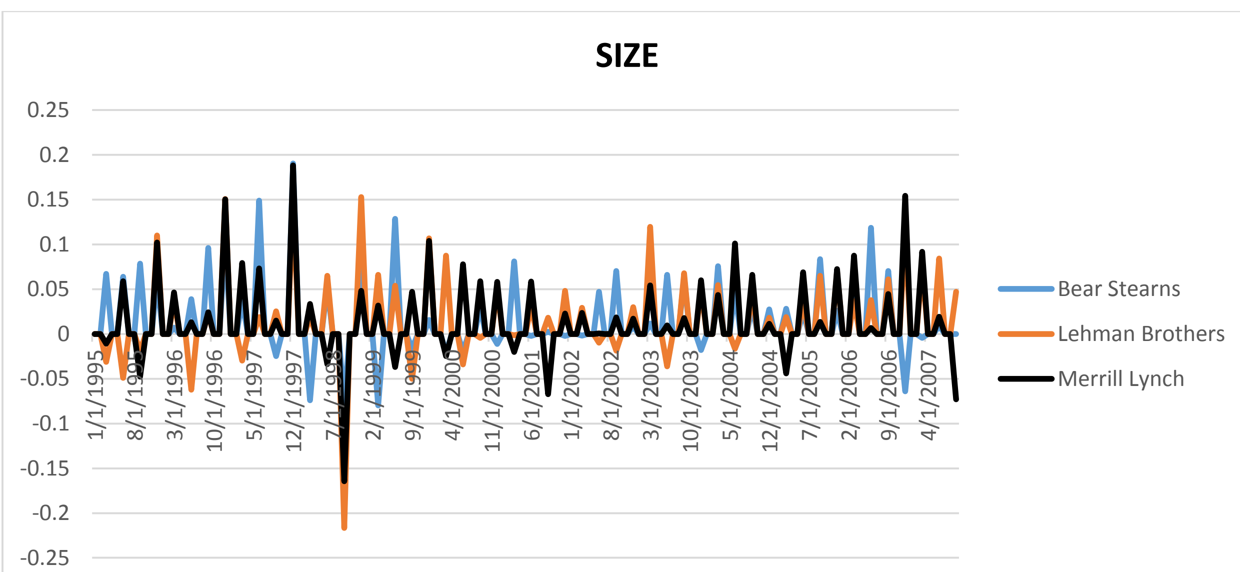


Figure 7. market and accounting based risk measures for 5 non bankrupt banks

The first three graphs show the accounting based risk measures for 5 non bankrupt banks (Bank of America, Citigroup, Deutche Bank, ING, and Royal Bank of Canada) from 1995 to 2015. The highest values of the leverage ratio are during the financial crisis and dot com bubble. Royal Bank of Canada has a very low, close to zero leverage ratio because it may uses equity rather than debt as a way to fund its liabilities. Moreover, as we can see all the banks in the graph have a similar variation in their profitability ratio with the lowest values during 2007-2008 and 2001. Finally, in the last diagram, most of the banks have a very low earnings variability ratio and without great variations throughout the years while ING and Citigroup have the greatest values during 2008-2009 and 2001. Consequently, we can observe that the leverage and profiatbility ratios may be more representative accounting ratios than the earnings variability.

Figure 7.1 Bank of America,Citigroup, Deutche Bank, ING and Royal Bank of Canada's leverage ratio

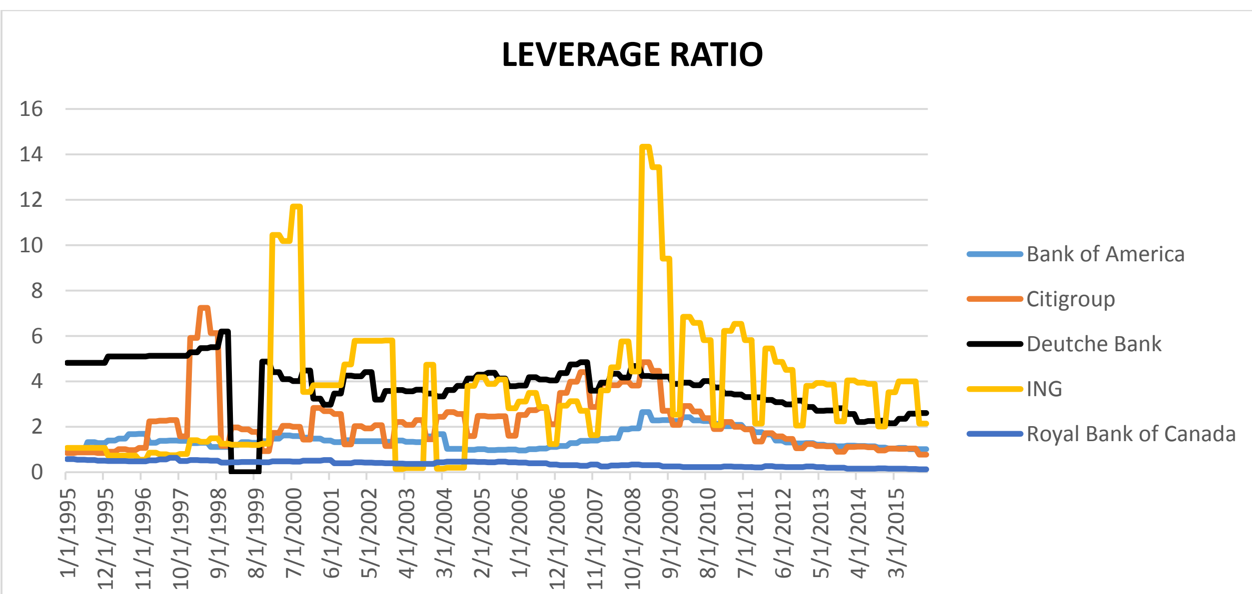


Figure 7.2 Bank of America,Citigroup, Deutche Bank, ING and Royal Bank of Canada's profitability ratio

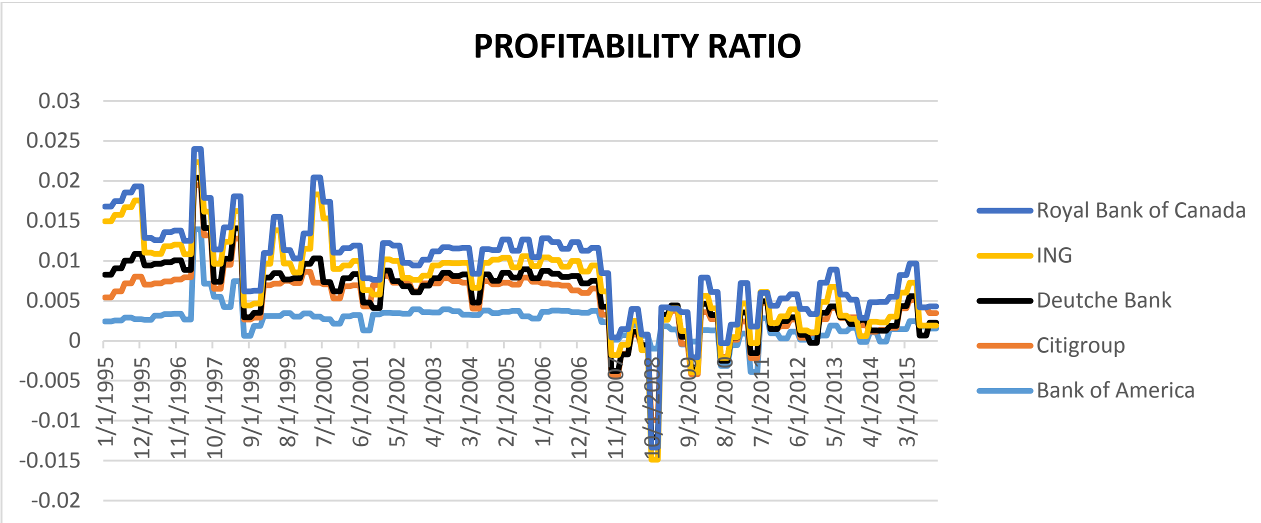
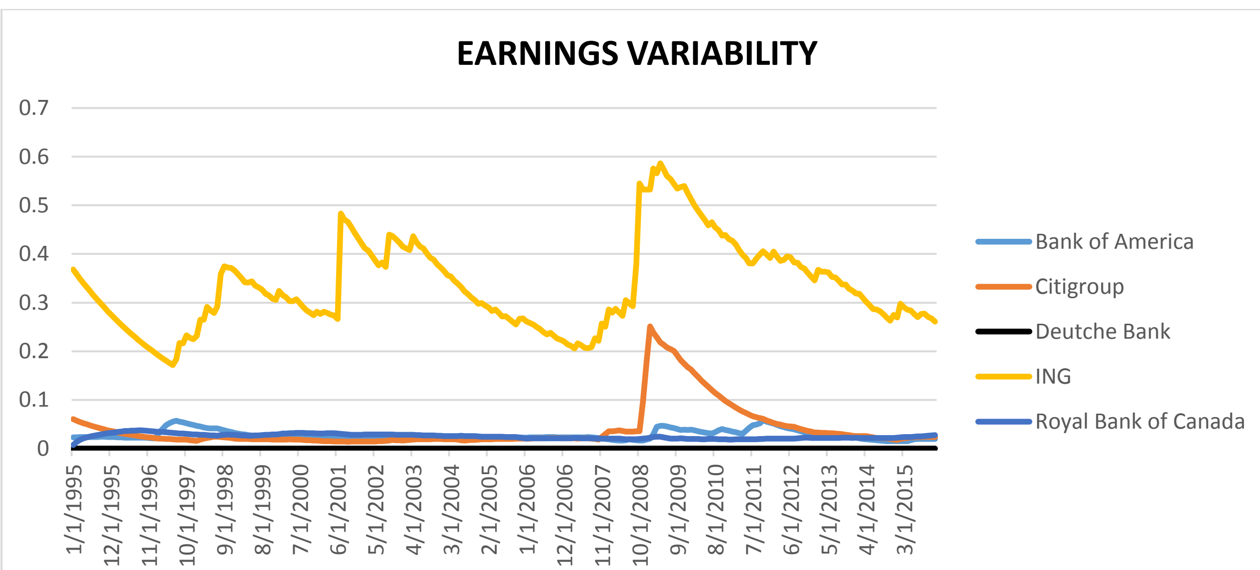


Figure 7.3 Bank of America,Citigroup, Deutche Bank, ING and Royal Bank of Canada's earnings variability



The following graphs show the market based risk measures for 5 non bankrupt banks from 1995 to 2015. Most of banks follow the same variation in the equity returns and equity volatility. Specifically, they have the lowest and greatest values in equity returns and equity volatility respectively, throughout the dot com bubble and the financial crisis except for Citigroup that has the highest equity return and equity volatility in 2011. In 2010, Citigroup accomplished a profitable year since 2007 but after that it was one of the five financial institutions that failed in its stress tests, which meant that Citigroup didn't keep enough capital to absorb huge losses in a financial crisis.

Also, all the banks except for ING and Bank of America, have a very low and close to zero market capitalization to total debt ratio. ING and Bank of America's market capitalization to total debt have the lowest values during 2008-2009 and 1998. The last market based risk measure, size, fluctuates in a similar way throughout the years for all banks. The lowest values of size are during the financial crisis and 1998. As we can see, we can conclude that the equity volatility may be more representative than the other market based risk measures.

