WHETHER INVESTOR SENTIMENT IS AFFECTED BY CHANGES IN THE STATUTORY LIMIT OF U.S. FEDERAL DEBT

by

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Resumen

Este estudio examina si los cambios en los límites de la deuda estatutaria de los Estados Unidos de Norteamérica tiene un efecto sobre el sentir del inversionista. Se utilizó el modelo de regresión de mínimos cuadrados ordinarios para establecer la relación que existe entre las variables explicativas y las que miden el sentir del inversionista (VIX y PCR). Se tomó en consideración nueve cambios a la deuda desde el 2007 hasta el 2012, incluidos en siete ventanas de eventos. Los resultados indican que los cambios en los límites de la deuda no tienen un efecto estadísticamente significativo sobre el sentir del inversionista en la mayoría de las ventanas de eventos. La mejor variable que explica la variación de VIX y PCR es la que representa el mercado en general. Para estudios futuros se recomienda incluir otras medidas del sentir del inversionista y otras variables explicativas.

Abstract

This study examines whether changes in the statutory debt limit of the United States has an effect on investor sentiment. The ordinary least squares regression model was used to establish the relationship between the explanatory variables and the investor sentiment proxies (VIX and PCR). There were seven event windows, which included nine changes to the debt limit from 2007 to 2012. The results indicate that changes in debt limit have no statistically significant effect on investor sentiment in most of the event windows. The best variable explaining the variation of the VIX and PCR is the one that represents the overall market. For future studies it is recommended the inclusion of other sentiment proxies and other explanatory variables.

To my mom and dad…

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especially during my years as a grad student

This one is for you!

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List of Abbreviations

CBO	Congressional Budget Office
CBOE	Chicago Board Options Exchange
CFSI	Cleveland Financial Stress Index
CFSI_IND	Cleveland Financial Stress Index
EMU	European Monetary Union
EPU	Economic Policy Uncertainty Index for United States
EPU_IND	Economic Policy Uncertainty Index
EU	European Union
EW	Event Window
GDP	Gross Domestic Product
IPO	Initial Public Offering
LM	Lagrange Multiplier
LNDEBT	Natural log of statutory debt limit
LNWILL5000	Natural log of the Wilshire 5000 Index prices
OLS	Ordinary Least Squares
OMB	Office of Management and Budget
PCR	Put/Call Ratio
REIT	Real Estate Investment Trust
S&P	Standard and Poor's
SAD	Seasonal Affective Disorder
SP	Sentiment Proxy
SPF	Survey of Professional Forecasters
TARP	Troubled Asset Relief Program
US	United States
USA	United States of America
VIF	Variance Inflation Factor
VIX	Chicago Board Options Exchange Volatility Index
WILL5000IND	Wilshire 5000 Total Market Index

Chapter 1: Introduction

1.1 Introduction

Recently, there have been governmental debt problems around the globe, especially in Europe and the United States of America (US). For example, in Europe countries like Greece, Italy, Spain, Ireland, and Portugal are immerse in a crisis because they have a lot of debt outstanding and the market does not trust them with their capacity to repay it. This situation makes it more difficult for those countries to continue issuing debt because investors do not want to lend them money and, if they do, it would be at higher rates. The problem in the US is that the debt is increasing at a higher pace; this means that soon lenders would begin to worry about the capacity to repay the debt and also the ability to control their spending.

As defined by the US Department of Treasury (2011), "the debt limit is the total amount of money that the United States government is authorized to borrow to meet its existing legal obligations, including Social Security and Medicare benefits, military salaries, interest on the national debt, tax refunds, and other payments. The debt limit does not authorize new spending commitments. It simply allows the government to finance existing legal obligations that Congresses and presidents of both parties have made in the past".

The United States federal government total debt is composed by the sum of debt held by the public and debt held by government accounts (Austin, 2008). The total debt can be increased in two ways: first, when the government sells debt to the public to finance budget deficits and acquire the financial resources needed to meet its obligations. Second, debt increases when the federal government issues debt to certain government accounts, such as the Social Security, Medicare, and Transportation trust funds, in exchange for their reported surpluses (Austin, 2008). Recent world economic crisis has made deficits higher in the United States, which also

has elevated the debt held by the public, forcing the government to increase debt limit at a higher rate than before. Other factor that raises spending, and therefore debt, is when the United States goes to war, and these days they have presence in Afghanistan and Iraq.

A common practice among governments is to establish a statutory debt limit, which is an amount that restrains what a government is allowed to borrow. This is done with the purpose of control overspending, which can lead to an increase in taxes.

The US Department of Treasury (2011) also says that "failing to increase the debt limit would have catastrophic economic consequences. It would cause the government to default on its legal obligations – an unprecedented event in American history. That would precipitate another financial crisis and threaten the jobs and savings of everyday Americans – putting the United States right back in a deep economic hole, just as the country is recovering from the recent recession. Congress has always acted when called upon to raise the debt limit. Since 1960, Congress has acted 78 separate times to permanently raise, temporarily extend, or revise the definition of the debt limit – 49 times under Republican presidents and 29 times under Democratic presidents."

Despite all the complications that a failure to increase the debt limit would cause to the United States economy, a big problem is how the investor (who is the lender) is reacting to governmental debt issues in the US market. This reaction can be described as the investor sentiment to a particular situation, like the current debt crisis. Generally, investor sentiment can be described as wild movements in the stock market that are seemingly unjustified by fundamentals (Tetlock, 2007).

1.2 Justification

In the year 2011, the debt limit (also known as the debt ceiling or statutory limit) became an issue between both, the executive power represented by President Obama (from the Democratic Party) and the Legislative power represented by Congress (from the Republican Party). Specifically, on May 16, 2011, federal debt reached its statutory limit, and declared a debt issuance suspension period, allowing certain extraordinary measures to extend Treasury's borrowing capacity until early August 2011 (Austin & Levit, 2011). The debate continued until both parts reached an agreement on the last day (August 2, 2011) and "President Obama signed into law the Budget Control Act of 2011 (S. 365), which included provisions aimed at deficit reduction and would allow three staged increases in the debt limit that total from $2,100 billion to $2,400 billion. Some increases are subject to congressional disapproval." (Austin & Levit, 2011)

The debate between the President and Congress has created another problem for the US government because Standard &Poor's (S&P) has downgraded their credit rating from AAA to AA+ for the first time in their history (Detrixhe, 2011). There was an impasse between S&P and the lawmakers that eventually culminated in the downgrade because the latter "put in place a plan to enforce $2.4 trillion in spending reductions over the next 10 years, less than the $4 trillion S&P had said it preferred" (Detrixhe, 2011). Meanwhile, the other credit rating agencies, Moody's and Fitch did not changed their ratings, but said "that downgrades were possible if lawmakers fail to enact debt reduction measures and the economy weakens" (Detrixhe, 2011).

As we can see, the changes in the debt limit were a normal issue historically, until it became more frequent and the government was divided (executive power by one party and legislative power by the other party) at some points. No prior studies were found that has

investigated the changes in the debt limit and how the investor sentiment has reacted to it. The importance of this research is to know how the investor reacted to changes in the debt limit as a separate event, helping us to identify one of the first steps to future problems in the economy.

1.3 Objective

The main objective of this research is to analyze whether changes in the US Federal Government debt limit affect the investor sentiment. Because there are many variables that could affect investor sentiment, metrics of market behavior, economic uncertainty and financial stress are included to evaluate if they also, affect investor sentiment. This research will help to understand better how the market could react after a change in the debt limit by the federal government, if we know how the investor has reacted during such changes in the past.

1.4 Limitations

Two important limitations for this study were: (1) the selection of an appropriate measure of investor sentiment among the many presented in the literature, and (2), the availability of the data for other sentiment proxies and other explanatory variables that could have been considered for the research. Another limitation was the proximity between some of the changes in debt limit, which forced us to select a narrower event window and to include two debt changes in one event window.

1.5 Research Outline

The next four chapters of this research will present information in more detail about the main subject, methodology, analysis of results, and conclusions. Chapter 2 discusses the concepts of U.S. and foreign debt, U. S. debt limit, investor sentiment, and measures of investor sentiment according to the literature review. Chapter 3 describes the methodology used in this

research; including the sample, data, and statistical model. Chapter 4 includes the empirical results and the discussion and analysis of the findings. Finally, Chapter 5 provides a discussion on the results section and suggests potential topics for future research.

Chapter 2: Literature Review

2.1 Overview

In this chapter; the concepts of sovereign debt, foreign debt, United States debt limit, investor sentiment and how to measure it, and sentiment proxies will be discussed in more detail according to the findings of the literature review. First, a definition of sovereign debt is discussed and how this has been a problem for some nations around the globe in recent years. Then, the *Foreign Debt* section presents examples of countries in Europe with a current debt crisis. Also, a history of the US debt limit that leads to an unprecedented debt crisis is provided. Finally, a series of definitions for investor sentiment and how it could be measured, including the most used instruments or proxies to measure investor sentiment in the literature is presented.

2.2 Sovereign Debt

According to Panizza, Sturzenegger, & Zettelmeyer (2009) the main reason for issuing sovereign debt is to smooth consumption by transferring income from good to bad states of the world. They also say that the main difference between corporate and sovereign debt is that the last one has limitations of legal penalties or remedies to enforce repayment of the debt in the event of a default. With limitations to enforce repayment, the only means of retaliating in the event of default would be through the denial of future credit (Panizza, Sturzenegger, & Zettelmeyer, 2009). This means, that without future credit, governments will have problems with their ability to repay past debt and maintain a sustainable economy for the future.

Global economy was shaken by the financial crisis of 2008, which was initially triggered by the growing threat of extensive defaults by subprime borrowers in the mortgage markets

(Longstaff, 2010). The crisis has spread from the financial markets to the general economies, and it has now come to affect government debt (Wehinger, 2010).

2.3 Foreign Debt

Blundell-Wignall & Slovik (2010) describes two interrelated crises in Europe: first the banking crisis, stemming from losses in capital market securities as well as problems in the property markets of some European Union (EU) countries. And second, the sovereign debt crisis exacerbated by recession, transfers to help banks, and in some cases very poor fiscal management over a number of years (Blundell-Wignall & Slovik, 2010).

In an attempt to stimulate the economy, the developed economies during the recent recession adopted extraordinary measures, infusing a surplus of liquidity in the system to unfreeze the illiquid credit markets (Das & Bhardwaj, 2011). Nonetheless, this has led to the ballooning of fiscal deficits worldwide with unsustainable debt levels, particularly among the developed countries (Das & Bhardwaj, 2011).

Greece is the worst case in the European debt crisis which is explained by Arghyrou & Tsoukalas (2010) as a result of: "(a) steady deterioration of Greek macroeconomic fundamentals over 2001-2009 to levels inconsistent with long-term Economic and Monetary Union (EMU) participation; and (b) a double shift in markets' expectations, from a regime of credible commitment to future EMU participation under an implicit EMU/German guarantee of Greek fiscal liabilities, to a regime of non-credible EMU commitment without fiscal guarantees, respectively occurring in November 2009 and February/March 2010". They also say that the risk of contagion to other periphery EMU countries is significant; and that without extensive structural reforms the sustainability of the EMU is in question (Arghyrou & Tsoukalas, 2010).

Apart from Greece, there are other countries that are vulnerable from a fiscal standpoint. According to Das & Bhardwaj (2011); Ireland, Portugal, France, and the United States of America (US) accompany Greece as the top 5 countries in the ranking of a fiscal vulnerability index constructed by them. The index was constructed based on variables of government finances, such as: general government debt to Gross Domestic Product (GDP), cyclically adjusted primary balance, automatic stabilisers as percentage of GDP, general government debt to revenue ratio, ratio of interest payments to government revenue, current account deficit as percentage of GDP and the political stability index (Das & Bhardwaj, 2011).

2.4 U.S. Debt Limit

As established by the Constitution of the United States of America under Article I, Section 8, Clauses 1 and 2, The Congress shall have the power to:

1. lay and collect taxes, duties, imposts and excises, to pay the debts and provide for the common defense and general welfare of the United States; but all duties, imposts and excises shall be uniform throughout the United States
2. borrow money on the credit of the United States

According to Krishnakumar (2005) the first clause imposes a fiscal obligation on Congress while the second confers broad fiscal authority. She also says that inherent in the clauses' language is a sense of balance, of congressional control and accountability for national borrowing and the debt it creates. From these clauses, Krishnakumar (2005) derives three principles of congressional borrowing and debt payment:

1. *Principle of Regulated Borrowing*: Congress has the power to regulate the terms and conditions under which the nation borrows funds.