__Figure 7.4 Bank of America,Citigroup, Deutche Bank, ING and Royal Bank of Canada's equity returns__

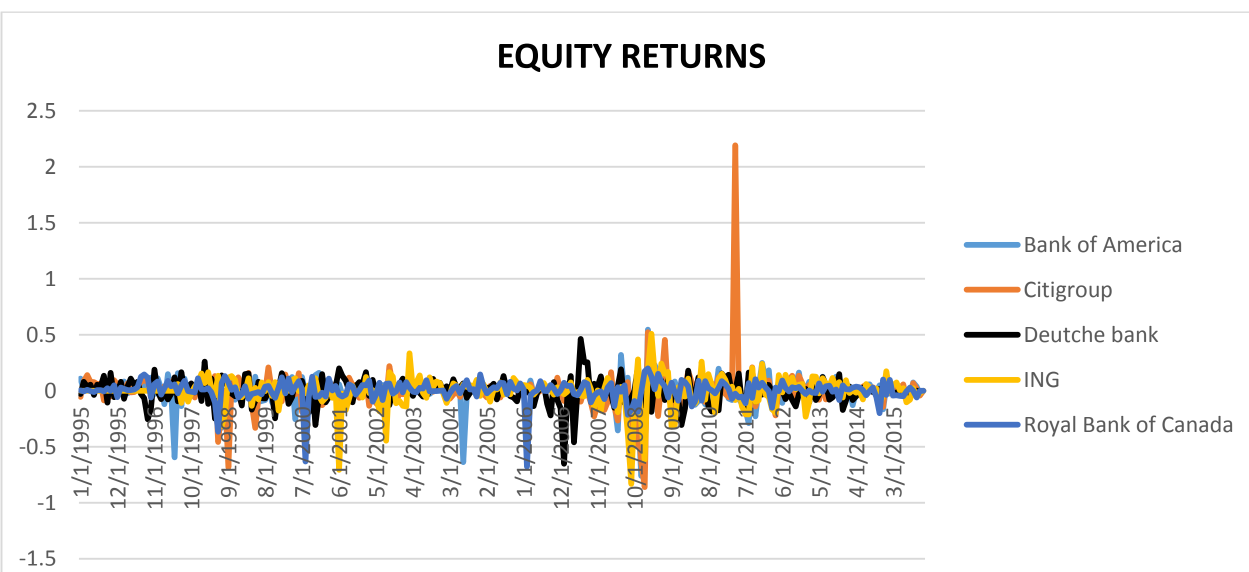


Figure 7.5 Bank of America,Citigroup, Deutche Bank, ING and Royal Bank of Canada's equity volatility

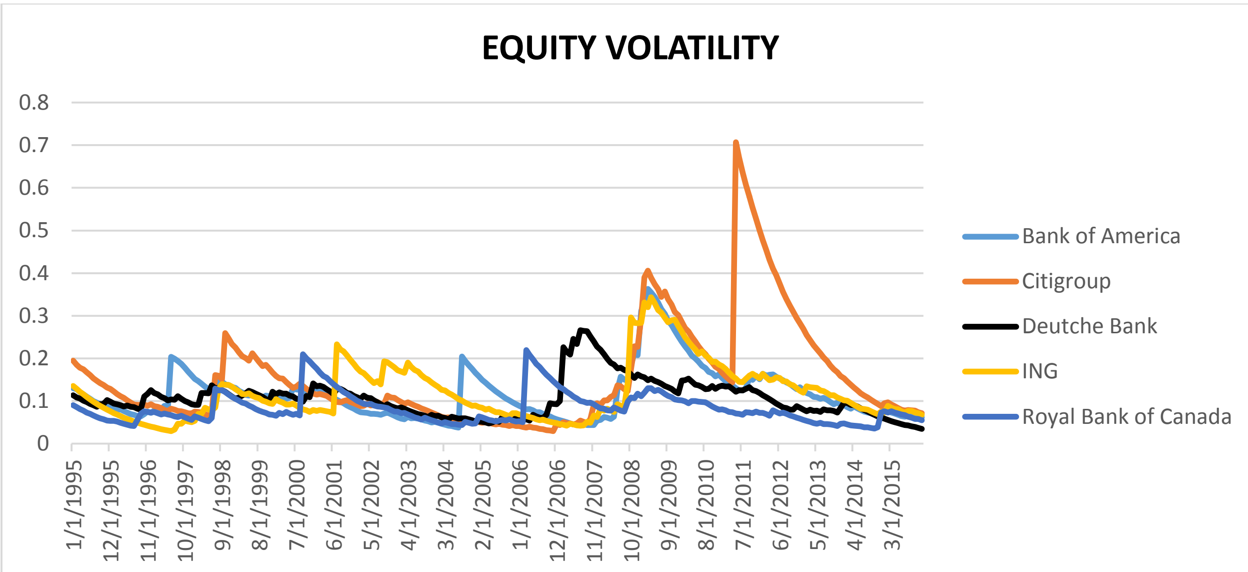


Figure 7.6 Bank of America,Citigroup, Deutche Bank, ING and Royal Bank of Canada's market capitalization/total debt ratio

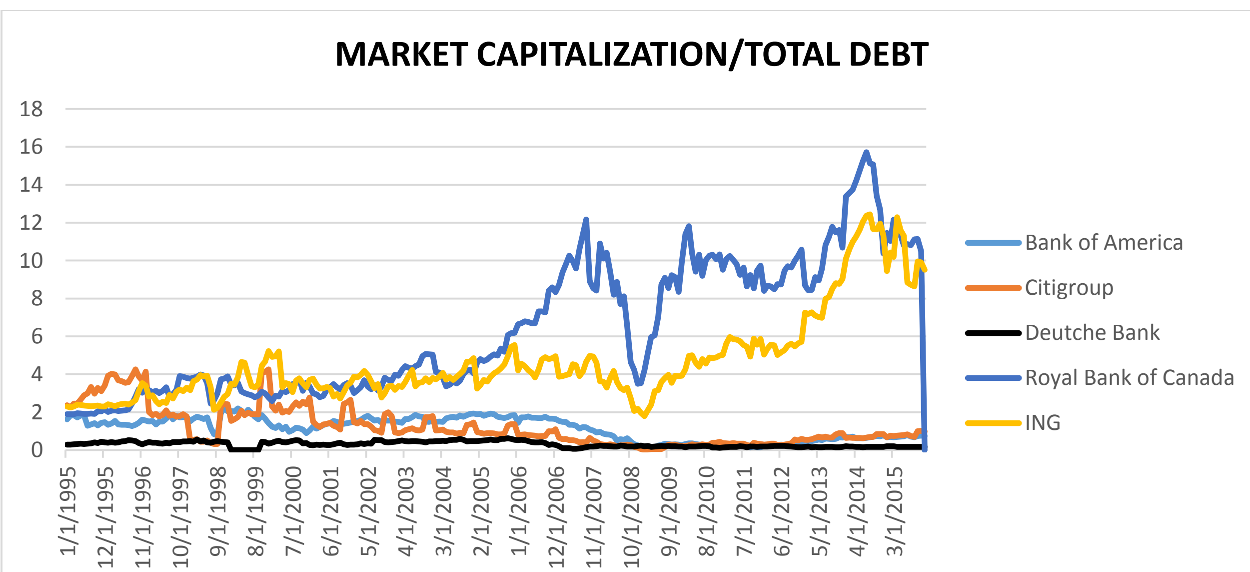
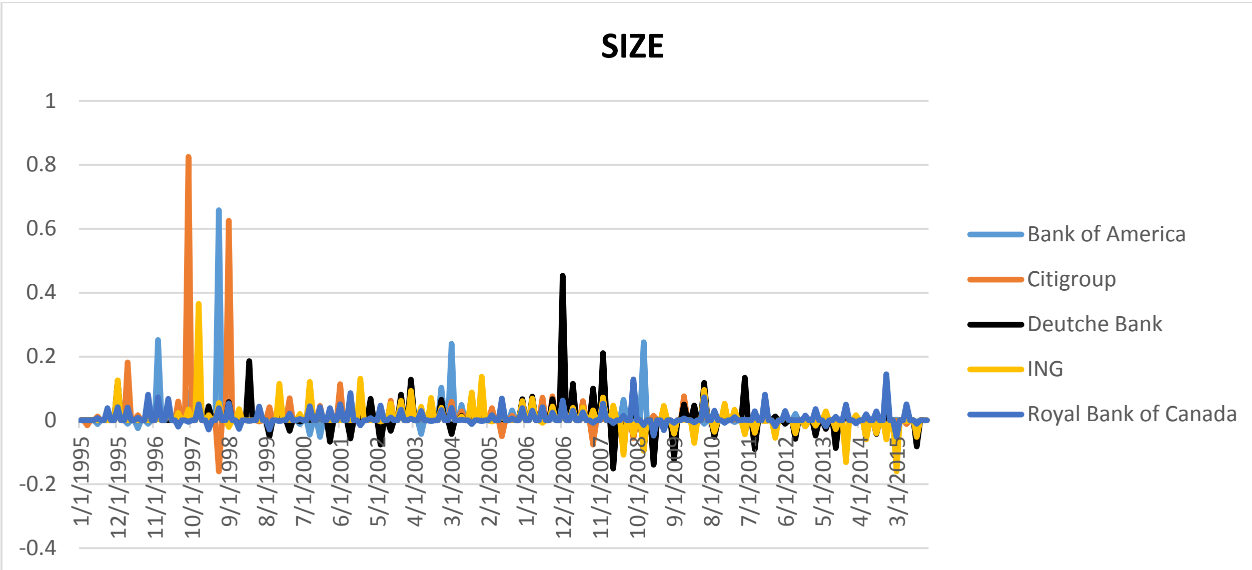


Figure 7.7 Bank of America,Citigroup, Deutche Bank, ING and Royal Bank of Canada's size



However, descriptive statistics alone do not allow us to make conclusions about the data or to deduce something about the hypothesis and the predictive ability of accounting and market based risk measures about the bank default. Based on figure 6 and 7 that show the variation of each of the market and accounting based risk measures around the two crisis period, we could highlight some interesting remarks regarding the research question of this thesis. Specifically, we can expect that leverage, profitability and equity volatility ratio may be more representative and specifically leverage and profitability ratio in comparison with equity volatility may be more illustrative in the prediction of bankruptcy.

6. Results

6.1 Calculation of default probabilities

First of all, the calculation of default probabilities for my analysis is necessary for each of the 18 banks in the sample. In the Merton model, the equity values and equity volatilities are used for the calculation of market value of bank's assets and their volatilities, which are not directly observable. In my master thesis I will use total assets values and asset volatilities derived from bank's balance sheet data instead of the derived market value and volatility of every bank's assets for the calculation of the marginal monthly default probability for each of the 18 banks in the sample. This is not in agreement with the Merton model, but all the banks in the sample are participating in the banking and financial sector and consequently it is expected the book value of their assets to be close to their market value, and consequently the majority of the assets in their balance sheet consist of marketable securities. Another assumption is that the forecasting horizon is 1 year.

The marginal defaults probabilities for the 18 banks give a default estimation for each of the 253 months from 1995-2015. From the default probabilities graphs, an increase in the default probabilities during 1998-2001 and 2007-2008 is observed. Figure 8 and 9 depict the Lehman Brother and Merrill Lynch's default probability graphs that constitute characteristic examples of the above observation.

<u>Figure 8. Lehman Brothers Merton model default probabilities</u>

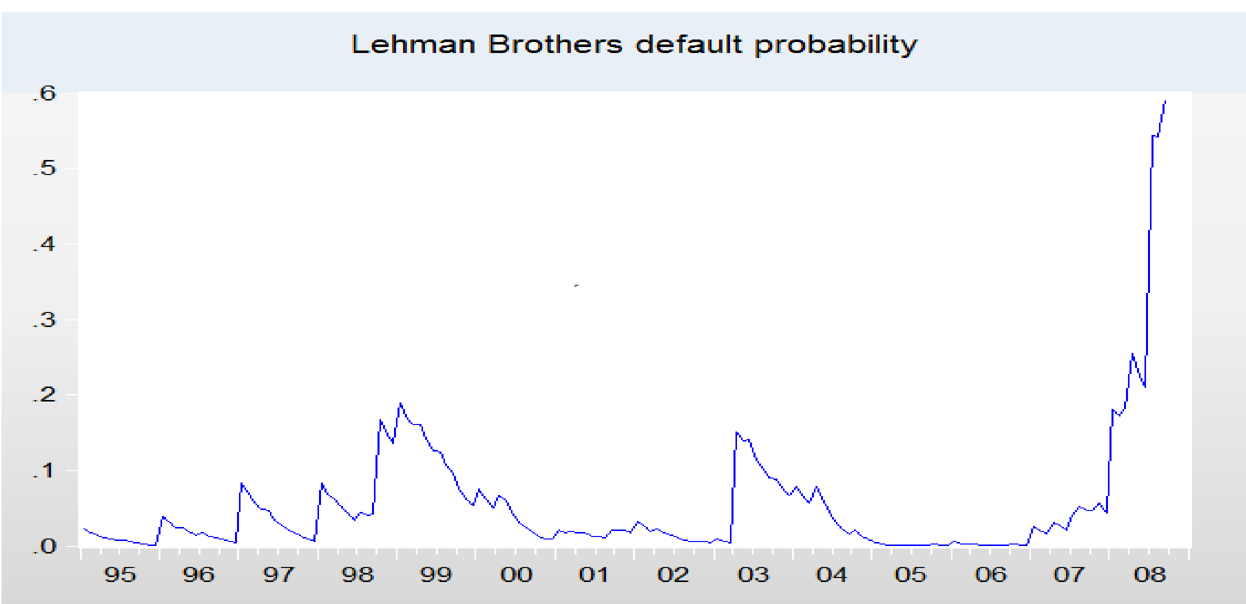
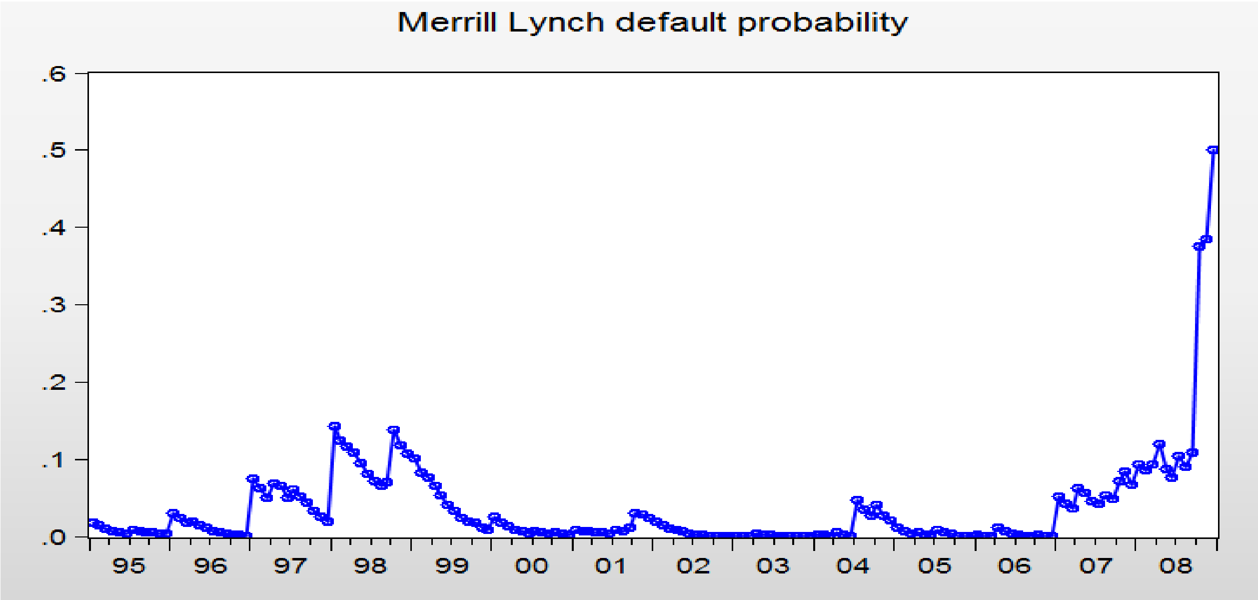