2. *Principle of Borrowing and Debt Control*: It is Congress's prerogative and duty to decide how much the nation will borrow and for what purposes.
3. *Principle of Repayment*: Debts incurred on behalf of the United States must be honored, and Congress has the power and obligation to ensure that payments are made on the national debt.

As we can see, Congress has the responsibility of issuing how much the debt should be, and ensuring that debt is going to be paid when it is due. But as described by Krishnakumar (2005), the historical evolution of the United States' debt can be broken down into three periods: 1789-1917, when debt was incurred exclusively to pay for wars and to sustain the economy during a recession, but paid down immediately upon return to peace and prosperity; 1917-1946, when Congress passed the debt limit statute granting the Treasury standing borrowing authority, but continued to manage debt incurrence and repayment in substantially the same manner as before; and 1946 to the present, when changed attitudes towards debt and the debt limit have produced sustained peacetime deficits and virtually no debt reduction.

Federal debt has always been subject to restrictions from Congress, but between World War I and World War II, the form of statutory restrictions on federal debt evolved into an aggregate limit that applied to nearly all federal debt outstanding (Austin & Levit, 2011). Before World War I, Congress often authorized borrowing for specified purposes, such as the construction of the Panama Canal (Austin & Levit, 2011). Also, the US Congress specified which types of financial instruments Treasury could employ, detailing the limited interest rates, maturities, and when bonds could be redeemed (Austin & Levit, 2011). In other cases, especially in time of war, Congress provided the Treasury with discretion, subject to broad limits, to choose debt instruments (Austin & Levit, 2011). A debt limit was instituted with the Second Liberty

Bond Act of 1917, but it was not until 1939 that Congress established the first aggregate limit ($45 billion) covering nearly all public debt (Austin & Levit, 2011). Congress has raised the debt limit more than seventy times since 1962, reaching a total of $16,699 billion in May 19, 2013 (Masters, 2013). Although debt limit gives the Congress some oversight authority and fiscal accountability, historically opposition parties have often used debt-limit negotiations to protest existing policies (Masters, 2013).

After the 2008 financial crisis, debt in the United States of America has grown to a point that is out of control; explained by Dodwell (2011) as a result of high federal expenditures and budget deficits combined with two unfunded wars, leading to the debt ceiling debate in 2011 and the Standard & Poor's credit downgrade of U.S. Treasury bonds. These events highlighted the seriousness of disproportionate spending and debt in the face of falling tax revenue that resulted from the Great Recession and the subsequent slow GDP growth (Dodwell, 2011). The market recognizes that the federal debt will seriously challenge future economic growth in the absence of the political will to effectively solve the issue (Dodwell, 2011).

If the debt limit is not raised, the U.S. Treasury has the power to take extraordinary measures to anticipate a default, the point at which the government fails to meet principal or interest payments on the national debt (Masters, 2013). These include under-investing in certain government funds, suspending the sales of nonmarketable debt, and trimming or delaying auctions of securities (Masters, 2013). This author also says that, if Congress does not act to raise the debt limit despite such emergency measures, they have to drastically cut federal spending or rise taxes significantly, or a combination of both.

If Treasury is unable to issue new debt or take further actions to bridge the deficit, the government would be forced to default on some of its financial commitments, limiting or

delaying payments to creditors, beneficiaries, vendors, and other entities (Masters, 2013). Among other things, these payments could include military salaries, Social Security and Medicare payments, and unemployment benefits (Masters, 2013).

In October 2013, the debate between the President and Congress ended in a Federal government shutdown that lasted for 16 days. It was the second longest since 1980 and the most significant on record, measured in terms of employee furlough days (Office of Management and Budget, 2013).

The Office of Management and Budget (2013) highlighted five key impacts and costs from the government shutdown of October 2013 in a report submitted to the Executive Office of the President of the United States on November 2013. First, Federal employees were furloughed for a combined total of 6.6 million days (Office of Management and Budget, 2013).

Second, the shutdown cost the Federal government billions of dollars, which included payroll cost on the lost productivity of furloughed employees; fees went uncollected; Internal Revenue Service enforcement and other program integrity measures were halted; and the Federal government had to pay additional interest on payments that were late (Office of Management and Budget, 2013).

Third, the shutdown had significant negative effects on the economy, for example, an estimated 120,000 fewer private sector jobs created during the first two weeks of October 2013; and also consumer and business confidence was badly damaged (Office of Management and Budget, 2013).

Fourth, the shutdown impacted millions of Americans who relied on critical programs and services halted by the shutdown (Office of Management and Budget, 2013), for example:

1. Patients were prevented from enrolling in clinical trials at the National Institutes of Health.
2. Almost $4 billion in tax refunds were delayed.
3. Agencies from the Food and Drug Administration to the Environmental Protection Agency had to cancel health and safety inspections.
4. Critical government-sponsored scientific research was put on hold.

Fifth, the shutdown could have a long-term impact on the governments' ability to attract and retain the skilled and driven workforce that they need (Office of Management and Budget, 2013). They also said that the shutdown followed a three-year pay freeze for Federal employees, cuts in training and support. These cuts will make it harder for the government to attract and retain the talent it needs to provide top level service to the American people (Office of Management and Budget, 2013).

There were also direct impacts of shutting down government services, as mentioned by the Office of Management and Budget report, some of which include:

1. Federal permitting and environmental and other reviews were halted, delaying job-creating transportation and energy projects.
2. Import and export licenses and applications were put on hold, negatively impacting trade.
3. Federal loans to small businesses, homeowners, and families in rural communities were put on hold.
4. Private-sector lending to individuals and small businesses was disrupted, because banks and lenders couldn't access government income and Social Security Number verification services.

5. Travel and tourism was disrupted at national parks and monuments across the country, hurting the surrounding local economies.

The debt crisis in Europe also has an effect on the United States, specifically on the operations of European banks with illiquidity problems (Dodwell, 2011). In addition, austerity measures implemented throughout Europe in reaction to its own debt crisis presents a problem to the U.S. export markets and multinational corporations invested there (Dodwell, 2011). These conditions dampen U.S. business and consumer sentiment, reinforcing ongoing slow growth or recession and attendant chronic unemployment and social discontent which exacerbate the budget deficit and debt (Dodwell, 2011).

2.5 What is Investor Sentiment and How to Measure it?

Baker & Wurgler (2007) defines investor sentiment as a belief about future cash flows and investment risks that is not justified by the facts at hand. In Zhang (2008), it represents market participants' beliefs about future cash flows relative to some objective norm, namely the true fundamental value of the underlying asset. Lei (2005) mentions that investor sentiment reflects the difference between what an asset price is and what an asset price should be. All of this assuming that there is a market with two groups of investors, one that holds rational expectations on an asset’s value and the other makes biased valuations. These definitions give us a general idea about how the investors behave based on beliefs when taking the decision to invest.

Measuring investor sentiment can be particularly difficult because is based on beliefs, according with the definitions previously described. This means that in order to measure beliefs we have to observe and record investor behavior. As extensively described in the literature, there are several ways to do it, but there is not a clear consensus among them in this issue. For

example, in Kasper (2008), investor sentiment is measured by a general probability model regarding the prospects of the success of a merger with determined parameters such as the risk free rate of return and the target company beta, both of which can be estimated. Beta can be defined as the systematic risk exposures of the portfolio, usually achieved through asset allocation (Blanchett & Kaplan, 2013). The model can track the daily changes in the sentiment as events emerge separating sentiment from market movement (Kasper, 2008).

In Zhang (2008), the author examines two approaches to measure investor sentiment: indirect market-based proxies and direct survey data. The problem with the indirect market-based proxies is that the data refers to investor expectations of price changes, and may not capture all elements of investor attitudes (Zhang, 2008). According to this author, direct survey data, is subject to response bias from the participants. Examples of the first approach includes closed-end fund discount, Initial Public Offering (IPO) under pricing; and a sentiment index based on six different financial proxies, constructed by Baker and Wurgler in 2006 and 2007. Examples of the second approach include the University of Michigan's Consumer Confidence Index and the Yale School of Management's Stock Market Confidence Index.

In another study by Bernile & Lyandres (2011), they investigated the effect of biased estimates of probabilities of future event outcomes on stock returns of publicly traded European soccer clubs around important matches. They used a proxy for investors' subjective expectations derived from contracts traded on betting exchanges (prediction markets); finding in the sample that investor sentiment is attributable in part to a systematic bias in the investors' expectations. Also, they mentioned that investors are overly optimistic about their clubs prospects and, on average, they end up disappointed after the match, leading to a negative post-event abnormal returns (Bernile & Lyandres, 2011).

2.5.1 Sentiment Proxies

According to Finter, Niessen-Ruenzi, & Ruenzi (2011), sentiment proxies are market variables or market statistics that can be seen as measures for investor sentiment. They also explain that there are two types of sentiment proxies. First, the explicit sentiment proxies refer to surveys that directly ask individuals how they feel about current or future economic and stock market conditions (Finter, Niessen-Ruenzi, & Ruenzi, 2011). Second, the implicit sentiment proxies which are indirect measures of sentiment, like trading patterns, price movements, or other market statistics that derive the overall degree of investor sentiment (Finter, Niessen-Ruenzi, & Ruenzi, 2011).

Baker & Wurgler (2007) mentions that surveys could have a gap between how people respond and how they actually behave. Those beliefs could be translated to observable patterns of securities trades, which are recorded (Baker & Wurgler, 2007). The authors also believe that the practical approach is to combine several imperfect measures such as surveys, mood proxies, retail investor trades, mutual fund flows, trading volume, closed-end fund discounts, option implied volatility, first day returns on initial public offerings (IPOs), and volume of initial public offerings. Some of these proxies are described in detail on the following sections.

2.5.1.1 Investor Surveys

Surveys are designed to collect information based on questions on a certain subject from a sample of people chosen by the researcher. In this case, those people are investors, but there are different types, including retail, day traders, international and professional money managers (Singhvi, 2001). Having a good sample could be a limitation when a survey is used to measure investor sentiment. Another problem with surveys is that the investor might give the researcher an answer on what they would do on a certain situation but act differently when presented with

the real situation (Baker & Wurgler, 2007). In other words, the sample should be representative of your underlying population, so that the inferences made from the sample actually apply to the population of interest.

Despite the problems that surveys might have, there are some researchers that have used this instrument in their studies like Brown and Cliff (2005) to forecast market returns. Lemmon and Portniaguina (2006) found evidence that consumer confidence exhibits forecasting power for the returns on small stocks and for future macroeconomic activity. As well, Qiu & Welch (2005) found that the sentiment component of consumer confidence is not strongly related to the closed-end fund discount.

2.5.1.2 Investor Mood

In behavioral finance, there are some key journal articles about how human emotions can affect stock prices or market returns. Kamstra, Kramer, and Levi (2002) studied how the seasonal affective disorder (SAD) has an influence on the stock market returns. SAD is described as a depressive disorder associated with shortness of daylight during fall and winter. Experimental research in psychology and economics indicates that depression, in turn, causes heightened risk aversion (Kamstra, Kramer, & Levi, 2002). They found evidence that the Seasonal Affective Disorder has an effect on market returns and is greater when the latitude is higher.

Akhtari (2011) found a relationship between the local weather of New York City and the Dow Jones Industrial index same day return. The author also mentions that "sunnier days are associated with investors being more willing to take on risky investments, such as stocks, as opposed to less risky investments, or bonds".

From another perspective, Edmans, Garcia, and Norli (2007) investigated the effect of international soccer results as a mood variable on the next-day return on the national stock market index. They concluded that losses in soccer games have an economically and statistically significant negative effect on the losing country's stock market, particularly among small stocks (Edmans, Garcia, & Norli, 2007).

2.5.1.3 Retail Investor Trades

The individual investor, also known as retail investor, is more subject to sentiment because of their lack of experience in comparison with the professional investor. Kumar and Lee (2006) used a large data set of retail trades to examine the effect of retail trading patterns on co movement in stock returns. They found that the trading activities of retail investors contain a common directional component. In other words, "when retail investors' buy (sell) one group of stocks, they tend to buy (sell) other groups. Similarly, when some investors are buying (selling) stocks, other individuals also tend to be buying (selling)" (Kumar & Lee, 2006).