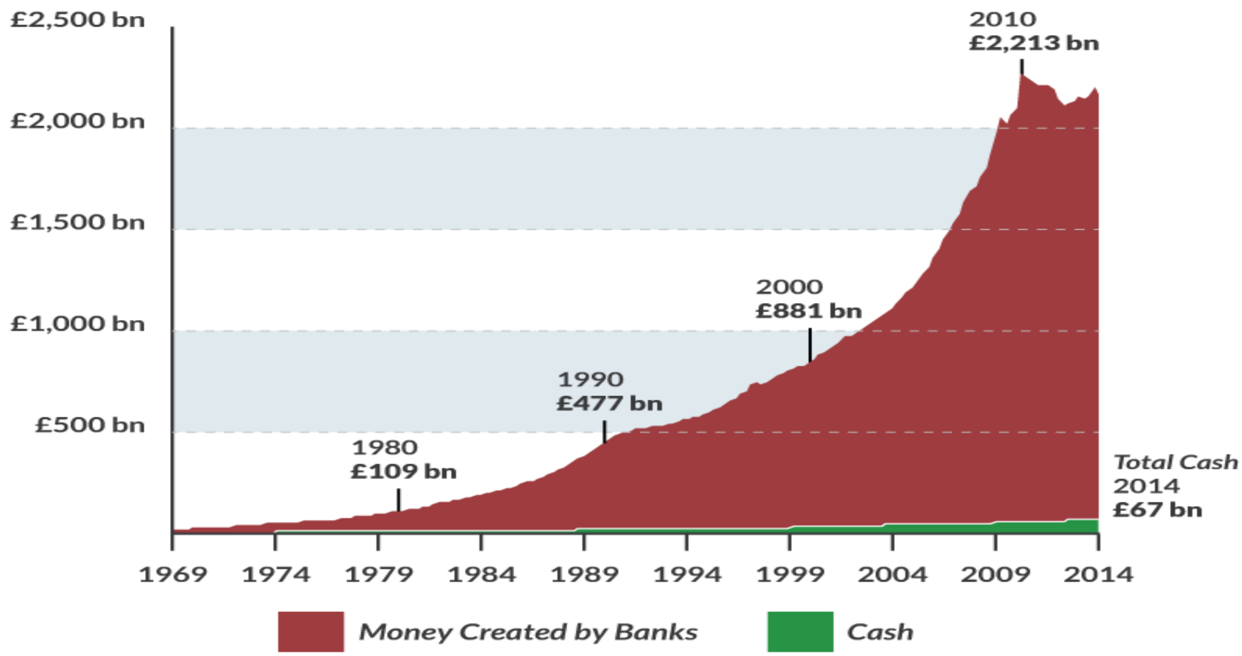
Figure 9. Merrill Lynch Merton model default probabilities



The increase in the default probabilities during 1999-2001 and during the financial crisis have several explanations. First of all, the dot com crisis and the financial crisis play a significant role in this increase. Specifically, the breakdown of Lehman Brothers in September 2008 caused negative consequences to the global financial system.

Another factor that is responsible for the increased default probabilities is the lack of regulation. The regulatory changes gave the chance to banks to buy risky financial instruments regardless of the capital requirements. Moreover, the regulation not only wasn't able to prevent the crisis but it also assisted its outbreak because it didn't create a mechanism where a bank would be able to bankrupt without causing negative effects to the whole financial system. In other words, regulation failed to constrain contagion of the transition of negative shocks throughout the financial system. Without being strictly regulated banks had the opportunity to invest heavily mortgage backed securities and other ambiguous securities. Figure 10 shows that banks created large amounts of money by making loans. Specifically, in the last 7 years banks doubled the amount of money and of course their debt.

Figure 10: increasing amount of money created by banks the last 7 years



Finally, the increased use of credit default swaps as insurance to a credit event may constitute a vital factor in the increase of the default probabilities. Commercial banks are the most active in the market and holds the biggest amount of CDS like JP Morgan Chase, Bank of America and Wachovia. Additionally, the CDS market is still largely unregulated market. Consequently, the contracts have the ability to be traded from trader to trader without anyone to ensure that the buyer is able to pay the losses if the security default. The situation became worse because of the huge trading volume of these instruments, the privacy of the trades and the lack of regulation. The nature of the credit default swaps market and CDS trading in general has impacted both the European sovereign crisis and the subprime crisis. If bond insurance becomes too costly or disappears, creditors will become more careful in evaluating the credit quality of borrowers.

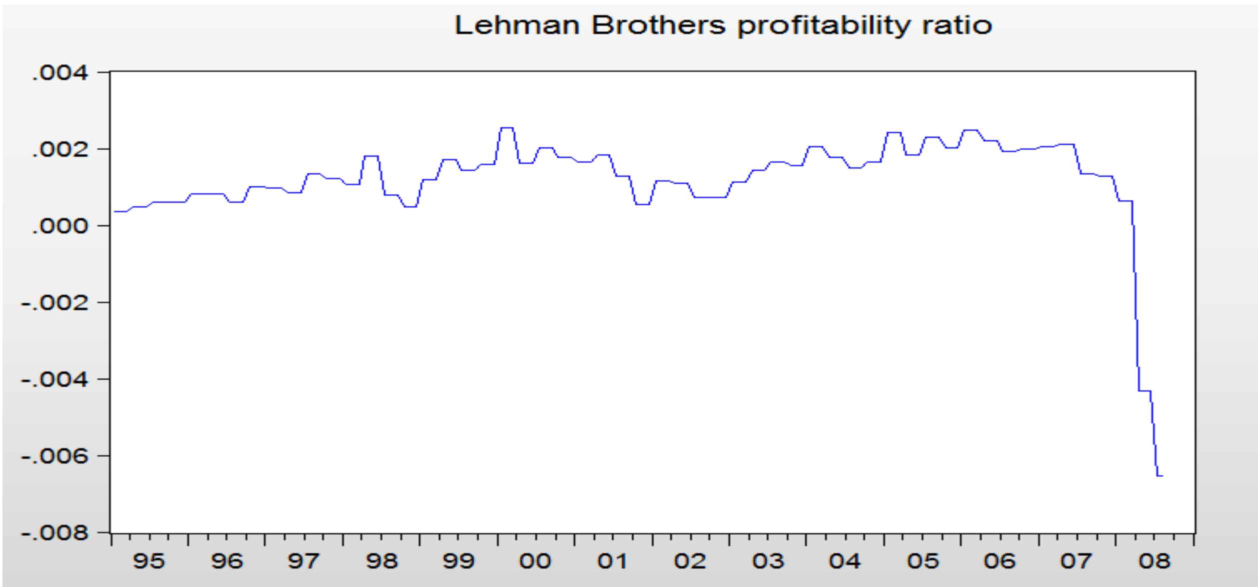
6.2 Predicting default probability with market-based and accounting-based risk measures

In the following regression, the default probabilities are used as dependent variables with a number of independent variables that consists the market and accounting based risk measures. The present analysis includes the profitability ratio, the leverage ratio and the earnings variability as accounting measures and the equity returns, equity volatility, market capitalization to total debt and finally the size of every bank as market based risk measures. Table 1 Panel A and B exhibit the regression results of the marginal default probability regressions. The method of the regressions is the Least Squares and the included observations for non-bankrupt banks are 253 and for bankrupt banks are 165.

Below in the Table 1 Panel B, there is the estimation of the marginal default probability regressions of two bankrupt banks, Lehman Brothers and Merrill Lynch.

The Lehman Brother's default probability regression shows as that the coefficients of the leverage ratio, profitability ratio, equity volatility, market capitalization to total debt equity ratio and Dcrisis appear to be statistically significant. On the other hand the coefficients of equity returns, earnings variability and size aren't statistically significant. Furthermore, the signs of the coefficients are not always in accordance to what theory would predict. Specifically, the market capitalization to total debt ratio although significant, appears to be positive, the opposite of what we would expect because a lower ratio implies a higher probability of default. The same holds for the size variable. A negative size shows that when the value of this measure is high should have a negative effect on the probability of default of the bank. However, it isn't statistically significant and with a positive sign. Moreover, the equity volatility ratio is significant but with a negative sign, something that is in contrast with our expectations because the higher the volatility, the riskier the bank and consequently the higher default probability. The variables that captures the default probability effect correctly is the profitability ratio, Dcrisis and leverage ratio. The volume and the sign of the profitability ratio and the leverage ratio shows a strong negative and positive relationship between profitability ratio/ leverage ratio and the default probability respectively. Additionally, the crisis dummy variable is significant and appears to be positive, the same of what we would expect; a higher probability of default during crisis years. The figure 8 and 11 show the negative strong relationship between the profitability ratio and the default probability. The default probability is greatest during 1999-2001 and 2007-2008. Additionally, the profitability has the lowest values in the same time periods.

<u>Figure 11. Lehman Brothers profitability ratio</u>



As we can see in Lehman Brother’s default probability regression, accounting and market based risk measures are all statistically significant. As a result, we cannot conclude that market or accounting based risk measures are more effective predictors for default probability. However, we can conclude that the profitability and leverage ratio have a stronger relationship with the default probability than the equity volatility and the market capitalization to total debt ratio.

TABLE 1 PANEL A

	Intercept	Earnings variability	Leverage ratio	Profitability ratio	Equity returns	Equity volatility	Market Capitalisation/Total Debt	Size	Dcrisis
Banco Santander	-0,002263	45,76189	0,002651	-1,414998	-0,015475	0,078465	-0,001808	-0,02902	-0,006638
	(-0,083379)	(2,626323)	(0,487773)	(-0,233371)	(-0,416514)	(0,784472)	(-3,547185)	(-0,355493)	(-0,462855)
Bank of America	-0,06699	1,754581	-0,025137	-9,847238	-0,033381	0,248596	0,058309	-0,044189	0,026017
	(-3,200142)	(4,145472)	(-2,088711)	(-4,905615)	(-1,402208)	(-3,408416)	(7,020267)	(-0,763177)	(3,36454)
Bank of New York Mellon	0,082316	-2,043736	-0,033611	-1,197857	-0,014077	0,095334	-0,005648	-0,086344	0,025712
	(10,49713)	(-7,333075	(-6,146397)	(-2,118863)	(-1,106717)	(2,618322)	(-4,670839)	(-3,08453)	(7,162582)
Barclays	-0,089255	-0,849632	0,017635	2,815586	-0,030846	0,446761	0,00487	-0,146037	-0,005816
	(-5,49655)	(-0,703542	(13,18652)	(0,916482)	(-1,177537)	(8,648903)	(5,13364)	(-1,639986)	(-0,618622)
Bear Stearns	-0,274455	3,145178	0,025643	-2,721339	0,00674	0,591562	0,136354	-0,202631	-0,023472
	(-4,973276)	(5,042497)	(3,79631)	(-0,487893)	(5,042497)	(5,356119)	(2,954192)	(-2,722492)	(-2,930629)
Capital One	0,005597	0,311239	0,003231	-1,028782	0,010125	-0,071441	0,002301	-0,025919	0,002601
	(0,448632)	(1,14773)	(1,924947)	(-1,614028)	(1,099235)	(-3,060636)	(0,688992)	(-1,254182)	(0,628221)
Citigroup	-0,117182	-0,73971	0,04589	-1,319775	0,024278	0,256864	0,040527	0,017441	0,002196
	(-5,906529)	(-4,881964	(8,246418)	(-0,449291)	(0,889447)	(4,880022)	(5,487281)	(-0,238187)	(0,15645)
Deutche Bank	0,027077	1946,311	-0,0035486	-21,82125	-0,149437	1,935736	-0,030694	-0,148636	-0,090162
	(0,84913)	(4,888448)	(-3,913147)	(-3,976728)	(-3,178656)	(7,746678)	(-0,447211)	(-1,296757)	(-4,949032)

1. Table 1: regression results for Banco Santander, Bank of America, Bank of New York Mellon, Barclays, Bear Stearns, Capital One, Citigroup, and Deutche Bank.
2. The values in parentheses are the t-statistic of each variable's coefficient, indicating its statistical significance