Barber, Odean, and Zhu (2003) concluded in their research that retail trades move markets, particularly among small stocks. They also found that individual investors systematically buy some stocks and sell others.

In France, Foucault, Sraer, & Thesmar (2011), studied the effect of retail trading activity as a determinant of volatility of stock returns. There was a reform that increased the relative cost of speculative trading for retail investors on the French stocks. Using this reform, they observe a significant drop in retail trading, which gave them away to identify the effect of retail investors on volatility. They found a significant and positive effect: the drop in retail trading reduces daily returns volatility by twenty basis points. This result is consistent with the view that retail investors behave as noise traders (Foucault, Sraer, & Thesmar, 2011).

2.5.1.4 Mutual Fund Flows

Researchers have focused on investigating how the mutual funds investors move money across fund categories as a measure of investor sentiment. Frazzini and Lamont (2008) found that when individual investor puts money on a mutual fund, the stocks included in the fund will perform poorly. They say that this can be used to do the opposite of what the individual investor is doing to get higher returns serving as a predictive tool.

Feldman (2010) used mutual funds data to make a new sentiment measure based on a perceived loss index. The results according to the author "provide evidence that the perceived loss index outperforms all other sentiment and systematic risk measures in predicting future medium run returns, especially for one and two-year horizons". Feldman (2010) also states that the loss index can be used as a quantitative measure to detect bubbles and financial crises in financial markets. Furthermore, Ben-Rephael, Kandel, & Wohl (2012) examine the movement between equity and fixed-income funds. There was a tendency of investors to transfer money from bond funds to stock funds, and vice versa when the stock market rises (Ben-Rephael, Kandel, & Wohl, 2012). They also found that 85% of the stock market tends to reverse itself in four months after the exchanges.

2.5.1.5 Trading Volume

Some researchers view trading volume (also known as liquidity) as an investor sentiment index. Baker and Stein (2004) stated, that in a market dominated by irrational investors the increase of trading volume reflects a rise in investor sentiment. Lei (2005) used past trading volume as an investor sentiment index to predict stock returns. The author defines investor sentiment as "the enthusiasm of irrational investors on an asset, relative to that of rational investors."

Tetlock (2007) studied the influence of the media in the stock market using trading volume as measurement. He found that "high media pessimism predicts downward pressure on market prices followed by a reversion to fundamentals, and unusually high or low pessimism predicts high market trading volume."

From a new perspective, Joseph, Babajide Wintoki, and Zhang (2011) examined how the online ticker searches (e.g. NFLX for Netflix, Inc.) could predict abnormal stock returns and trading volumes. "The intensity of search for ticker symbols serves as a valid proxy for investor sentiment which, in turn, is useful for forecasting stock returns and volume" (Joseph, Babajide Wintoki, & Zhang, 2011).

2.5.1.6 Chicago Board Options Exchange Volatility Index (VIX)

The CBOE Volatility Index, also known as VIX, is a forward-looking index of the expected return volatility of the S&P 500 Index over the next 30 days and is implied from the prices of S&P 500 index options, which are predominantly used by the market as a means of insuring the value of stock portfolios (Whaley, 2009). High levels of the VIX reflect investor anxiety regarding a potential drop in the stock market (Whaley, 2009). Also, when the VIX is high, investor sentiment is presumed to be low since investors are assumed to be risk averse (Bandopadhyaya & Jones, 2008). The VIX Index is also known as an "investor fear gauge" (Baker & Wurgler, 2007).

2.5.1.7 Put/Call Ratio (PCR)

The Put/Call ratio (PCR) presents a proportion of investors betting on stock price drops versus investors betting on stock price increases (Bandopadhyaya & Jones, 2008). PCR is also viewed as a short-term, leading technical indicator of sentiment of the direction of future moves in the stock market (Tsuji, 2009). However, most technical analysts use the PCR as a contrarian

indicator because they believe that the less sophisticated public, not professionals, dominates options' trading (Tsuji, 2009).

Using residuals from a random-walk regression of the S&P 500 index to represent variations in assets prices not explained by economic factors, Bandopadhyaya & Jones (2008) found that the PCR is a better measure of such factors than the VIX and, thus, the PCR is a better choice as a measure of market sentiment. Several studies have used the PCR as a sentiment indicator of stock markets: see, for example, Dennis & Mayhew (2002), Billingsley & Chance (1988) and Pan & Poteshman (2006).

In their paper, Dennis & Mayhew (2002) investigated the cross-sectional and time-series determinants of risk-neutral skews implicit in the prices of individual stock options. One of the variables used in the study was the put/call volume ratio, which may be viewed as a proxy for trading pressure or market sentiment (Dennis & Mayhew, 2002).

Billingsley & Chance (1988) scientifically tested the effectiveness of the PCR in market timing and concluded that PCRs are a good market forecasting tool and can be used effectively to gauge the direction of the market. Meanwhile, Pan & Poteshman (2006) studied the informational content of option trading for future movements in underlying stock prices. They found strong evidence that option trading volume contains information about future stock prices.

2.6 Other Factors

An individual or an investor in this case could change their sentiment over time for various reasons. The variables that could affect the sentiment of an investor are: the macroeconomic conditions, firm-specific conditions, expert and analyst views, or even on false information or on genuine insider information (Lawrence, McCabe, & Prakash, 2007). This means that investors who have sold (bought) stock can later purchase (sell) it at a higher (lower)

price (Lawrence, McCabe, & Prakash, 2007). This can lead to high volumes of trading at each price level, which may cause the market price to be away above or below the efficient market hypothesis-based fundamental price of the stock (Lawrence, McCabe, & Prakash, 2007).

2.7 Summary

Governments around the globe are confronting problems with debt, which can make more difficult to them, recuperate from recent crisis and recessions. In the United States they have dealing with the financial crisis of 2008, and, since then the debt limit has become a more public issue. The debates and impasses between Congress and the President aggravated the problem of the debt limit concluding in a downgrade of the government credit rating in 2011 and a government shutdown in 2013.

All of these events have an effect in the stock markets and their investors. This is why the previous sections of this chapter described in more detail the concept of investor sentiment, which can be viewed as a behavior of the investor based more on beliefs than facts. In addition to that, it is also explained, how other researchers were able to measure investor sentiment using different approaches and proxies. This can be divided in two categories: first, the explicit sentiment proxies, which includes surveys. And, second, indirect proxies such as trading patterns, price movements, or other market statistics.

Chapter 3: Methodology

3.1 Introduction

The study focus on whether the changes in the U.S. debt limit could affect investor sentiment. The period under study concentrates on the debt limit changes that have occurred since a year before the 2008 Financial Crisis until one year after the 2011 debt limit crisis, specifically from September 29, 2007 to January 27, 2012. During this period, there were nine changes in debt limit, increasing it from $9,815 billion to $16,394 billion. To examine whether investor sentiment is affected by changes in the statutory limit of U.S. federal debt, an event study using an Ordinary Least Squares (OLS) regression model was performed.

3.2 Sample and Variables

In this section, the sample and variables will be described in more detail. Including the date range in which the study was performed, the sentiment proxies that were used, debt limit changes, and how the data was obtained. The independent variables described are: the Cleveland Financial Stress Index (CFSI), Economic Policy Uncertainty Index for United States (EPU), Wilshire 5000 Total Market Index (WILL5000IND), and the natural log of the statutory debt limit. Then, the dependent variables (sentiment proxies) are explained: Chicago Board Options Exchange Volatility Index (VIX) and the Put/Call Ratio (PCR).

3.2.1 Sample

The data for the debt limit changes came from *Table 7.3 Statutory Limits on Federal Debt: 1940-Current* prepared by the Office of Management and Budget (The White House, 2014). The VIX and the PCR were used as proxies to measure investor sentiment. VIX and PCR data were collected from the Chicago Board Options Exchange (CBOE) website. EPU was

extracted from the Economic Policy Uncertainty website. The WILL5000IND was downloaded from the Federal Reserve Bank of St. Louis website, while the CFSI was downloaded from the Federal Reserve Bank of Cleveland website. All data is presented on a daily basis.

3.2.2 Cleveland Financial Stress Index

According to the Federal Reserve Bank of Cleveland, the Cleveland Financial Stress Index (CFSI) is designed to track distress in the U.S. financial system on a continuous basis. The CFSI is an indicator of systemic stress, where a high value of CFSI indicates high systemic financial stress (Federal Reserve Bank of Cleveland, 2014). The units of CFSI are expressed as standardized differences from the mean (z-scores), under the assumption of normality. To interpret the CFSI measure of stress, it is divided into four levels, which are called grades. The grades are dynamic and move slowly over time (Federal Reserve Bank of Cleveland, 2014). The four grades are described in Table 3.1.

Table 3.1: Cleveland Financial Stress Index Grades

Grade	Description	Range
Grade 1	Low stress period	CFSI < -0.733
Grade 2	Normal stress period	-0.733 ≥ CFSI < 0.544
Grade 3	Moderate stress period	0.544 ≤ CFSI < 1.82
Grade 4	Significant stress period	CFSI ≥ 1.82

Source: Federal Reserve Bank of Cleveland

The CFSI combines 16 measures of conditions in 6 major types of financial markets: credit, equity, foreign exchange, funding, real estate, and securitization (Federal Reserve Bank of Cleveland, 2014). These measures are described in Table 3.2.

Table 3.2: Cleveland Financial Stress Index Components

Markets	Component	Description
Credit	Covered Interest Spread	Measures uncertainty about government bond markets.
	Corporate Bond Spread	Measures the broad perceptions of medium- to long-term risk in corporations of all sectors.
	Liquidity Spread	Measures changes in the bid and ask prices on three-month Treasury bills, which reflect liquidity in financial markets.
	Commercial Paper and T-bill Spread	Measures the short-term risk premium on financial companies' debt.
	Treasury Yield Curve Spread	Measures the likelihood of recession because it captures long-term uncertainty and short-term liquidity.
Equity	Stock Market Crashes	Measures the extent to which equity values in the S&P 500 financial Index have dropped over the previous year. It also captures expectations about the future of the banking industry.
Foreign exchange	Weighted Dollar Crashes	Measures flight from the U.S. dollar toward a broad set of foreign currencies.
Funding	Financial Beta	Measures the contribution of the banking sector to overall stock market volatility
	Bank Bond Spread	Measures the broad perceptions of medium- to long-term risk in banks issuing A-rated bonds.
	Interbank Liquidity Spread	Measures the perception of counterparty risk in interbank lending.
	Interbank Cost of Borrowing	Measures the degree of apprehension with which banks loan to one another.
Real Estate	Commercial Real Estate	Measures the risk associated with investing in commercial real estate.
	Residential Real Estate	Measures the risk associated with investing in residential real estate.
Securitization	Residential MBS	Measures the ability of agencies to raise capital and relative riskiness of the securitized asset.
	Commercial MBS	Measures the ability of originators to raise capital and relative riskiness of the securitized asset.
	Asset-Backed Securities	Measures the ability of originators to raise capital and relative riskiness of the securitized asset.

Source: Federal Reserve Bank of Cleveland

3.2.3 Economic Policy Uncertainty Index for United States

To measure movements in policy-related economic uncertainty over time, a new index was constructed by Baker, Bloom, & Davis (2013), the Economic Policy Uncertainty Index for United States (EPU). These index captures three aspects of economic policy uncertainty: (a) the frequency of references to policy-related economic uncertainty in 10 leading U.S. newspapers, (b) the number and revenue impact of federal tax code provisions set to expire in future years, and (c) the extent of disagreement among economic forecasters over future government purchases and future inflation (Baker, Bloom, & Davis, 2013). The EPU index spikes near major events like tight presidential elections, wars, and terrorist attacks, but recently, it rose to historic highs after the Lehman bankruptcy and Troubled Asset Relief Program (TARP) legislation, the 2010 midterm elections, the Euro zone crisis, and the U.S. debt-ceiling dispute (Baker, Bloom, & Davis, 2013).