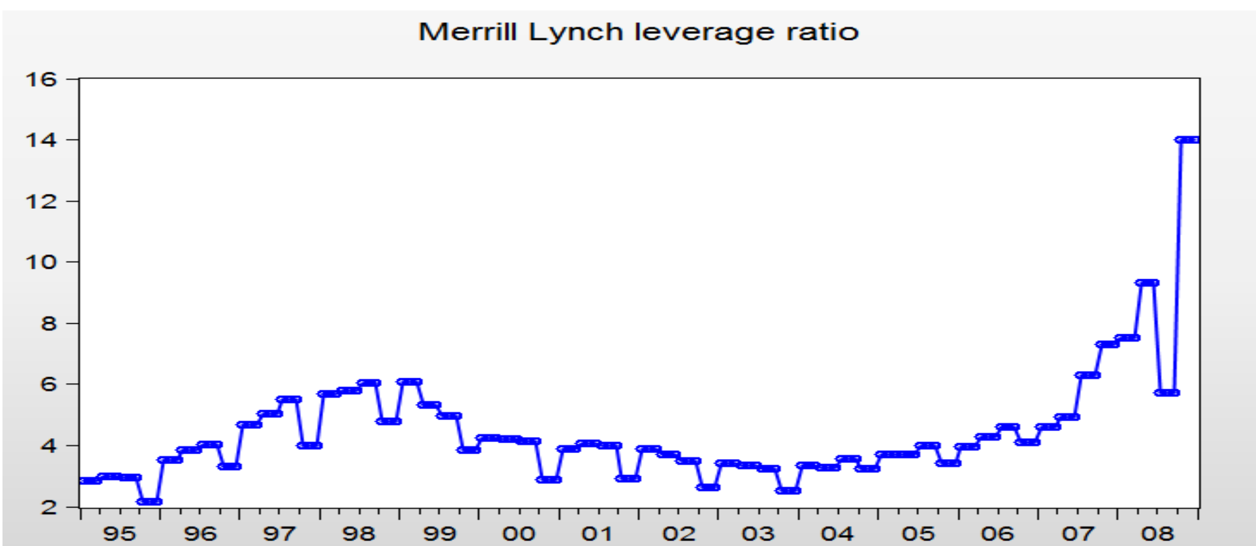
TABLE 1 Panel B

	Intercept	Earnings variability	Leverage ratio	Profitability ratio	Equity returns	Equity volatility	Market Capitalisation/Total Debt	Size	Dcrisis
HSBC	0,014534	0,032961	-0,000763	-0,540682	-6,61E-05	-0,175846	-0,002296	0,001206	-0,002529
	(3,3032)	(2,796223)	(-1,290519)	(-5,639684)	(-0,005728)	(-3,741728)	(-0,450056)	(0,067537)	(-1,353864)
ING	0,036511	-0,147343	0,00686	-11,88192	-0,040425	0,575438	0,000122	-0,0395531	-0,020188
	(0,994331)	(-0,691124)	(5,254901)	(-6,840001)	(-1,890221)	(1,943107)	(4,72194)	(-0,532728)	(-2,912101)
JP Morgan	0,123811	0,042692	-0,064374	-22,87524	-0,056599	0,608593	-0,017205	-0,115911	0,020642
	(3,040486)	(0,118194)	(-3,432018)	(-6,647497)	(-2,155592)	(8,278397)	(-1,1341)	(-2,193226)	(2,378087)
Lehman Brothers	-0,091153	0,397376	0,033724	-31,6847	0,044879	-0,159526	0,051253	0,010098	0,024677
	(-2,162844)	(0,776182)	(5,739556)	(-7,651651)	(1,914406)	(-2,213559)	(1,221822)	(0,122312)	(2,530921)
Merrill Lynch	-0,108117	0,115422	0,024715	-3,504846	0,032476	0,135012	0,044017	-0,03598	-0,020529
	(-7,179487)	(1,526547)	(12,1768)	(-3,960748)	(2,305976)	(3,253677)	(2,381346)	(-0,826815)	(-4,801022)
PNC	-0,080203	1,615665	0,001153	-4,526639	-0,134259	1,265837	-0,01090	-0,05283	-0,006467
	(-2,639333)	(1,893188)	(0,183293)	(-2,901878)	(-3,627796)	(12,66839)	(1,76005)	(-0,921111)	(-0,868008)
Royal Bank of Canada	0,099051	0,156696	-0,184731	-2,563091	-0,01344	0,088841	-0,004558	-0,170518	-0,002043
	(5,402385)	(0,428695)	(-7,283945)	(-0,797862)	(-0,903315)	(2,241323)	(-4,473931)	(-2,969988)	(-0,615375)
Toronto Dominion Bank	0,029361	-0,944739	0,032459	-5,670462	-0,009836	0,251867	-0,00098	-0,083301	-0,001213
	(1,205056)	(-2,959543)	(0,876454)	(-2,501611)	(-0,4329)	(3,810832)	(-0,567777)	(-1,320634)	(-0,190518)
Wells Fargo	-0,213399	8,086053	0,060837	-18,68388	-0,072954	0,425963	0,005518	-0,073632	-0,016551
	(-5,549544)	(7,275889)	(9,30157)	(-6,870869)	(-4,268429)	(13,5219)	(0,635012)	(-1,663692)	(-1,898492)

1. Table 2: regression results for HSBC, ING, JP Morgan, Lehman Brothers, Merrill Lynch, PNC, Royal Bank of Canada, Toronto Dominion Bank and Wells Fargo.
2. The values in parentheses are the t-statistic of each variable's coefficient, indicating its statistical significance

On the other hand, in the Merrill Lynch regression all the accounting and market based risk measures are statistically significant except for size. Additionally, in this regression also the signs of the coefficients are not always in accordance to what theory would predict. First of all, equity returns and crisis dummy have an opposite sign of what we would expect. Equity returns shows a positive relationship with default probability, something that reflects that they might include random information that is not relevant to the financial distress. Also, the dummy crisis coefficient has a negative sign while we expect a positive relationship with the default probability, something that indicates that the general increase in the default probability may be a general trend, irrelevant to the crisis years. The variables that are statistically significant and their coefficients with the expected signs are the leverage ratio, profitability ratio and equity volatility. In addition, R^2 is 82,57%, something that shows data are close to the fitted regression line. The accounting and market based risk measures in this regression are all significant and effective predictors of default probability. However, profitability ratio and leverage ratio present a stronger positive relationship with Merrill Lynch's probability of default as we can observe on figure 9 and figure12.

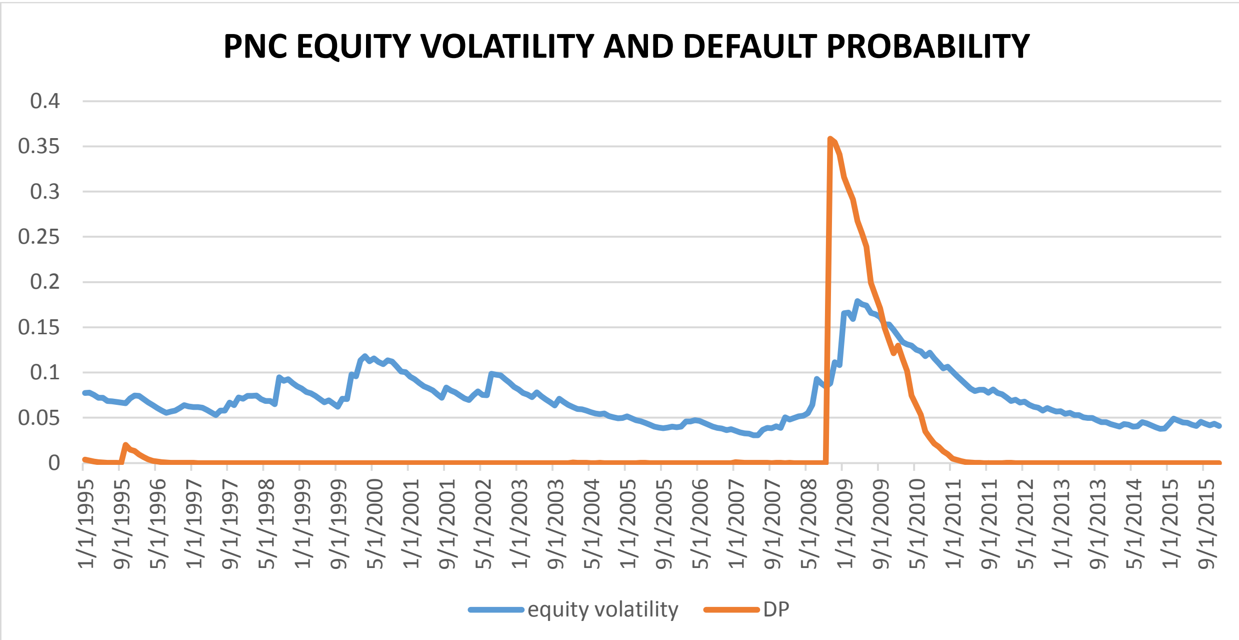
Figure 12. Merrill Lynch leverage ratio



Next, we can observe the marginal default probability for other non-bankrupt financial institutions in the sample, PNC and Barclay in table 1 panel A and B.

The results are a bit different to the ones of the Lehman Brothers probability of default regression. As we can see, all the coefficients of market based risk measures of PNC are statistically significant and with expected signs. Equity volatility has a strong positive relationship with the default probabilities, something that we would expect because a bank that is more volatile has a greater probability of default. Furthermore, in PNC default probability regression, market capitalization to total debt has the expected negative sign because the lower the value of this ratio, the more likely it is for the bank to become insolvent and financially distressed. Additionally, in this regression, size has a negative relationship with the default probability but it is not statistically significant. However, not all the accounting based risk measures are significant. Specifically, the coefficient of leverage ratio is not statistically significant but it has the expected sign. However, in PNC regression we have a difference in the crisis dummy. It is not only statistically significant but also negative, the opposite of what we would expect, which is to have a higher probability of default during the crisis years. Finally, the R^2 of the regression is 50,7% which means that the independent variables explain the variability in the default probability efficiently and significantly. For the PNC's default probability regression we can observe that the market based risk measures are more effective predictors than the accounting risk measures. In the graph below we can see the PNC default probability and the equity volatility. As we can observe the default probability takes its greatest value during 2008-2010 in the period of the financial crisis. Also, the following diagram shows that the equity volatility has a strong relationship with the PNC default probability. As we can see on 2008-2010 during the financial crisis the equity volatility has the greatest value such as the default probability. As a result, equity volatility consists a powerful and consistent predictor for the likelihood of financial distress over time.

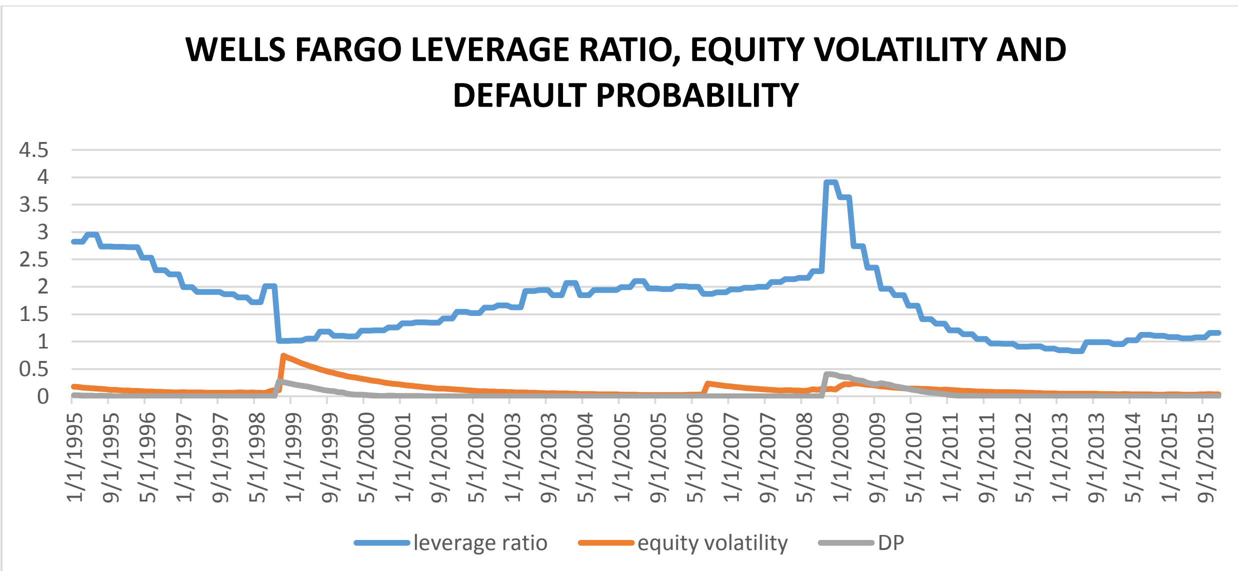
Figure 13. PNC Merton model default probabilities and equity volatility



In the Barclay's default probability regression, all the coefficients of market based risk measures are statistically significant, something that reflects that they are efficient predictors of default probability and with the expected signs, except for market capitalization to debt ratio that has a positive sign. However, the coefficients of the profitability ratio and the earnings variability ratio are statistically insignificant while the leverage ratio is significant and indicates a strong positive relation with the default probability as we expected. Also, the crisis dummy variable has again a negative sign.