The news-based component of the index reflects automated text-search results for 10 large newspapers: USA Today, Miami Herald, Chicago Tribune, Washington Post, Los Angeles Times, Boston Globe, San Francisco Chronicle, Dallas Morning News, New York Times, and the Wall Street Journal (Baker, Bloom, & Davis, 2013). To meet the criteria of the authors for the index, the articles selected must include terms in all three categories pertaining to uncertainty, the economy, and policy. The articles are searched from the archives of each paper since January 1985 (Baker, Bloom, & Davis, 2013).

The second component of the index relies on Congressional Budget Office (CBO) sources that list federal tax code provisions set to expire in coming years and their projected revenue effects (Baker, Bloom, & Davis, 2013). Scheduled tax code expirations are a source of uncertainty because Congress often waits until the last hour before deciding whether to extend

them, undermining stability in and certainty about the future path of taxes (Baker, Bloom, & Davis, 2013). These authors also mentions that CBO uses current law as a baseline, taking into account all scheduled tax expirations, while the Office of Management and Budget (OMB) uses current policy as a baseline under its assessment of which temporary provisions are likely to be extended. Over the past several years, the gap between these two federal spending projections has grown along with a greater use of temporary tax provisions (Baker, Bloom, & Davis, 2013).

The third component of the EPU index is based on the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters (SPF). Each quarter, SPF participants receive a request to provide forecast values for a range of variables at various horizons (Baker, Bloom, & Davis, 2013). Including, individual-level forecast data for inflation, purchases of goods and services by the federal government, and purchases of goods and services by state and local governments (Baker, Bloom, & Davis, 2013). The authors used those variables because they are heavily influenced by monetary and fiscal policy decisions and because they are available back to 1985 (Baker, Bloom, & Davis, 2013). According to Baker, Bloom & Davis (2013) the overall index is normalized to 100, which means that values above 100 are considered above average levels of uncertainty and below 100, are considered below average levels of uncertainty.

3.2.4 Wilshire 5000 Total Market Index

As stated by Wilshire Associates Incorporated (2010) on their website, the Wilshire 5000 Total Market Index is designed to represent the total U.S. equity market. This includes all U.S. equity securities that have readily available prices (Wilshire Associates Incorporated, 2010). To be included in the Wilshire 5000 index, an issue must be: the primary equity issue; a common stock, a real estate investment trust (REIT) or a limited partnership (Wilshire Associates Incorporated, 2010). Also that its primary market listing in the United States; and not be a

bulletin-board issue because they generally do not have consistently readily-available prices (Wilshire Associates Incorporated, 2010). The company's primary issue for index valuation is determined based on market capitalization, trading volume, institutional holdings and conversion rules (Wilshire Associates Incorporated, 2010). To normalize prices fluctuations of the Wilshire 5000 index, a natural log of the index was used.

3.2.5 Natural log of statutory debt limit

Logarithmically transforming variables is a very common way to handle situations where a non-linear relationship exists between the independent and dependent variables (Benoit, 2011). Logarithmic transformations are also a convenient means of transforming a highly skewed variable into one that is more approximately normal (Benoit, 2011). In this study, the researcher used the U.S. statutory limit, which is in billions of dollars for the period from 2007 to 2012. In order to normalize the fluctuations of the U.S. Statutory limit, a natural logarithm was used.

3.2.6 VIX

The VIX is an index computed on a real-time basis throughout each trading day and measures volatility instead of price (Whaley, 2009). When the VIX was introduced it had two purposes, first, it was intended to provide a benchmark of expected short-term market volatility and to provide an index upon which futures and options contracts on volatility could be written (Whaley, 2009). The author emphasizes that the VIX is forward-looking, measuring volatility that the investors expect to see and not backward-looking, measuring volatility that has been recently realized. Therefore the VIX is implied by the current prices of S&P 500 index options and represents expected future market volatility over the next 30 calendar days (Whaley, 2009).

Technically, volatility means unexpected up or down moves, but the S&P 500 index option market has become dominated by hedgers who buy index puts when they are concerned

about a potential drop in the stock market. In other words, they are buying insurance in the portfolio. As such, the VIX is an indicator that reflects the price of portfolio insurance; the more investors demand, the higher the price (Whaley, 2009). Generally VIX values greater than 30 are associated with a large amount of volatility as a result of investor fear or uncertainty, while values below 20 generally correspond to less stressful, even complacent, times in the markets (Katsanos, 2009).

3.2.7 Put/Call Ratio

The Put/Call Ratio is calculated by dividing the volume of put option contracts by the volume of call option contracts (Bandopadhyaya & Jones, 2008). It is said that buyers of put options are betting on stock price drops and may be considered pessimists, while buyers of call options are betting on stock price increases and may be considered optimists (Bandopadhyaya & Jones, 2008). Using trading volume as the basis of measurement, the PCR therefore reflects "pessimism" as a percentage of "optimism". If the PCR is greater than one, then, pessimists outweigh the optimists (Bandopadhyaya & Jones, 2008). If the PCR is less than one, then, optimists outweigh the pessimists (Bandopadhyaya & Jones, 2008).

Although a value of 1.0 might seem to be a "neutral" reading, empirically it has been observed that there are more calls than puts bought on what would be considered an "average" day (Bandopadhyaya & Jones, 2008). As a result, a PCR of approximately 0.80 is considered "normal" (Bandopadhyaya & Jones, 2008). According to the authors, markets are considered "strong" when the ratio falls below 0.7 since the optimists clearly outweigh the pessimists. Markets are considered "weak" when the ratio rises above 1.1 since the pessimists outweigh the optimists (Bandopadhyaya & Jones, 2008).

3.3. Event Study and OLS Regression Analysis

Event studies have become a standard method of measuring security price reaction to some announcement or event (Binder, 1998). The basic structure of an event study measures abnormal returns deviations from market predictions (Corrado, 2011). For this research, the objective is not to measure security prices or returns, but to focus on whether the investor sentiment is affected by changes in the U.S. statutory debt limits. The approach of the event study methodology in this research is different from most studies found in the literature.

3.3.1 Event Windows

In an event study the researcher stipulates the event window in which study will be conducted. In this research, two dependent variables (VIX and PCR) will be examined for each event window. Even if the event being considered is an announcement on a given date, it is typical to set the event window length to be larger than one (Mackinlay, 1997). For this research, there were seven event windows for the nine changes in the statutory debt limit between 2007 and 2012. After 2012, there have been two changes in debt limit with different characteristics than those selected for the study. According to the Office of Management and Budget of the White House (2014), these two changes involved a suspension of existing debt limit for a period of time, and then the limit was prospectively increased to accommodate the increase in such debt outstanding as of the date of the change. Therefore these two changes were not included in the study.

This research has three different event window lengths. First, event windows 1 and 7 have two months before and after the event date. Second, event windows 2, 3 and 4 have one month before and after the event date. And third, event windows 5 and 6 have two event dates within, covering from one month before the first event date and one month after the second event

date. Table 3.3 summarizes in detail each one of the event windows selected for this research. Note that some event windows are larger than others, particularly if no additional debt changes occur around those dates and some event windows include two changes in the statutory limit instead of one, due to the proximity of those events.

Table 3.3 – Event Windows Summary

Event Window	Statutory Debt Limit Changes	Period Start	Period End	Daily Observations
1	September 29, 2007	July 29, 2007	November 28, 2007	86
2	July 30, 2008	June 30, 2008	August 29, 2008	44
3	October 3, 2008	September 03, 2008	November 03, 2008	44
4	February 17, 2009	January 17, 2009	March 17, 2009	41
5	December 28, 2009 and February 12, 2010	November 28, 2009	March 12, 2010	72
6	August 2, 2011 and September 21, 2011	June 02, 2011	November 21, 2011	121
7	January 27, 2012	November 27, 2011	March 27, 2012	83

3.3.2 OLS model and Assumptions

For each of the seven event windows selected for this research, an OLS regression analysis was performed between each investor sentiment proxy (VIX and PCR) and the explanatory variables (CFSI, EPU, natural log of the Wilshire 500 index and the natural log of the statutory debt limit)[1]. The OLS Regression model for each event window and sentiment proxy can be written as:

$$Y_i = \beta_0 + \beta_1 X_1 + \beta_2 \mathrm{X}_2 + \ldots + \beta_k \mathrm{X}_\mathrm{k} + \varepsilon \qquad (3.1)$$

[1] See Section 3.2.4 and 3.2.5 for reasoning behind transformation of the corresponding variables.

where, Y_i is the dependent variable sentiment proxy (VIX or PCR) for each event window EW_i. The X_i represents the independent variables [Cleveland Financial Stress Index (*CFSI_INDEX*), Economic Policy Uncertainty (*EPU_INDEX*), the natural log of the statutory debt limit (*LNDEBT*) and the natural log of the Wilshire 5000 Index prices (*LNWILL5000*)] and ε represents the error term.

The classical linear regression model consists of a set of assumptions about how a data set will be produced by an underlying "data-generating process" (Greene, 2002). The theory will specify a deterministic relationship between the dependent variable and the independent variables (Greene, 2002). To validate the use of the OLS regression analysis, some assumptions must be examined using statistical inference. Four assumptions were reviewed in this research and are described in the following sections.

3.3.2.1 Normality

The assumption of normality of the residuals produces distributions of some test statistics which are useful for a statistical assessment of the validity of the regression model (Greene, 2002). Although there are several tests that analyzed the normality assumption (i.e Shapiro–Wilk test and Anderson-Darling), for this study, a histogram and the p-value of the Jarque-Bera statistic were used to examine the normal distribution of the residuals[2].

The histogram is a crude density estimator, and the rectangles in the figure are called bins, which are constructed of equal width (Greene, 2002). The parameters of the histogram are the number of bins, the bin width and the leftmost starting point (Greene, 2002). This author also

[2] These diagnostic tests were provided in the econometrics software used for the analysis (*EViews 7 – Student version).*

said that each parameter is important in the shape of the end result and the frequency count in the bins sums the sample size. The null hypothesis for the normality assumption is that the data is normally distributed. We will reject the null hypothesis if the calculated *p*-value is lower than the significance level of 5%.

3.3.2.2 Independence

The independence assumption implies that errors of two variables will not necessarily influence each other. In order to test for autocorrelation in the residuals of the OLS, the Breusch-Godfrey Lagrange Multiplier (LM) was used. The *Obs*R-squared* statistic is the Breusch-Godfrey LM test statistic. This LM statistic is computed as the number of observations, times the (uncentered) R^2 from the test regression. Under quite general conditions, the LM test statistic is asymptotically distributed as a $\chi^2(p)$ (Eviews 7, 2009). Basically, this test takes the residuals of the model and makes a regression analysis resulting in test statistics. This was used to determine the validity of the model according to the level of significance of the study. The null hypothesis for the independence assumption is that there is no serial correlation. The null hypothesis is rejected if the calculated *p*-value of the Chi-Square distribution is lower than the significance level of 5% for this study.

If the model presents serial correlation, violating the assumption of independence, it can be corrected adding one autoregressive disturbance term (AR). It is recommended then to add an AR (1) term, which is a first-order autoregressive autocorrelation disturbance term. This can be viewed as a type of disturbance in which a variable is determined by lagged values of itself (Dougherty, 2002). The first order means that the residual values are auto correlated with one lag.

3.3.2.3 Linearity

The linearity assumption states that the relationship between the dependent variables (VIX and PCR) and the independent variables (*CFSI_INDEX, EPU_INDEX, LNDEBT* and *LNWILL5000*) is linear. In order to examine the linearity assumption the Variance Inflator Factor (VIF) test was analyzed.

The VIF is based on the proportion of variance the *i*th independent variable shares with the other independent variables in the model (O'Brien, 2007). The author also states that the VIF is a measure of the *i*th independent variable's collinearity with the other independent variables in the analysis and is connected directly to the variance of the regression coefficient associated with this independent variable. There are two forms of the Variance Inflation Factor: centered and uncentered. The centered VIF is the ratio of the variance of the coefficient estimate from the original equation divided by the variance from a coefficient estimate from an equation with only that regressor and an intercept.