In table 1 panel B, we can observe the results of Wells Fargo's default probability regression. All the coefficients of the accounting based risk measures are statistically significant and with the expected signs and specifically, the leverage ratio reflects a strong positive relationship with the default probability. On the other hand, all the coefficients of the market based risk measures are not statistically significant. Market capitalization to total debt ratio is not statistically significant and with positive sign, something that we would not expect. The coefficients of equity volatility and equity returns indicate a strong positive and negative relationship with default probability respectively. The coefficient of crisis dummy variable is statistically significant but shows a negative relationship with default probability. Although, in the Wells Fargo's default probability regression, all the accounting based risk measures are efficient predictors of bank failures, the equity volatility has the strongest relationship with the default probability, something that we can see in the following graph.

<u>Figure 14. Wells Fargo Merton model default probabilities, equity volatility and leverage ratio</u>



In the ING's default probability regression, all the accounting based risk measures are statistically significant with expected signs except for earnings variability. Furthermore, all the market based risk measures are statistically significant except for size. Also, the statistically significant market based risk measures don't have the signs that we would expect. For this regression, we could conclude that the accounting based risk measures are better and more efficient predictors of bank failures than the market based risk measures.

Table 1 panel A and B exhibit the regression results of the marginal default probability regressions. As mentioned above, results tend to be mixed as far as the marginal default probability regressions are concerned. There is no consistency regarding any of the independent variables among different financial institutions. However, we can make some general remarks.

First, regarding the accounting variables, the only variables that are consistently significant and have a large negative and positive impact on the default probability respectively, are each institution's profitability, which is, as previously mentioned, measured as the ratio of net income over total assets and leverage ratio which is measured as the total debt over equity. The earnings variability's effect on the marginal default probabilities tend to vary considerably. One of the reasons that the earnings variability ratio doesn't have a strong relationship with the default probability is that we have overinflated market values in recent years that have distorted the bank's price to earnings ratio. Also, according to *Beaver, Kettler; and Scholes (1970)* the measure that we use for earnings variability may not be the best choice and may have had an impact on the results.

On the other hand, regarding the market based risk measures, the only variable that is consistently significant and has a strong positive relation on the default probability is the equity volatility. The striking result is that in many regressions, the effect of equity, debt and crisis variables on the default probability as measured by the Merton model is the opposite than expected. We generally expect the value of equity to be negatively related to the marginal default probability of each institution. There is however the case when inflated equity values may indicate that a stock is overvalued. This may lead to mass stock short sales and consequently a drop in market value, reasonably related with increases in the marginal default probabilities. The opposite stands for the crisis dummy variable. While we expect it to be positively related to increases in the marginal default probability, in most cases the opposite stands. This indicates that the general increase in the marginal default probabilities may be a general trend, irrelevant to the crisis years. This means that the default probability measure does not have to do with years that the economy was in a recession or high debt, and is attributed to other factors. There is, however, another possible explanation. If the model has a reasonable forecasting ability for the default probabilities, it is reasonable that the greatest increase in the probabilities of default is obvious just before the crisis years, and not during the crisis itself.

Furthermore, equity returns and size are the variables that are not significant in most of the 18 marginal default probability regressions. This suggests that equity returns are not significantly related with the default probabilities. That is something that is not expected, because equity returns play a significant role in the financial health of a bank. Also, the R^2 of most of the regression is high with few exceptions. One of them is Capital One's default probability regression in which the R^2 is really low (7,33%). This show us that there are more specific factors that affect the default probability of Capital One. Specifically, in 1995 Capital One began as a 'monoline' that means that the biggest part of its business was in credit cards. The attempt to remain a monoline has the effect to give to the bank more profitability in good times and less profitability in bad times. In 2005, Capital one increased in size with subprime customers but during the subprime financial crisis Capital one ended its mortgage platform. These facts may be able to explain better the volatility of the default probability for Capital One.

It is really interesting to mention that if equation 1 with the combination of market and accounting risk measures is separated in two equations, one with only market based risk measures and one with only accounting risk measures the R^2 of the default probability regression is really low. This situation indicates that the accounting and market based risk measures complement each other to predict the default probability of each financial institution.

The results of the 18 default probability regressions are mixed and we aren't be able to conclude that the market based risk measures are better predictors than accounting based risk measures but we can highlight some interesting remarks.

7. <u>Limitations</u>

The estimation of default probability is a significant activity for risk managers and regulators. Consequently, there are a plethora of accounting and market based models that tries to predict default and to be more accurate and close to real default probabilities. However, the changes in macroeconomic environment and the fact that the financial world is an interconnected system and in a financial crisis a shock event has the ability to transmit and have negative consequences to the global financial stability, makes the prediction of the default of a bank more difficult and demanding. As a result, limitations can be observed in this analysis. *Avesani (2006)* suggests a method for the calculation of the individual default probabilities with the use of default intensities. The default intensity is defined as the CDS spread over a bond's loss given default. However, my time period includes years for which data for CDS are not available. Consequently, default intensities and default probabilities have to be estimated in a different way.

Another method for the estimation of the individual default probability is the use of the Merton model which calculates the default probability as the normal cumulative density function of the negative distance to default measure. Merton model is a market based model and very attractive but it lacks empirical performance. It has an advantage and disadvantage simultaneously. The most significant inputs are the market value of equity, the face value of debt and the volatility of equity. When the market value of equity decreases, the default probability rises. The condition in which the model works well is the situation where the model assumptions are met and simultaneously markets must be effective and efficient. The Merton model gives a way to understand why default probabilities are greater in the risk-neutral world than in the real world. In a risk-neutral world, the expected growth rate of the firm's assets is the risk free rate. On the other hand, in the real world, the growth rate of the firm's assets is greater regarding a risk premium demanded by the market. Thus, the probability of the value of the assets declining below the face value of the debt at a future time is greater in the risk-neutral world than in the real world. This model has two drawbacks. The first drawback is the assumptions of the model (all liabilities with maturity of one year, no safety covenants, bankruptcy triggered only at maturity and single class of zero coupon bond). The second drawback is the measurement errors. Specifically, value and volatility of assets are not observable. As a result, probability derived from the Merton model is not an adequate statistic for bankruptcy but a useful bankruptcy predictor. Moreover, in order to avoid the plethora of computations of the non-observable market value of assets and their volatility, I used the corresponding book values recognizing that the use of book values could bias results.

Another limitation of this analysis is the use of equity prices of the banks in the regression. First of all, equity prices might include random information that is not relevant to financial distress. Therefore, this might introduce noise to the sample and negative impact the accuracy of the model. In this analysis, I used the assumption that the equity prices have the ability to reflect all the public information regarding the expected future cash flows. Also, the equity prices include all the information that is related to default probability. Another assumption about the equity prices is that they will move according to the financial conditions and macroeconomic information and consequently enhance the power of the model.

An inclusion of more control variables and macroeconomic variables to the default probability regressions could lead to results that are more robust. Specifically, a measure about inflation and a measure that captures the influences of the situation of macroeconomic environment in the default probability would play a significant role in this analysis because a high value of inflation which is the result of a weak macroeconomic environment rises the number of banking crises.

Finally, in my sample I include only 18 banks from Europe and America. The sample of this analysis doesn't have the ability to generalize the results because it doesn't include banks from all over the world. The data that are necessary for the estimation of the market and accounting based risk measures are not available for all the banks, something that makes the inclusion of others banks difficult. Moreover, it is very important to maintain a homogeneity of the sample so I tried to avoid the inclusion of very small banks.

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8. Conclusion

The purpose of this paper is to identify which of the market or accounting based risks measures are better and more effective predictors for bank default. In prior literature, many attempts have been made to support the superiority of market based risk measures over accounting and vice versa in the prediction of default probabilities of firms. The present paper tries to provide an answer to the debate between the accounting and market data as predictors of the default of banks and how are related regarding the forecasting of default probability. Consequently, this analysis is very useful to analysts, regulators and central banks to prevent the high costs that are related to a bank default.

I use the Merton model to calculate the default probabilities of 15 European and American banks and 3 bankrupt banks. Also, I select market and accounting based risk measures as independent variables in the default probability regression, which is analyzed in detail in the methodology section. Specifically, the market based risk measures are equity returns, equity volatility, market capitalization to total debt and size of the bank while the accounting variables are profitability ratio, leverage ratio and earnings variability.

However, conclusions cannot be easily derived. The results from the default probability regressions are mixed and we aren’t be able to conclude that the market based risk measures are better predictors than accounting based risk measures but we can highlight some interesting remarks. Neither market based risk measures nor accounting based risk measures are proved to be statistically significant with the expected signs and consequently powerful predictors in all the regressions. However, profitability, leverage ratio and equity volatility have the ability to predict the default probability of the banks effectively throughout the years from 1995 to 2015. Furthermore, the combination of accounting and market variables in the default probability regressions shows that market and accounting variables complement each other. Although, the accounting based risk measures are criticized that are backward looking measures, they have three advantages. First of all, bank failure is not an unexpected event. The situations where banks with good profitability and great balance sheet numbers become bankrupt due to an unexpected change in the economic environment are rare. Bank default is the peak point of many years of negative performance, something that accounting based risk measures have the ability to capture it. Another benefit is that the loans covenants rely on accounting numbers and the accounting variables are more likely to include information about loan covenants. Finally, the double entry system gives the flexibility that a change in accounting policies will have a minimum effect on the measures that combine different views of accounting information simultaneously. Consequently, accounting based risk measures provide an important economic benefit over the market based risk measures and together have the ability to improve the prediction of default probability of every bank.

Furthermore, some suggestions for future research are necessary. First of all, the determination of other variables to which banks might react and the specification of their association with the accounting and market based risk measures. Another area for study is a further clarification that both accounting and market based risk measures fail to reflect the ¨true¨ default risk. Also, the variation of equity prices shows that the market is efficient so that information can be enclosed in prices quickly and in a way that is not biased. As a result, the existence of a bias of the reported method that indicates an association with prices is necessary of further research because the reported methods are more visible than the unreported.

9. References

Agarwal V., Taffler R. (2008), Comparing the performance of market-based and accounting-based bankruptcy prediction models, Journal of Banking & Finance 32 (2008) 1541–1551

Agusman, A., Monroe, G.S., Gasbarro, D., Zumwalt, J.K., 2008. Accounting and capital market measures of risk: Evidence from Asian banks during 1998-2003. Journal of Banking and Finance 32, 480-488

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. Journal of Finance, 23, 589–609

Avesani, Renzo, Antonio Pascual and Jing Li, 2006, *A New Risk Indicator and Stress Testing Tool: A Multifactor Nth-to-Default CDS Basket,* IMF Working Papers 06/105

Beaver, William H.; p. Kettler; and M. Scholes. "The Association Between Market Determined and Accounting Determined Risk Measures." *Accounting Review,* October 1970, pp. 654-682

Bharath, Sreedhar and Tyler Shumway, 2004, *Forecasting default with the KMV-Merton model,* University of Michigan.

Bildersee, John S. (1975), "The Association Between a Market Determined Measure of Risk and Alternative Measures of Risk," Accounting Review, 50 (1), 81–98.

Black, F. and M. &holes, 1973, The pricing of options and corporate liabilities. Journal of Political Economy 3, 637-654.

Chan-Lau (2006), Market-Based Estimation of Default Probabilities and Its Application to Financial Market Surveillance, IMF Working Paper, Monetary and Financial Systems Department

Core, J., and Schrand, C., (1999), the effect of Accounting –Based debt covenants on Equity Valuation, Journal of Accounting and Economics, 27 (1) , 1-34

Das Sanjiv R., Hanouna P., Sarin A. (2009), Accounting-based versus market-based cross-sectional models of CDS spreads, Journal of Banking & Finance 33 (2009) 719–730

DRAGAN Oana Raluca, 2013, SYSTEMIC RISK IN BANKING SECTOR, The USV Annals of Economics and Public Administration, Volume 13, Issue 1(17)

Duffie, D., Lando, D. (2001), Term structures of credit spreads with incomplete accounting information, Econometrica, 69 (3), 633-664

Elgers, Pieter T.S. (1980), “Accounting-Based Risk Predictions: A Re-Examination,” Accounting Review, 55 (3), 389–408.

Giglio, Stefano, 2011, Credit default swap spreads and systemic financial risk, Proceedings of the Federal Reserve Bank of Chicago, 5, 104–141

Gonedes, Nicholas. “Evidence on the Information Content of Accounting Numbers: Accounting-Based and Market-Based Estimates of Systematic Risk.” Journal of Financial and Quantitative Analysis 8, 407–444, (June 1973)

Hillegeist, S. A., Keating, E. K., Cram, D. P., & Lundstedt, K. G. (2004). Assessing the probability of bankruptcy. Review of Accounting Studies, 9, 5–34

Hosmer, D.W. & Lemeshow, S. (1980) A goodness-of-fit test for the multiple logistic regression model. Communications in Statistics, 10, 1043–1069

Huang, Xin, Hao Zhou, and Haibin Zhu, 2009, A Framework for Assessing the Systemic Risk of Major Financial Institutions, Journal of Banking and Finance, vol 33 no. 11

Jarvela M., Kozyra J., Potter C., 2009, The Relationship between Market and Accounting Determined Risk Measures: Reviewing And Updating The Beaver, Kettler, Scholes (1970) Study, College Teaching Methods & Styles Journal, Special Edition 2009, vol 5 no.1

Kritzman M., Li Y., Page S. , and Rigobon R., 2010, Principal Components as a Measure of Systemic Risk, MIT Sloan School Working Paper 4785-10

Lakonishok J., Shapiro A., 1986, Systemic risk, total risk and size as determinants of stock market returns, Journal of Banking and Finance 10 (1986) 115-132. North-Holland

Li, M.Y.L., Miu, P., 2010. A hybrid bankruptcy prediction model with dynamic loadings on accounting-ratio- based and market-based information: a binary quantile regression approach. Journal of Empirical Finance 17, 818–833

Litzenberger, R. and Ramaswamy K., 1979, the effect of personal taxes and dividends on capital asset prices: Theory and empirical evidence, Journal of Financial Economics 7, June, 114-16

Mensah, Y.M., 1984. An examination of the stationarity of multivariate bankruptcy prediction models: a methodological study. J. Acc. Res. 22, 380–395.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. Journal of Finance, 29, 449–470

Ohlson, J. A., 1980, Financial ratios and the probabilistic prediction of bankruptcy, *Journal of Accounting Research* 18,109–131.

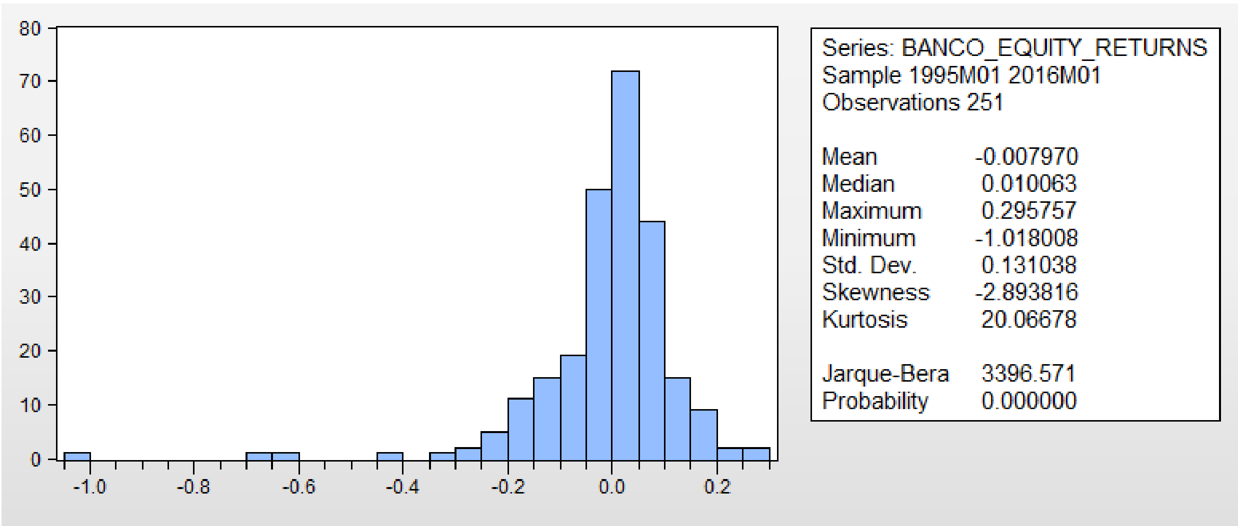
Reisz A., Perlich C. (2007), A market-based framework for bankruptcy prediction, Journal of Financial Stability 3 (2007) 85–131

Tinoco M., Wilson N. (2013), Financial distress and bankruptcy prediction among listed companies using accounting, market and macroeconomic variables, International Review of Financial Analysis 30 (2013) 394–419

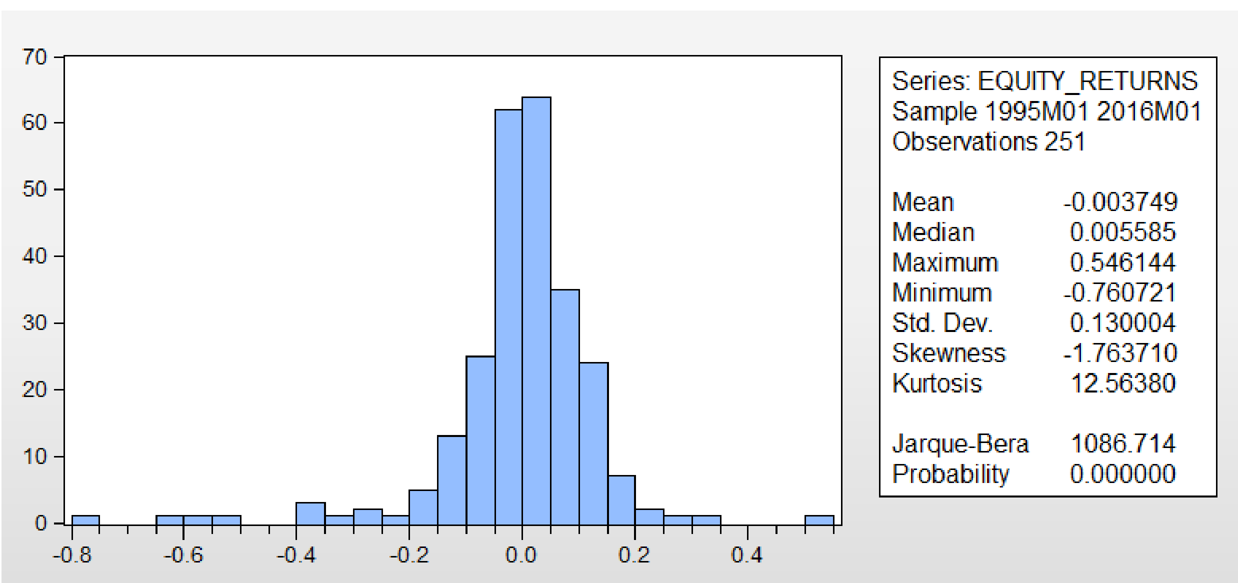
Van Oordt Maarten, Zhou Chen, 2015, Systemic risk of European banks: Regulators and markets, DNB Working Paper, No. 478

Appendix 1. Histograms and descriptive statistics of banks

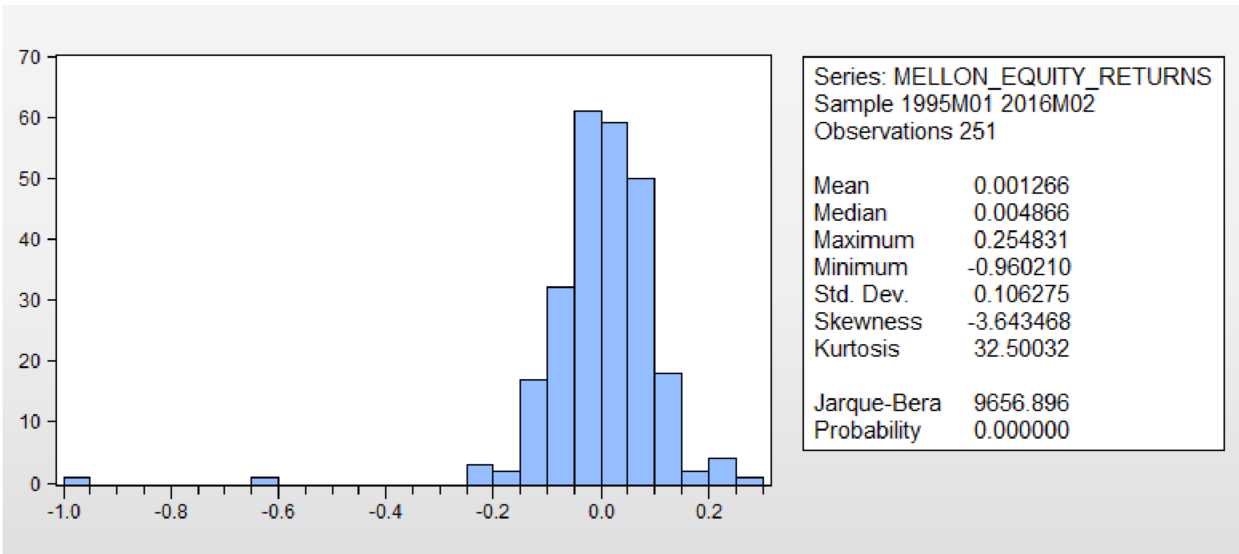
Histogram and Descriptive statistics of Banco Santander's stock returns



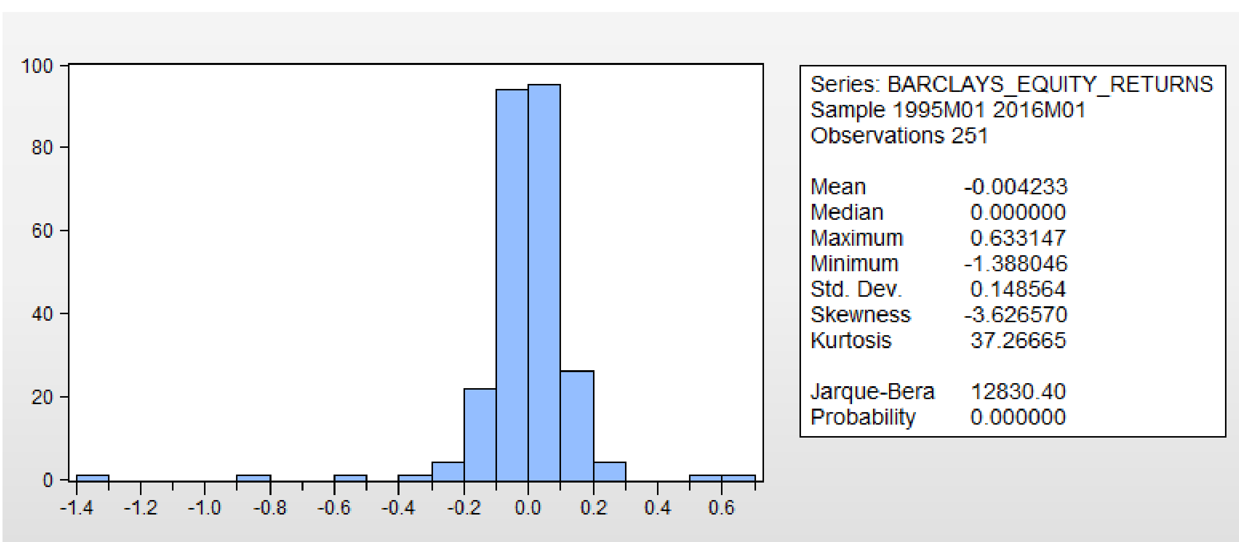
Histogram and Descriptive statistics of Bank of America's stock returns



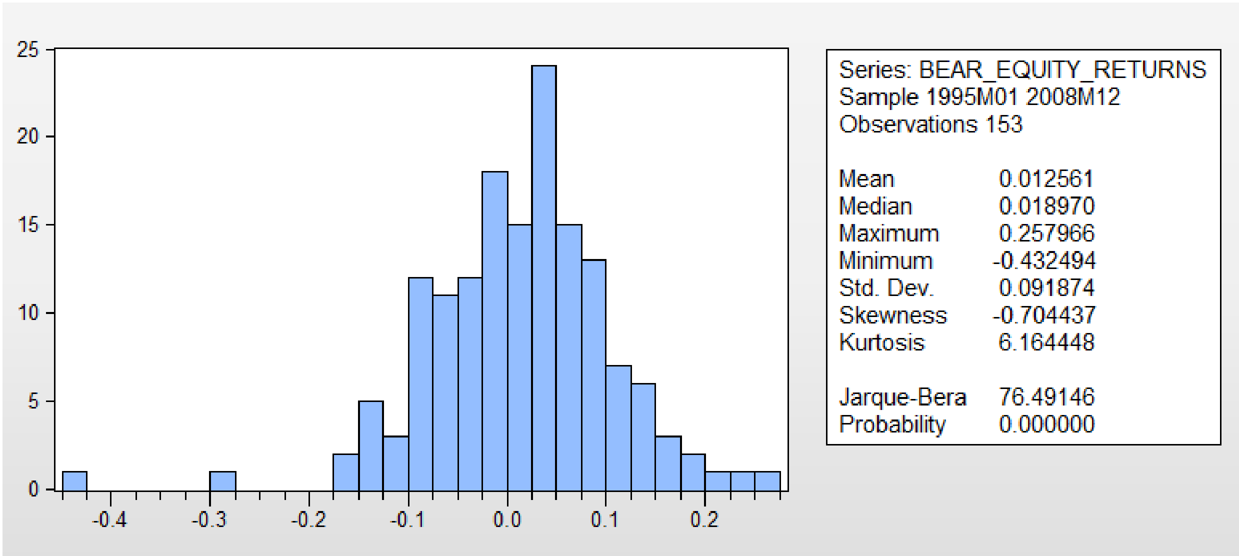
Histogram and Descriptive statistics of Bank of New York Mellon's stock returns