Several rules of thumb for values of VIF have appeared in the literature: the rule of 4, rule of 10, etc. When VIF exceeds these values, these rules often are interpreted as casting doubts on the validity of the results of the regression analysis (O'Brien, 2007). For example, a variance inflation factor of 10 indicates that (all other things being equal) the variance of the *i*th regression coefficient is 10 times greater than it would have been if the *i*th independent variable had been linearly independent of the other independent variable in the analysis (O'Brien, 2007). Thus, it tells us how much the variance has been inflated by this lack of independence (O'Brien, 2007). For this study, the rule of thumb of 10 is used, meaning that if VIF is less than 10, then there is low collinearity among the variables. According to Greene (2002), the problem faced by

applied researchers when regressors are highly, although not perfectly, correlated include the following symptoms:

1. Small changes in the data produce wide swings in the parameter estimates.
2. Coefficients may have very high standard errors and low significance levels even though they are jointly significant and the R^2 for the regression is quite high.
3. Coefficients may have the "wrong" sign or implausible magnitudes.

3.3.2.4 Homoscedasticity

The assumption of Homoscedasticity implies that the errors in the model have the same finite variance. In order to evaluate this assumption, a Heteroscedasticity White Test was used. The White test is computed by implementing a regression on the squared errors, on a constant plus the original independent variables, their squares, and the cross-products (Long & Ervin, 1998). The White statistic is $W = nR^2$, where n is the number of observations and R^2 is the coefficient of determination (Long & Ervin, 1998). The statistic is asymptotically distributed as a χ^2 with degrees of freedom equal to the number of slope coefficients (excluding the constant) in the test regression (Eviews 7, 2009). According to the authors, if the errors are homoscedastic, W is distributed as independent variables squares with degrees of freedom equal to the number of regressors in the auxiliary regression, excluding the constant.

A significant value of W leads to the rejection of the null hypothesis of homoscedasticity (Long & Ervin, 1998). For this research, the null hypothesis of no heteroscedasticity is rejected when p-values are lower than the significance level of 5%.

3.4 Expected Relationship among Variables

Regression analysis is used to determine the relationships between a dependent variable and one or more independent variables (also known as explanatory variables). The relationships

between the variables are expected to be either positive or negative in a linear regression. This means that, if one independent variable has a positive relation with the dependent variable, when the first increase, the second would increase too. And, the contrary happens when the relationships between the variables are negative.

The VIX is expected to have a positive relation with the explanatory variables (CFSI, EPU and the natural log of the statutory debt limit). The natural log of the Wilshire 5000 index is expected to have a negative relation with the VIX. In other words, an increase (decrease) in the explanatory variables with a positive relation should result in an increase (decrease) on the volatility measured by the VIX which is a proxy for investor sentiment; and vice versa when the variables have a negative relation.

The PCR is expected to have a positive relation with the explanatory variables (CFSI, EPU and the natural log of the statutory debt limit) and negative relation with the natural log of the Wilshire 5000 index. According to Bandopadhyaya & Jones (2008) the PCR reflects "pessimism" as a percentage of "optimism". An increase in the PCR means that pessimists are more than the optimists, while a decrease in the PCR means that the optimists surpass the amount of pessimists.

As we can see, the VIX and the PCR are expected to have a positive relation with the variables (*CFSI*, *EPU* and *LNDEBT*) because an increase in financial stress, economic policy uncertainty and debt limit should also increase the volatility in the VIX and the pessimism in the PCR. The variable *LNWILL5000* is expected to have a negative relationship with both sentiment proxies (VIX and PCR) because when market prices increases, investors have optimism or less fear. This means that an increase in market prices should decrease the volatility in the VIX and the pessimism in the PCR.

3.5 Summary

This chapter presented the variables, event windows, and the model that was used to examine whether the changes in the U.S. debt limit could affect investor sentiment. This included: two dependent variables (VIX and PCR), four independent variables (*CFSI_INDEX*, *EPU_INDEX*, *LNDEBT* and *LNWILL5000*) and seven event windows for the nine changes in statutory debt limit. The expected relationship between the variables was explained. The assumptions of normality, independence, linearity, and homoscedasticity for the regression model (OLS) were also discussed.

Chapter 4: Results and Analysis

4.1 Overview

This chapter presents the results and analysis from an Ordinary Least Squares Regression, to study whether investor sentiment is affected by changes in the statutory limit of U.S. federal debt. First, the descriptive statistics will be presented; second, the OLS assumptions analysis, and finally the OLS interpretation of the data used in this study.

4.2 Descriptive Statistics

Tables 4.1 thru 4.7 present the descriptive statistics for each event window (EW) analyzed in this research. For the dependent variable (VIX), EW-3 and EW-4 presents the highest mean values at 47.13 and 45.88 respectively. For the remaining EW's, the mean values stayed between 20 and 30. This means that EW-3 and EW-4 experienced a higher volatility on the market than the other five, which were within normal ranges. As mentioned before, VIX values greater than 30 are associated with a large amount of volatility as a result of investor fear or uncertainty, while values below 20 generally correspond to less stressful, even complacent, times in the markets (Katsanos, 2009).

In terms of the standard deviation of the VIX, EW-3 and EW-6 experienced the highest values at 17.62 (mean = 47.13) and 8.30 (mean = 29.17), respectively. This means that for those two periods the dispersion among the values was higher than the other five EW's that stayed between a standard deviation of two and four. The maximum value of the VIX registered among all periods was 80.06 on EW-3, and the minimum value was 14.26 on EW-7.

The Put/Call ratio (PCR) presented average values over one for EW-1 (1.036), EW-3 (1.083) and EW-6 (1.114). This means that in those periods, pessimists in the market outweighed

the optimists. For the remaining EW's, the PCR had averages values below one, therefore the optimists in the market outweighed the pessimists. In terms of the standard deviation, EW-3 registered the highest value at 0.191 (mean = 1.083). Meaning that for this period, the dispersion of the values of the PCR with respect to the average was higher in comparison to the other EW's.

For the independent variable (*CFSI_INDEX*), EW-4 presented the highest average at 2.13, which means that this period on average fell into the index grade of significant stress. The EW-5 reported the lowest average of 0.115, which belongs to the normal stress period grade of the index. The rest of the EW's were on average in the index grade of 0.544 to 1.82. This grade is considered to be a moderate stress period. EW-6 reported the highest variation among its values with a standard deviation of 0.719 (mean = 1.40), and EW-3 reported the lowest variation with a standard value of 0.102 (mean = 1.53). The lowest value of the *CFSI_INDEX* was -0.585 on EW-5 and the highest value was 2.78 on EW-4. This means that the variable passed thru all grades at some point, from a low stress period to a significant stress period.

The *EPU_INDEX* presented high average values for EW-3 (225.05) and EW-4 (217.59). This means that those periods experimented high levels of economic policy uncertainty. Before those periods, the average values of EW-1 (72.95) and EW-2 (90.22) were the lowest among all EW's. The remaining EW's average values stayed between 125 and 175. As mentioned before, the EPU Index is normalized to 100, which means that values above 100 are considered above average levels of uncertainty and below 100, are considered below average levels of uncertainty (Baker, Bloom, & Davis, 2013). The highest variations in the EPU Index was on EW-3 with a standard deviation of 106.25 (mean = 225.05). This period also presented values from a minimum of 33.39 to a maximum of 626.03.

The Wilshire 5000 Index average price started at a highest value among all EW's of $15,008.97 on EW-1, and experienced consecutive drops until reaching the lowest average price at $7,976.24 on EW-4. Then, the average price of the index had consecutive increases on the next three EW's until it reached an average price value of $13,843.81.Variations on the Wilshire 5000 Index were high at EW-3 with a standard deviation of $1,473.80 (mean = $10,966.29). The lowest variations were registered on EW-2 with a standard deviation of $213.62 (mean = $12,948.66). The minimum price of this index was registered in EW-4 at $6,858.43. And, the maximum priced was on EW-1 at $15,806.69.

The U. S. debt limit started at $8,965 billion on EW-1 and ended in $16,394 billion on EW-7. Including two changes on EW-5 ($12,394 billion and 14,294 billion), and two changes on EW-6 ($14,694 billion and 15,194 billion).

As we can see, EW-3 presented the highest mean values and standard deviation for the VIX, PCR and *EPU_INDEX*. EW-3 included the financial crisis of 2008, which is an event that was on the public eye and affected stock markets and economies around the globe. This could explain why the values for those variables were higher in that event window in comparison with the other EW's.

In the other hand, the *CFSI_INDEX* presented high mean values on EW-4, which was the period after the financial crisis and after the presidential election. These events could also explain the high mean values for the *CFSI_INDEX* for that event window. The standard deviation for *CFSI_INDEX* was the highest on EW-6, which included the debt ceiling crisis of 2011. This is the only event window, from the selected in this study in which the debt limit created a crisis that was under extreme public scrutiny.

Table 4.1 - Descriptive Statistics for Event Window 1

	CFSI_INDEX	EPU_INDEX	LNDEBT	LNWILL5000	US_DEBT	WILL5000IND	VIX	P_C_RATIO
Mean	0.810839	**72.95314**	29.86859	9.615980	9.38E+12	**15008.97**	22.92814	**1.036163**
Median	0.681140	64.96633	29.82435	9.609589	8.97E+12	14907.04	22.98500	1.015000
Maximum	2.002990	236.4259	29.91493	9.668189	9.82E+12	**15806.69**	31.09000	1.530000
Minimum	0.056578	21.00502	29.82435	9.557216	8.97E+12	14146.41	16.12000	0.730000
Std. Dev.	0.461553	38.71026	0.045545	0.029243	4.27E+11	439.3343	3.719083	0.176089
Skewness	0.904200	1.586110	0.046524	0.069193	0.046524	0.110346	0.141654	0.608855
Kurtosis	3.109499	6.064615	1.002165	1.956946	1.002165	1.944681	2.174416	3.078857
Observations	86	86	86	86	86	86	86	86

Table 4.2 - Descriptive Statistics for Event Window 2

	CFSI_INDEX	EPU_INDEX	LNDEBT	LNWILL5000	US_DEBT	WILL5000IND	VIX	P_C_RATIO
Mean	1.629114	**90.21591**	29.95589	9.468614	1.02E+13	12948.66	22.58273	0.984318
Median	1.568140	79.17851	29.99329	9.468741	1.06E+13	12948.58	21.79000	0.980000
Maximum	1.873562	285.2327	29.99329	9.496118	1.06E+13	13307.96	28.54000	1.210000
Minimum	1.485125	39.49040	29.91493	9.424651	9.82E+12	12390.07	18.81000	0.760000
Std. Dev.	0.124965	47.77157	0.039590	0.016563	4.04E+11	**213.6176**	2.462832	0.111739
Skewness	0.596636	2.306046	-0.091003	-0.489741	-0.091003	-0.452532	0.705399	0.130655
Kurtosis	1.920113	8.879726	1.008282	2.764831	1.008282	2.706264	2.736649	2.213377
Observations	44	44	44	44	44	44	44	44

Table 4.3 - Descriptive Statistics for Event Window 3

	CFSI_INDEX	EPU_INDEX	LNDEBT	LNWILL5000	US_DEBT	WILL5000IND	VIX	P_C_RATIO
Mean	1.536510	**225.0498**	30.02522	9.293583	1.10E+13	10966.29	**47.13136**	1.083182
Median	1.546930	216.1913	30.02522	9.324403	1.10E+13	11208.56	45.99000	1.065000
Maximum	1.734059	**626.0275**	30.05715	9.474799	1.13E+13	13027.26	**80.06000**	1.510000
Minimum	1.336592	**33.38503**	29.99329	9.048104	1.06E+13	8502.400	21.43000	0.790000
Std. Dev.	**0.102448**	**106.2490**	0.032300	0.136345	3.54E+11	**1473.796**	**17.62421**	**0.191236**
Skewness	-0.084619	0.910023	4.34E-16	-0.157226	9.47E-18	-0.077004	0.161770	0.342357
Kurtosis	1.941665	5.989096	1.000000	1.436413	1.000000	1.386917	1.731462	2.312436
Observations	44	44	44	44	44	44	44	44

Table 4.4 - Descriptive Statistics for Event Window 4

	CFSI_INDEX	EPU_INDEX	LNDEBT	LNWILL5000	US_DEBT	WILL5000IND	VIX	P_C_RATIO
Mean	**2.133339**	**217.5892**	30.09168	8.981654	1.17E+13	**7976.242**	**45.87878**	0.873171
Median	2.089451	194.2841	30.12456	8.988960	1.21E+13	8014.120	45.49000	0.880000
Maximum	**2.775929**	548.9508	30.12456	9.084078	1.21E+13	8813.840	56.65000	1.180000
Minimum	1.775619	99.76295	30.05715	8.833234	1.13E+13	**6858.430**	39.66000	0.670000
Std. Dev.	0.311083	84.21982	0.034112	0.073023	3.99E+11	571.6851	3.577745	0.129121
Skewness	0.532262	1.991641	-0.048795	-0.506273	-0.048795	-0.417252	0.793859	0.398908
Kurtosis	1.901923	7.616277	1.002381	2.087247	1.002381	1.987650	3.609133	2.375318
Observations	41	41	41	41	41	41	41	41