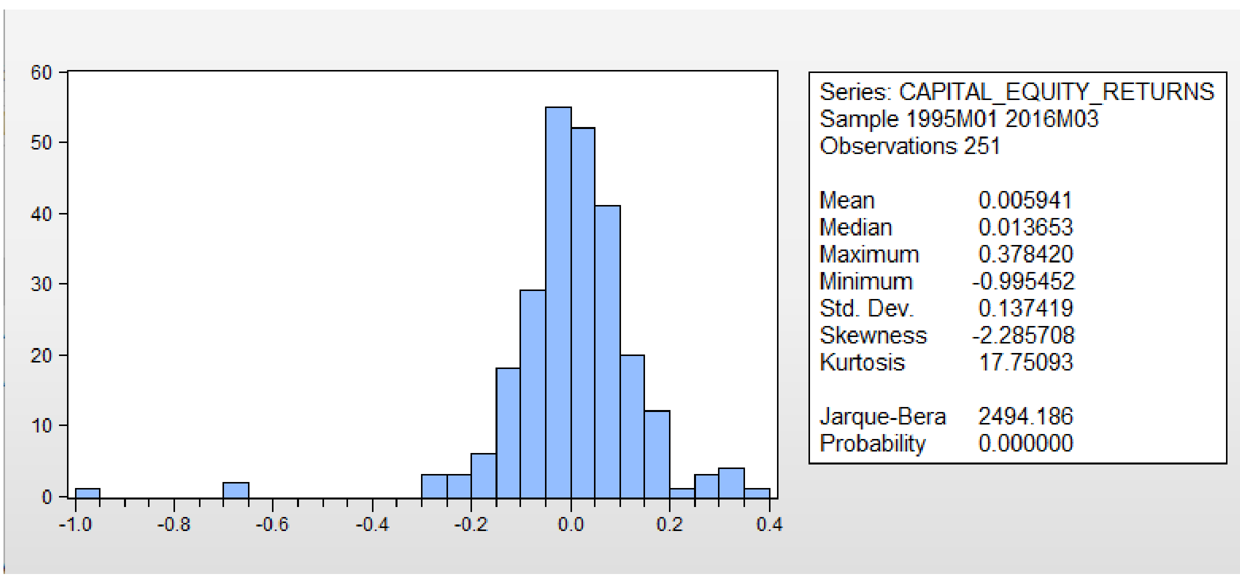
Histogram and Descriptive statistics of Barclay's stock returns



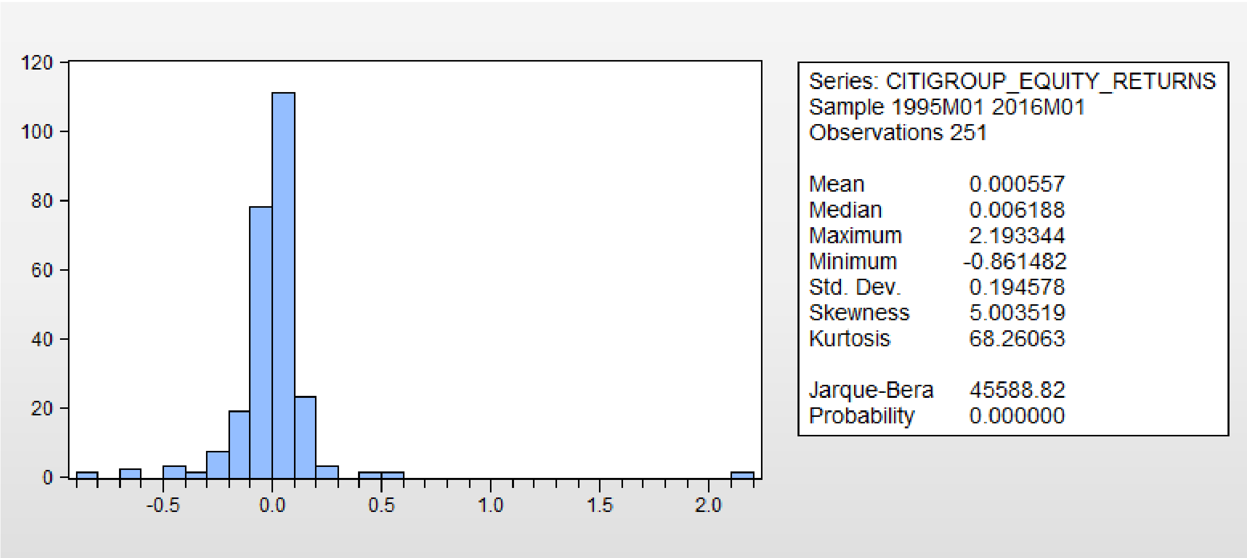
Histogram and Descriptive statistics of Bear Stearn’s stock returns



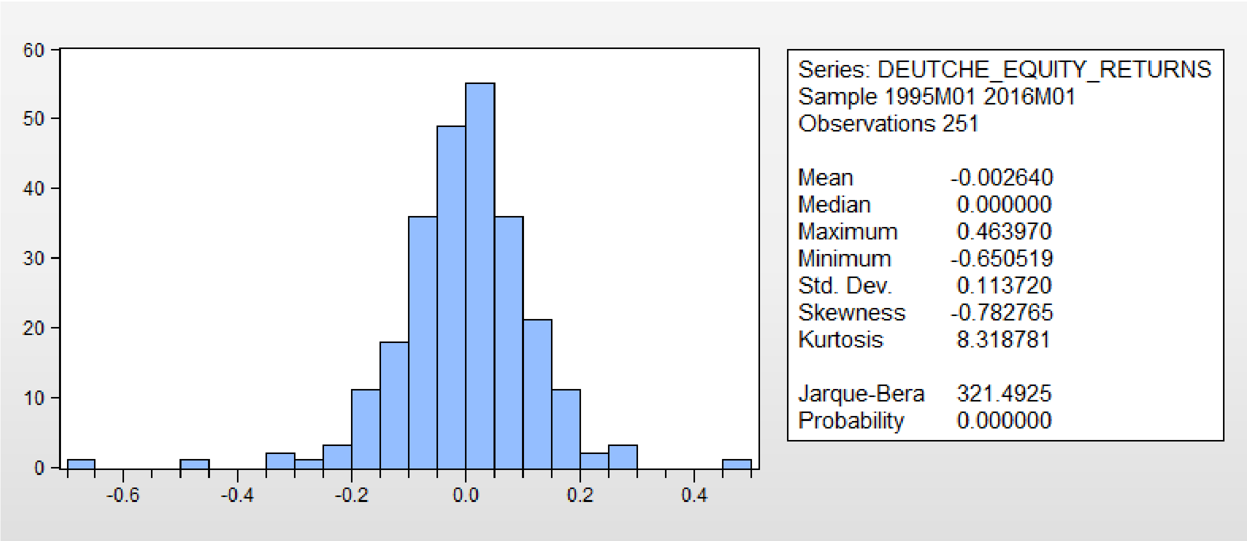
Histogram and Descriptive statistics of Capital One’s stock returns



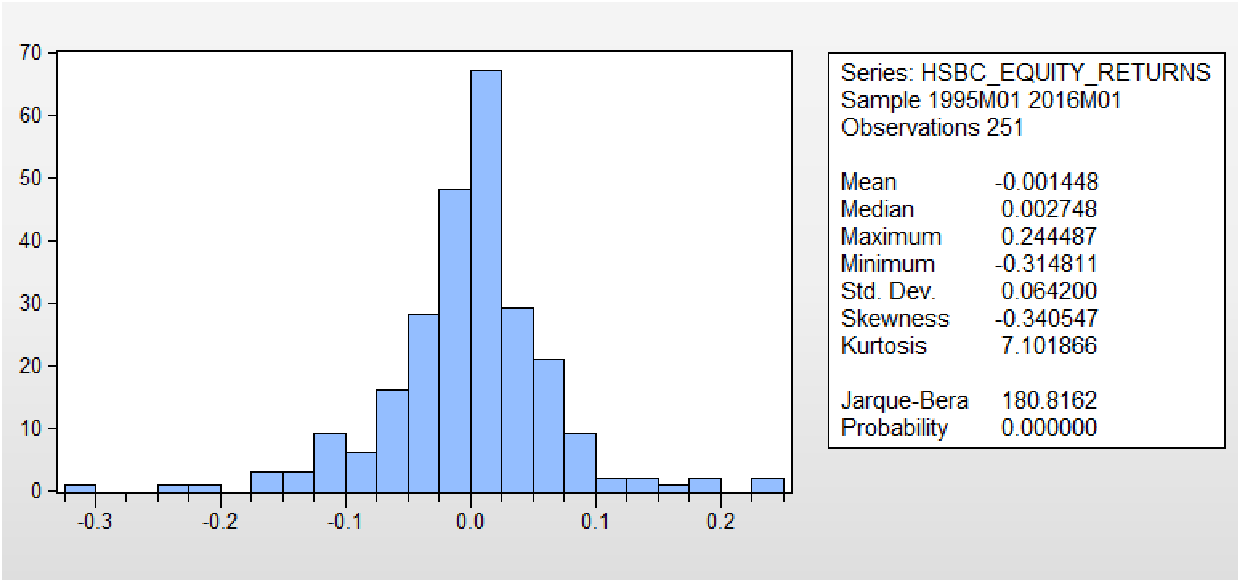
Histogram and Descriptive statistics of Citigroup's stock returns



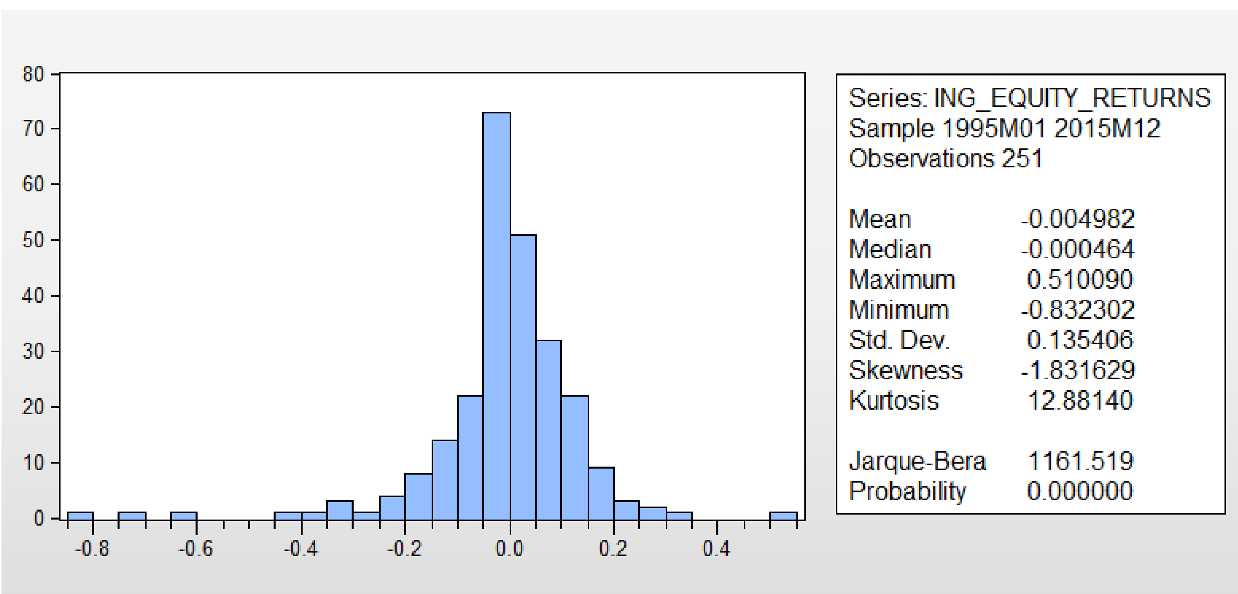
Histogram and Descriptive statistics of Deutche Bank's stock returns



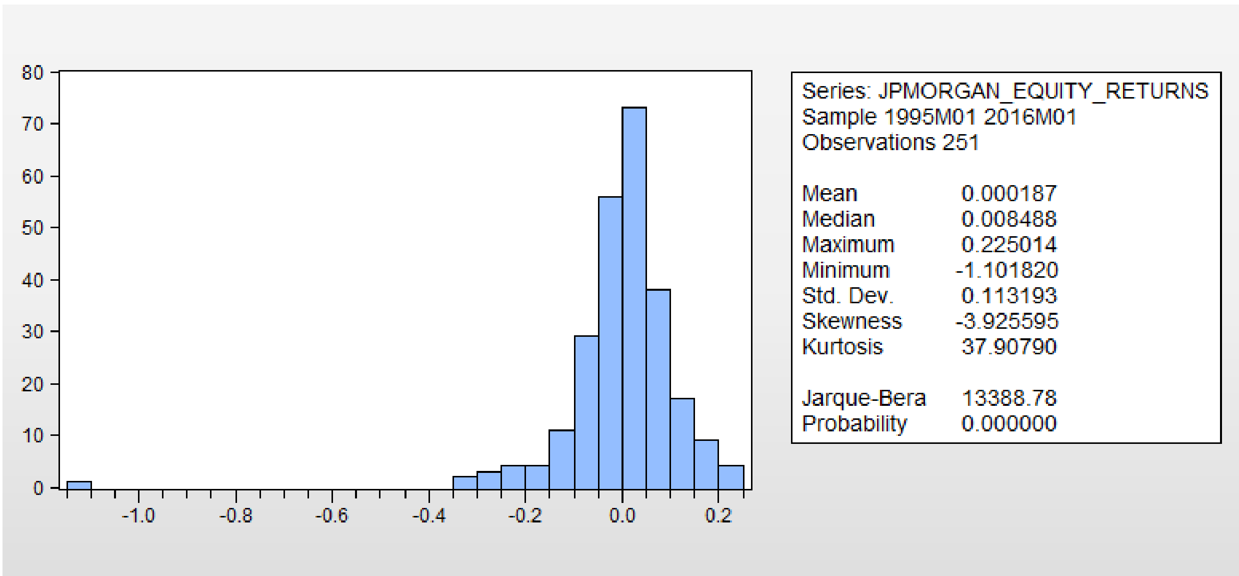
Histogram and Descriptive statistics of HSBC's stock returns