Table 4.5 - Descriptive Statistics for Event Window 5

	CFSI_INDEX	EPU_INDEX	LNDEBT	LNWILL5000	US_DEBT	WILL5000IND	VIX	P_C_RATIO
Mean	**0.115076**	130.8752	30.18128	9.352583	1.28E+13	11531.55	21.11403	0.865000
Median	0.137878	118.7004	30.14823	9.350612	1.24E+13	11505.87	20.87500	0.875000
Maximum	0.612998	339.4887	30.29086	9.396643	1.43E+13	12047.87	27.31000	1.210000
Minimum	**-0.585272**	61.82451	30.12456	9.302622	1.21E+13	10966.74	17.42000	0.600000
Std. Dev.	0.302104	48.63787	0.069145	0.022940	9.15E+11	264.6068	2.559469	0.116498
Skewness	-0.118579	1.651374	0.923134	0.021669	0.933115	0.064525	0.521048	0.071989
Kurtosis	2.182592	6.961146	1.955383	2.262536	1.959268	2.247755	2.440338	3.147873
Observations	72	72	72	72	72	72	72	72

Table 4.6 - Descriptive Statistics for Event Window 6

	CFSI_INDEX	EPU_INDEX	LNDEBT	LNWILL5000	US_DEBT	WILL5000IND	VIX	P_C_RATIO
Mean	1.403906	173.5773	30.32105	9.472994	1.47E+13	13024.22	29.17041	**1.114380**
Median	1.925204	146.2644	30.31846	9.466080	1.47E+13	12914.16	31.32000	1.120000
Maximum	2.117770	490.8903	30.35192	9.574933	1.52E+13	14399.28	48.00000	1.490000
Minimum	0.265784	65.81203	30.29086	9.346562	1.43E+13	11459.36	15.87000	0.670000
Std. Dev.	**0.718576**	86.97791	0.025892	0.056343	3.82E+11	732.6481	**8.298295**	0.163900
Skewness	-0.448640	1.374999	0.066943	-0.052474	0.082162	0.030962	-0.042109	-0.050389
Kurtosis	1.327425	4.958621	1.399525	2.005635	1.398005	1.978343	1.889190	2.718121
Observations	121	121	121	121	121	121	121	121

Table 4.7 - Descriptive Statistics for Event Window 7

	CFSI_INDEX	EPU_INDEX	LNDEBT	LNWILL5000	US_DEBT	WILL5000IND	VIX	P_C_RATIO
Mean	1.537743	126.1503	30.39039	9.534469	1.58E+13	**13843.81**	20.46711	0.927229
Median	1.667587	118.8813	30.42794	9.539008	1.64E+13	13891.16	19.40000	0.900000
Maximum	2.004004	284.9390	30.42794	9.610017	1.64E+13	14913.43	32.13000	1.260000
Minimum	0.505656	51.90079	30.35192	9.436154	1.52E+13	12533.42	**14.26000**	0.700000
Std. Dev.	0.376081	49.69035	0.038236	0.047830	6.04E+11	657.4974	4.157162	0.121156
Skewness	-1.423372	0.846072	-0.024098	-0.288488	-0.024098	-0.230354	0.825856	0.404009
Kurtosis	4.395675	3.516835	1.000581	1.903889	1.000581	1.861985	3.085639	2.691411
Observations	83	83	83	83	83	83	83	83

4.3 OLS Assumptions

This section will present the OLS assumptions results for each sentiment proxy (VIX and PCR) examined in each event window (EW), for the proposed OLS Regression Analysis.

4.3.1 Normality Assumption

As mentioned on Chapter 3 the normality assumption was examined both graphically and via statistical inference, using a histogram and a Jarque-Bera statistic test on the standardized residuals, respectively. In order to validate this assumption, the p-value of the Jarque-Bera statistic is compared to a significance level of 5%.

4.3.1.1 Event Window 1 (September, 2007) Results

The results for the examination of the normal distribution of each sentiment proxy (VIX and PCR) on EW-1 are presented next. Figure 4.1 shows the results for the histogram and the Jarque-Bera statistic test for the VIX on EW-1. As we can see the histogram has a bell shaped form, which implies that the residuals are normally distributed. The results of the Jarque-Bera statistic test confirm that the residuals of the VIX do not deviate significantly from normality, with a p-value of 0.22.

In Figure 4.2, the results of the PCR are displayed using also the histogram and the Jarque-Bera statistic test for EW-1. As we can see, the histogram also has a bell shaped form, implying the normality of the residuals. The p-value (0.53) of the PCR also shows that the residuals do not deviate significantly from normality.

Figure 4.1 Normality Test for VIX on Event Window 1

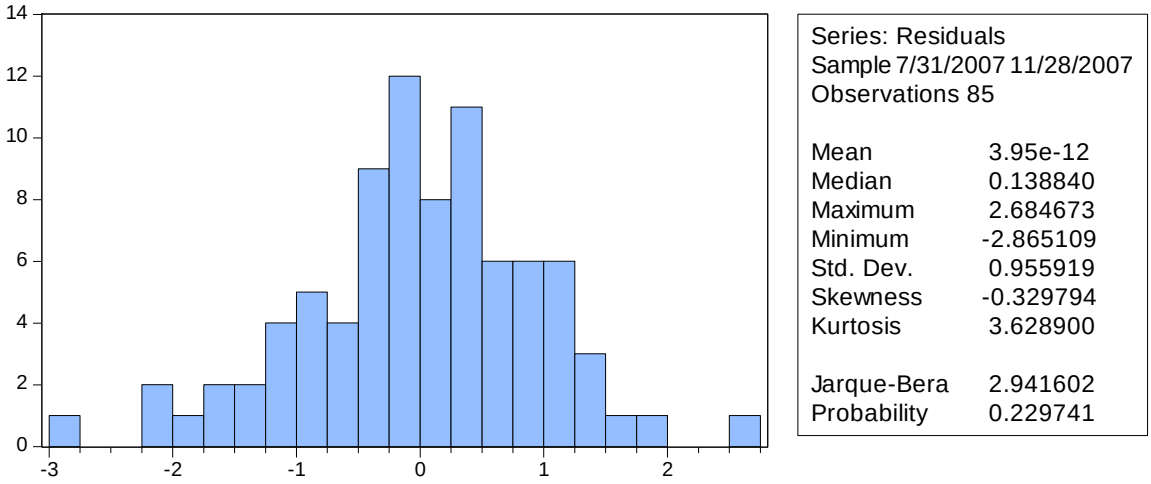
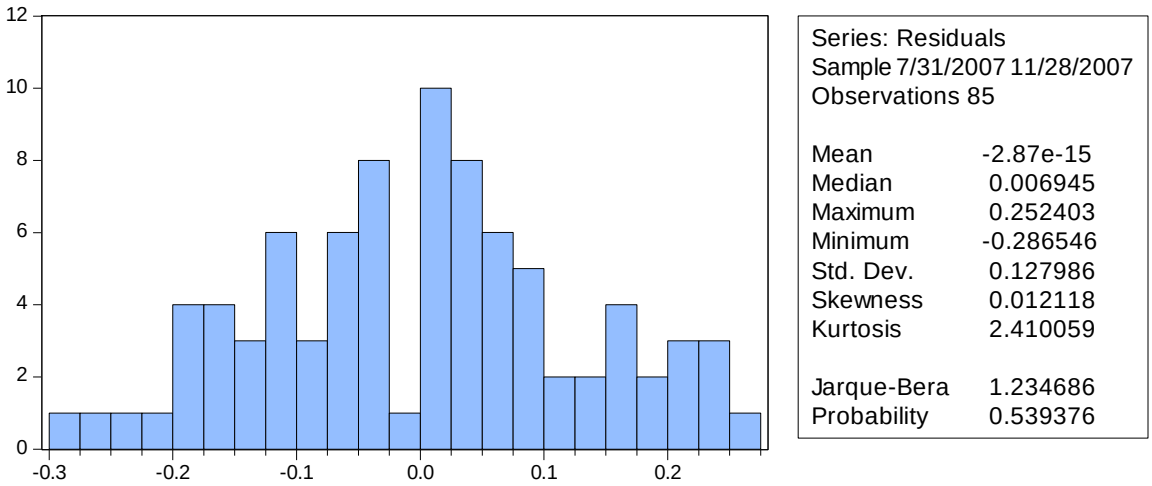


Figure 4.2 Normality Test for PCR on Event Window 1



4.3.1.2 Event Window 2 (July, 2008) Results

This section presents the results for the normal distribution analysis of each sentiment proxy (VIX and PCR) on EW-2. In Figure 4.3, the results of the VIX are displayed using the histogram and the Jarque-Bera statistic test for EW-2. As we can see, the histogram has a bell shaped form, which implies that the residuals do not deviate significantly from a normal

distribution. The p-value (0.35) of the VIX also shows that the residuals do not deviate significantly from normality.

Figure 4.4 shows the results for the histogram and the Jarque-Bera statistic test for the PCR on EW-2. As we can see the histogram has a bell shaped form, which implies that the residuals do not deviate significantly from normality. The results of the Jarque-Bera statistic test on the PCR confirm that the residuals do not deviate significantly from normality, with a p-value of 0.81.

Figure 4.3 Normality Test for VIX on Event Window 2

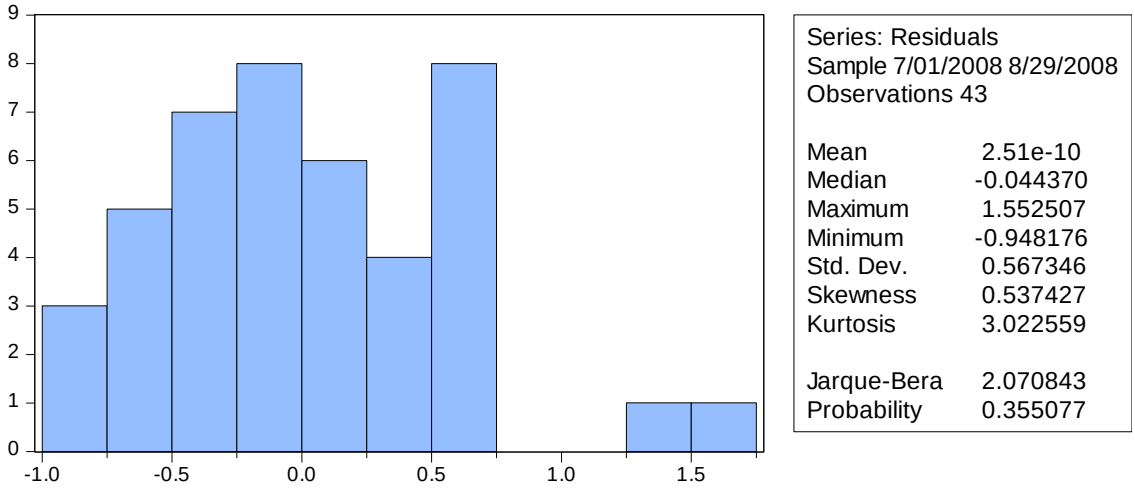
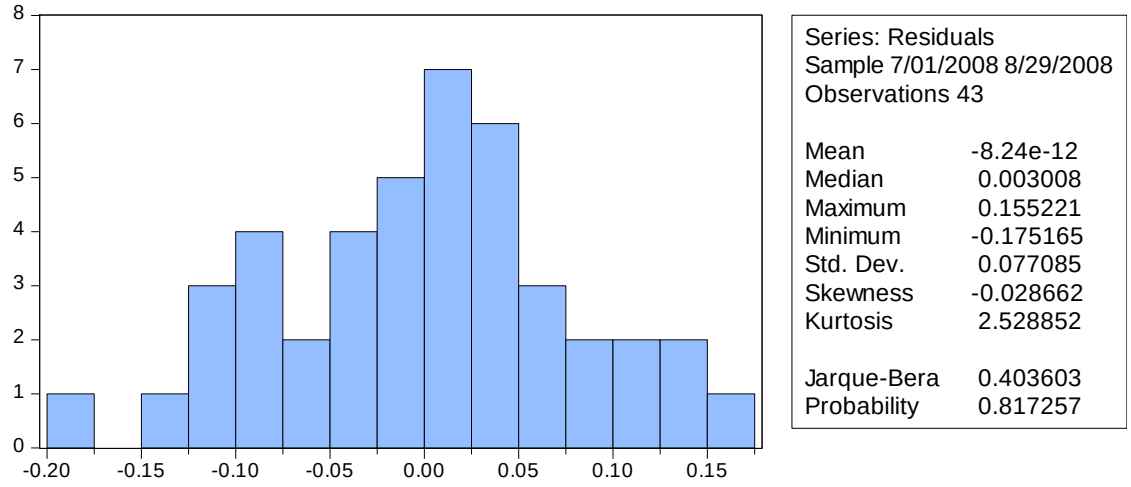


Figure 4.4 Normality Test for PCR on Event Window 2



4.3.1.3 Event Window 3 (October, 2008) Results

The following section presents the results for the normal distribution analysis of each sentiment proxy (VIX and PCR) on EW-3. Figure 4.5 shows the results for the histogram and the Jarque-Bera statistic test for the VIX on EW-3. As we can see the histogram has a bell shaped form, which implies that the residuals do not deviate significantly from normality. The results of the Jarque-Bera statistic test confirm that the residuals of the VIX do not deviate significantly from normality, with a p-value of 0.48.