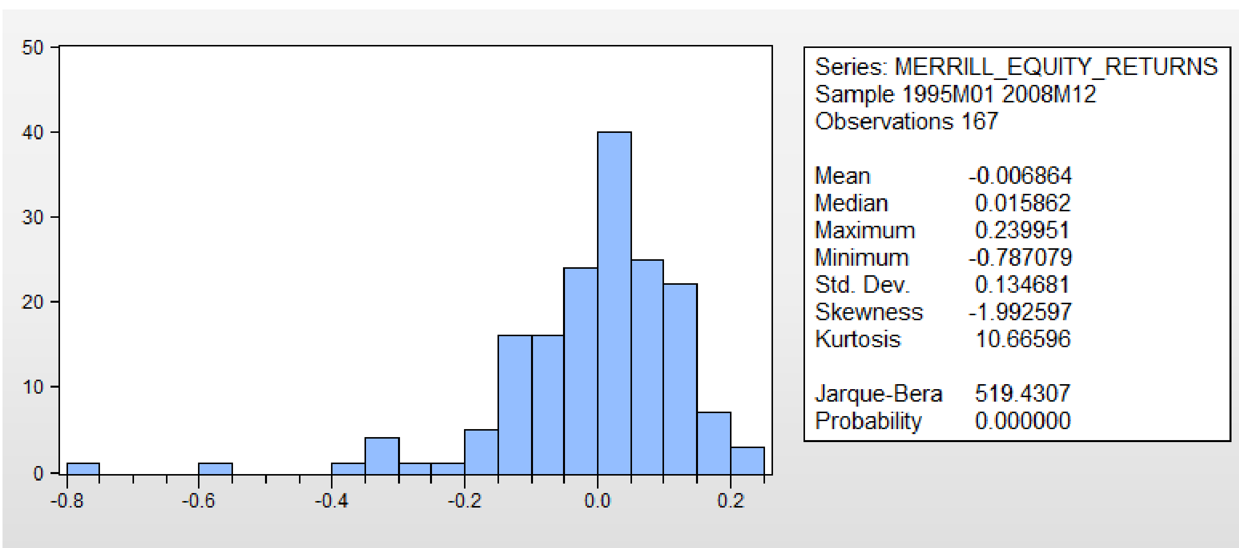
Histogram and Descriptive statistics of ING's stock returns



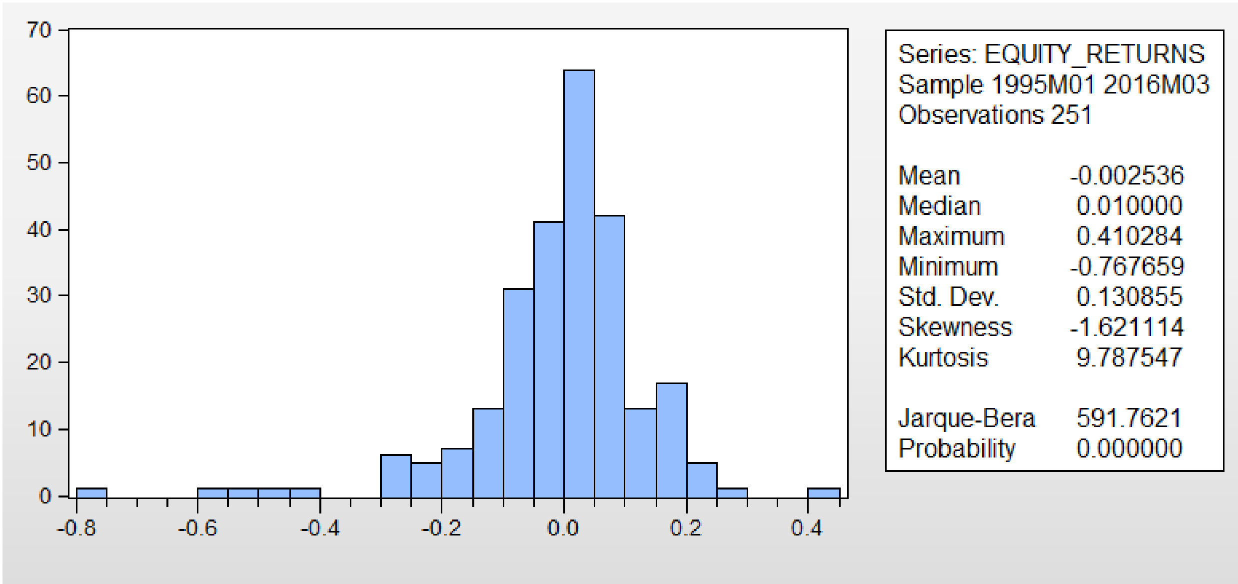
Histogram and Descriptive statistics of JP Morgan's stock returns



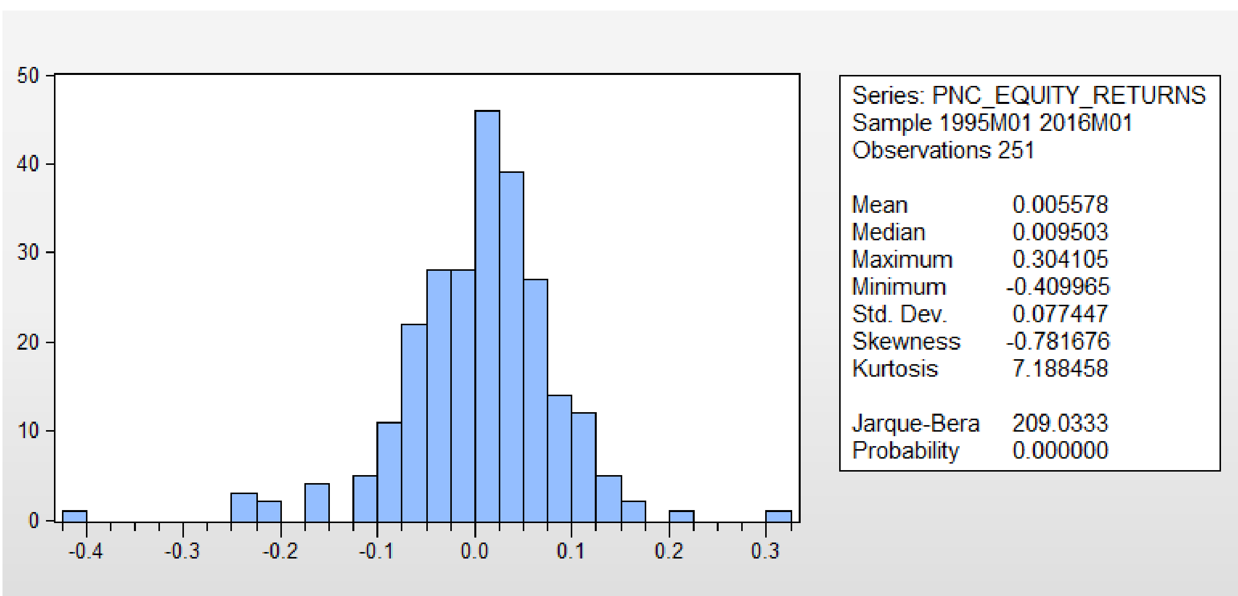
Histogram and Descriptive statistics of Merrill Lynch's stock returns



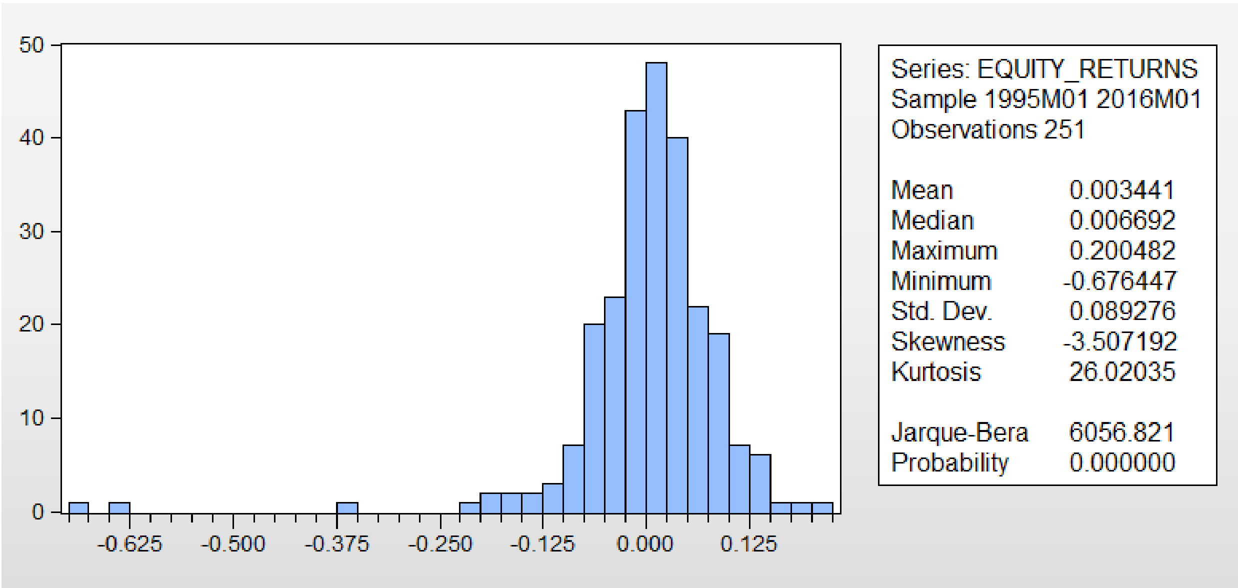
Histogram and Descriptive statistics of Morgan Stanley's stock returns



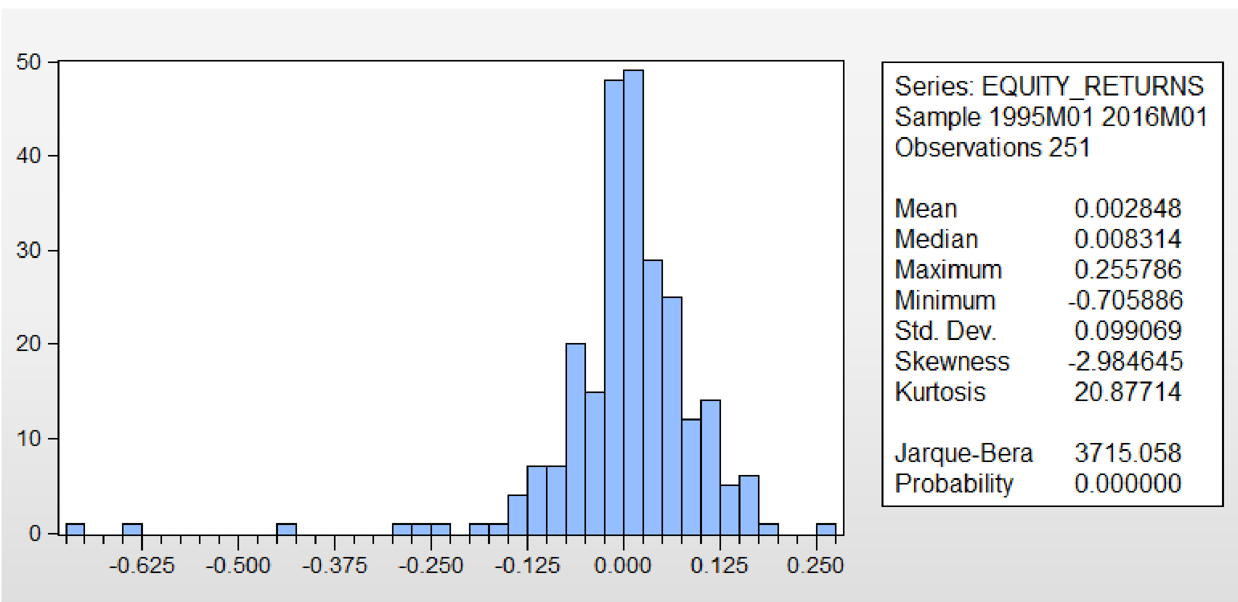
Histogram and Descriptive statistics of PNC's stock returns



<u>Histogram and Descriptive statistics of Royal Bank of Canada's stock returns</u>



<u>Histogram and Descriptive statistics of Toronto Dominion Bank's stock returns</u>



Histogram and Descriptive statistics of Wells Fargo’s stock returns