In Figure 4.2, the results of the PCR are displayed using also the histogram and the Jarque-Bera statistic test for EW-3. As we can see, the histogram also has a bell shaped form, implying that the residuals do not deviate significantly from normality. The p-value (0.24) of the PCR also shows that the residuals do not deviate significantly from normality.

Figure 4.5 Normality Test for VIX on Event Window 3

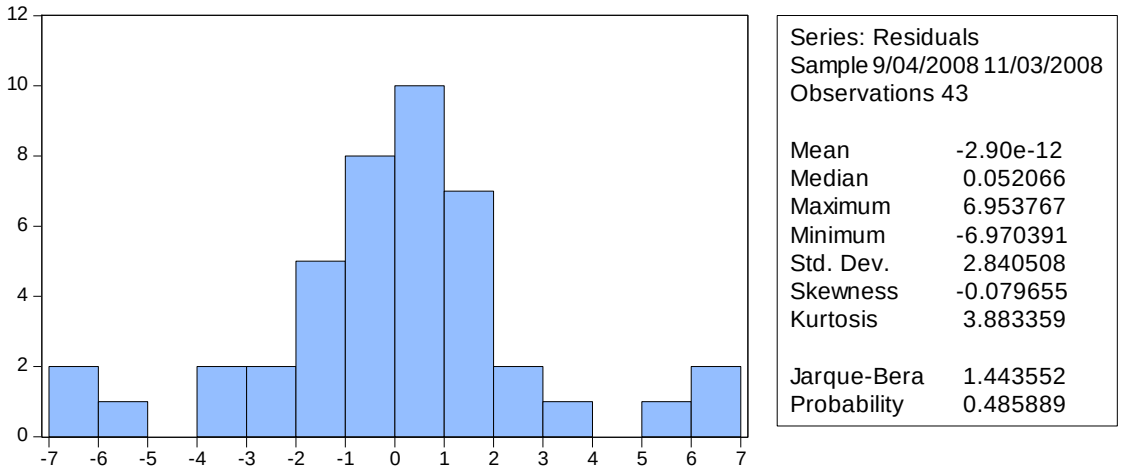
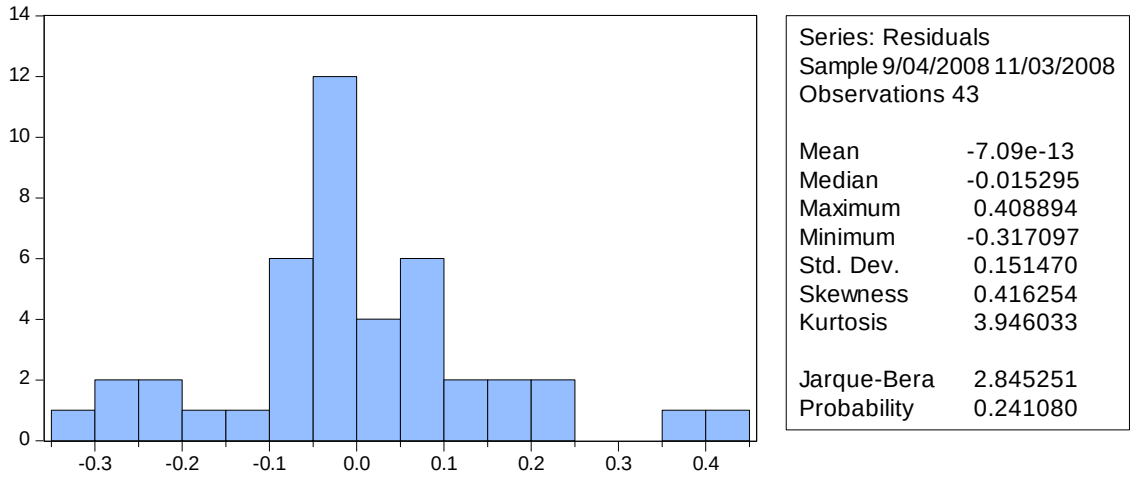


Figure 4.6 Normality Test for PCR on Event Window 3



4.3.1.4 Event Window 4 (February, 2009) Results

The results for the examination of the normal distribution of each sentiment proxy (VIX and PCR) on EW-4 are presented next. In Figure 4.7, the results of the VIX are displayed using the histogram and the Jarque-Bera statistic test for EW-4. As we can see, the histogram has a bell shaped form, which implies that the residuals do not deviate significantly from normality. The VIX shows that the residuals do not deviate significantly from normality, with a p-value of 0.62.

Figure 4.8 displays the results for the histogram and the Jarque-Bera statistic test for the PCR on EW-4. As we can see the histogram has a bell shaped form, which implies that the residuals do not deviate significantly from normality. The results of the Jarque-Bera statistic test on the PCR confirm that do not deviate significantly from normality, with a p-value of 0.56.

Figure 4.7 Normality Test for VIX on Event Window 4

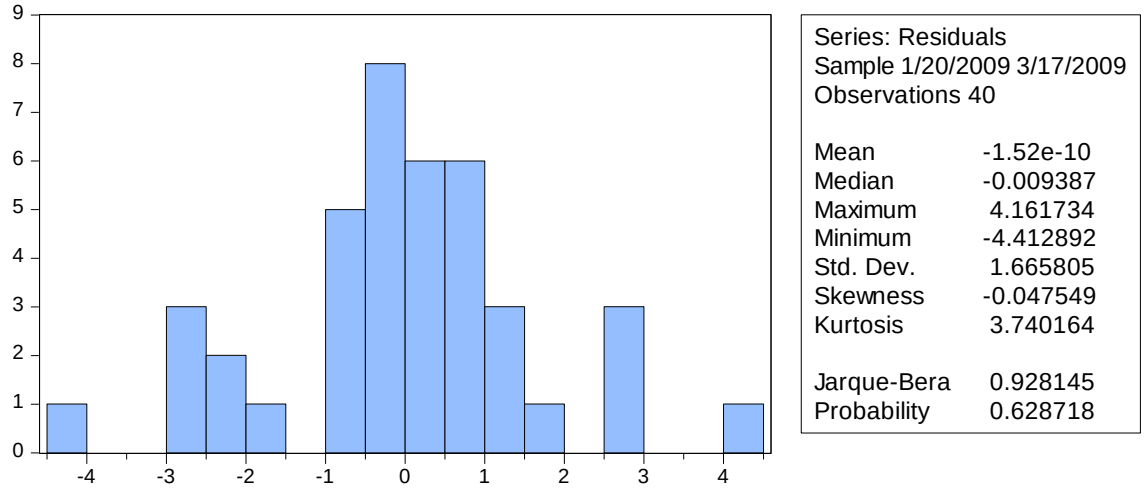
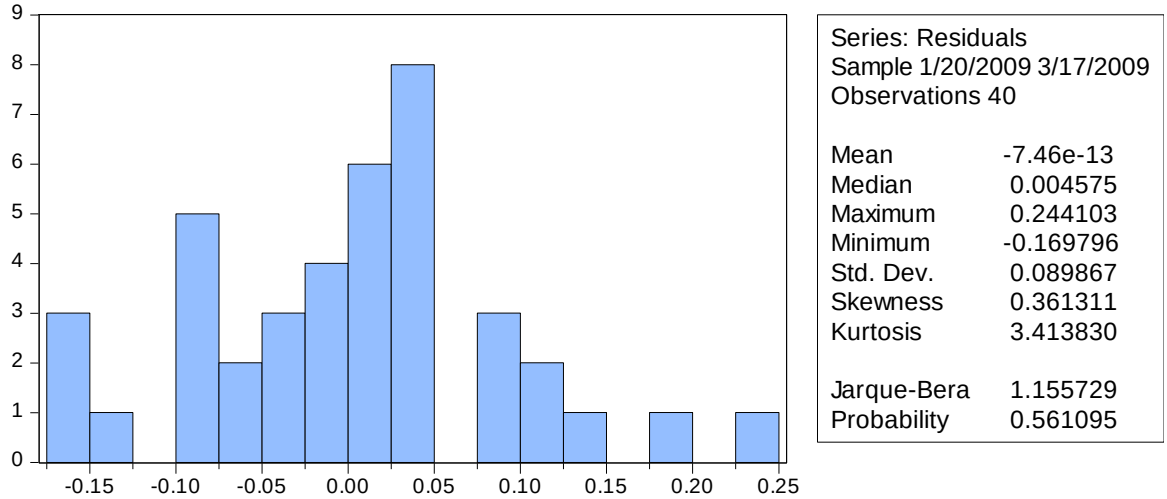


Figure 4.8 Normality Test for PCR on Event Window 4



4.3.1.5 Event Window 5 (December, 2009 and February, 2010) Results

This section presents the results for the normal distribution analysis of each sentiment proxy (VIX and PCR) on EW-5. In Figure 4.9, the results of the VIX are displayed using the histogram and the Jarque-Bera statistic test for EW-5. As we can see, the histogram has a bell shaped form, but it also has skewness to the left, which implies that the residuals deviate

significantly from normality. The p-value of the VIX also shows that the residuals deviate significantly from normality, with a p-value of 0.00.

Giving that the normality assumption was not met, and also seems that the data was highly autocorrelated for consecutive terms, a transformation of the VIX variable was done. According to Osborne (2002), three of the most common data transformations utilized for improving normality are the square root, logarithmic, and inverse transformations of the dependent variable. To correct the normality violation for this model, a logarithmic transformation was performed and ARMA model was used. The autoregresive model includes lagged terms on the series itself, and the moving includes lagged terms on the residuals. The order of the model is ARMA (3, 5).

After performing the transformation on the VIX variable, the normality assumption was reached, as shown on Figure 4.9a. Now the VIX shows that the residuals do not deviate significantly from normality, with a p-value of 0.18.

Figure 4.10 shows the results for the histogram and the Jarque-Bera statistic test for the PCR on EW-5. As we can see the histogram has a bell shaped form, which implies that the residuals do not deviate significantly from normality. The results of the Jarque-Bera statistic test on the PCR confirm that the residuals do not deviate significantly from normality, with a p-value of 0.49.

Figure 4.9 Normality Test for VIX on Event Window 5

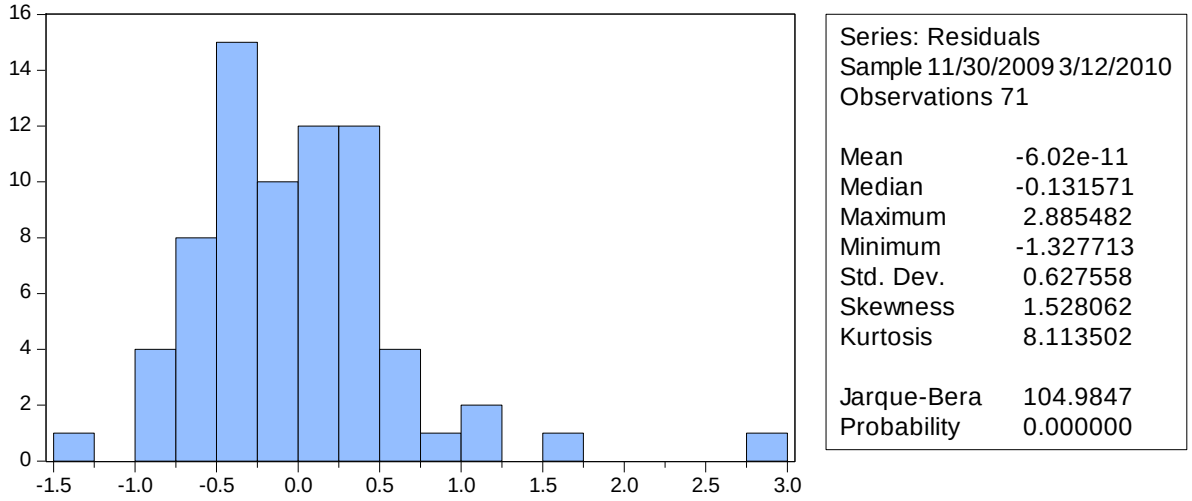


Figure 4.9a Normality Test for transformed VIX on Event Window 5

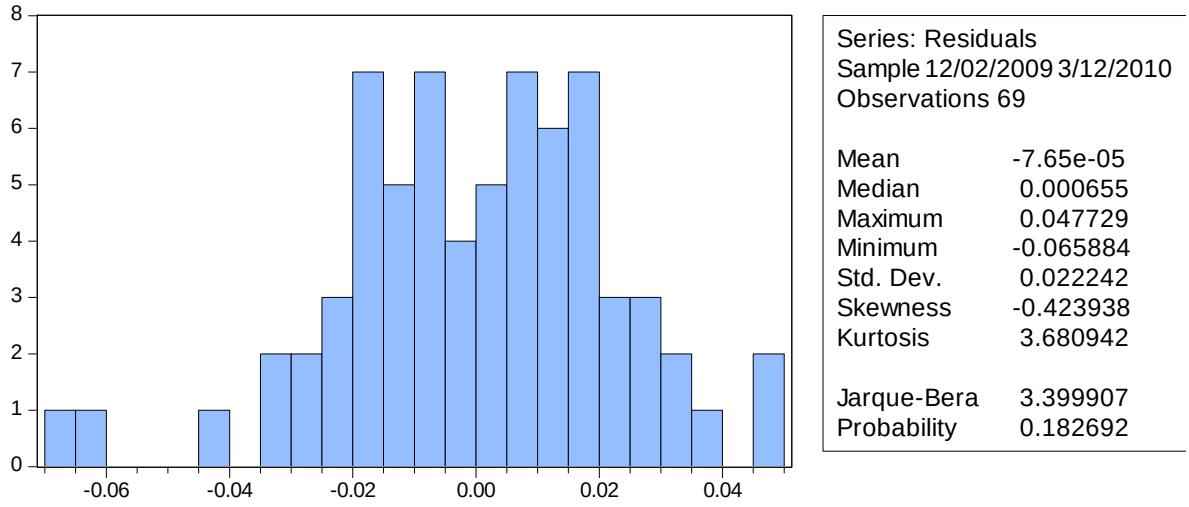
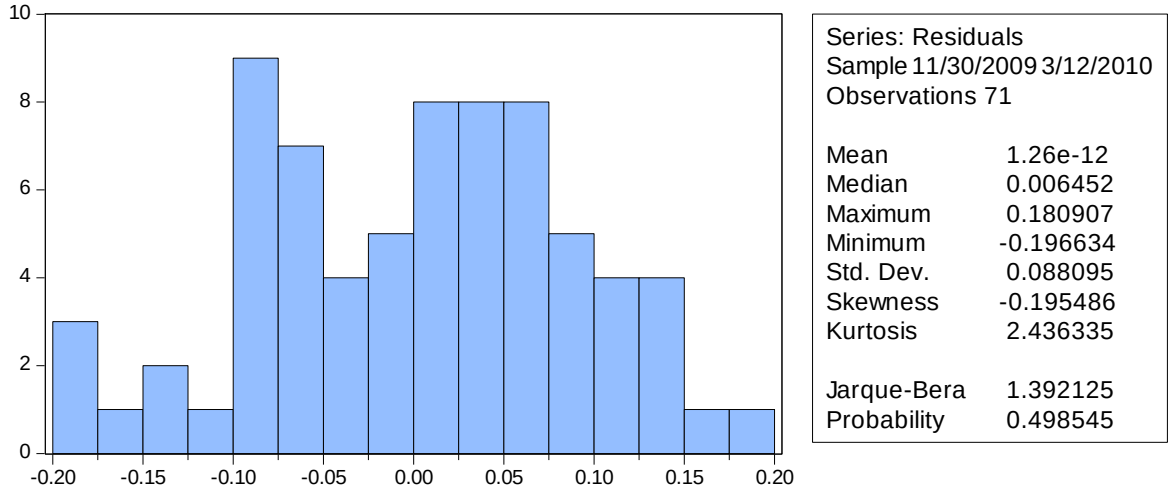


Figure 4.10 Normality Test for PCR on Event Window 5



4.3.1.6 Event Window 6 (August and September, 2011) Results

The results for the examination of the normal distribution of each sentiment proxy (VIX and PCR) on EW-6 are presented next. Figure 4.11 shows the results of the VIX in which a histogram and the Jarque-Bera statistic test for EW-5 were used. As we can see, the histogram has a bell shaped form, which implies that the residuals do not deviate significantly from normality. The p-value of the VIX in the other hand shows that the residuals deviate significantly from normality, with a p-value of 0.00.

As mentioned in section 4.3.1.5 to manage the non-normality of the residuals for this event window a transformation was applied to the dependent variable VIX. This time, the OLS model was estimated using the square root of VIX. After performing the transformation on the VIX variable, the normality assumption was reached, as shown on Figure 4.11a. Now the VIX shows that the residuals do not deviate significantly from normality, with a p-value of 0.24.

The results of the PCR are presented in Figure 4.12, using the histogram and the Jarque-Bera statistic test for EW-6. As we can see, the histogram also has a bell shaped form, implying

that the residuals do not deviate significantly from normality. PCR also shows that the residuals do not deviate significantly from normality, with a p-value of 0.76.

Figure 4.11 Normality Test for VIX on Event Window 6

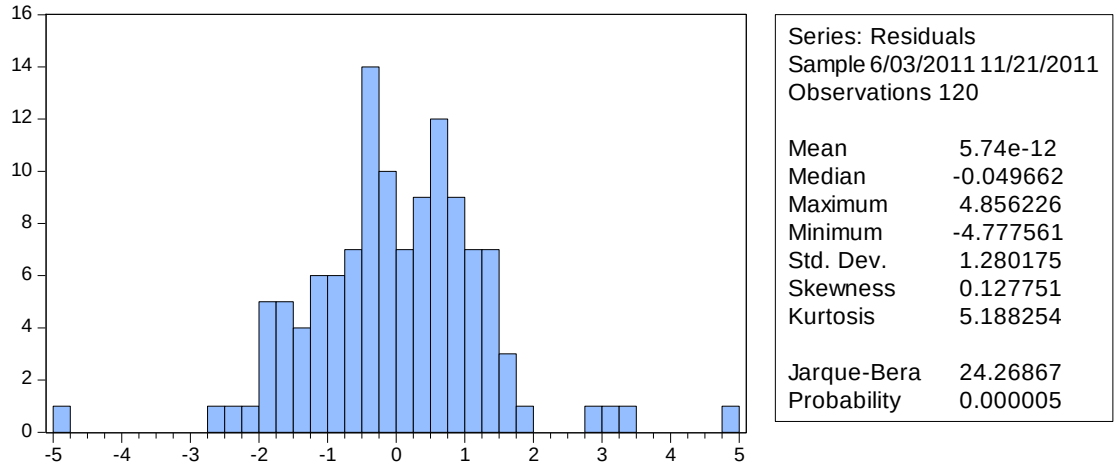


Figure 4.11a Normality Test for transformed VIX on Event Window 6

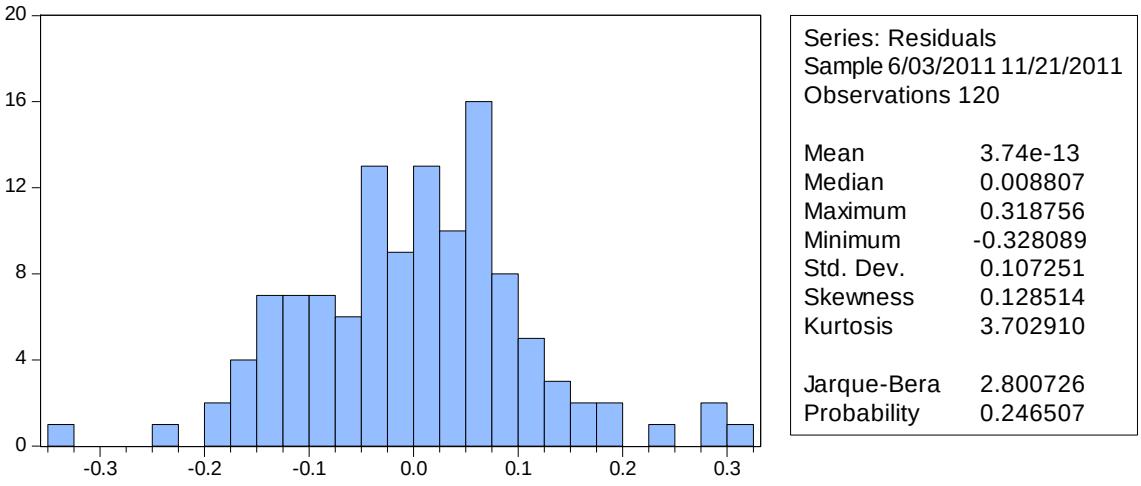
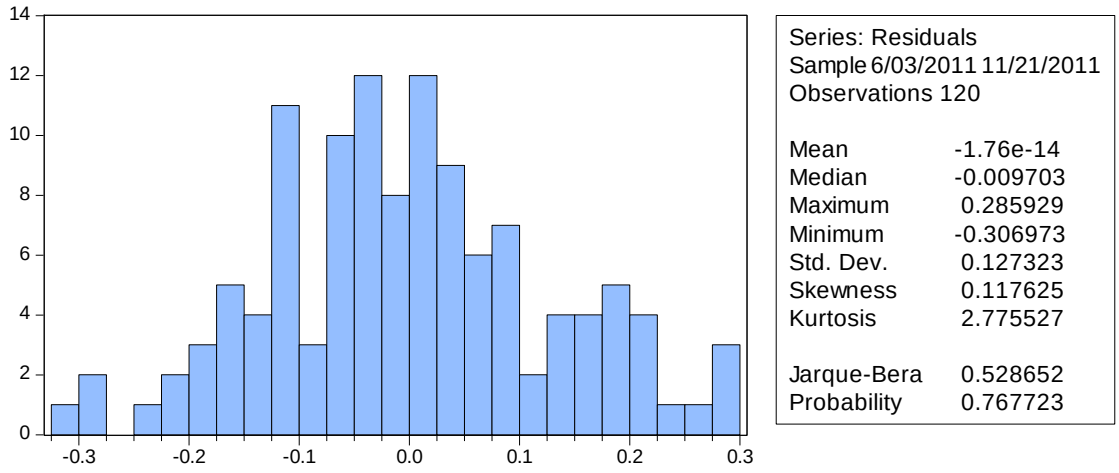


Figure 4.12 Normality Test for PCR on Event Window 6



4.3.1.7 Event Window 7 (January, 2012) Results

The following section presents the results for the normal distribution analysis of each sentiment proxy (VIX and PCR) on EW-7. Figure 4.13 shows the results for the histogram and the Jarque-Bera statistic test for the VIX on EW-7. As we can see the histogram has a bell shaped form, which implies that the residuals do not deviate significantly from normality. The results of the Jarque-Bera statistic test confirm that the residuals of the VIX a do not deviate significantly from normality, with a p-value of 0.99.

In Figure 4.14, the results of the residuals of the PCR are displayed using also a histogram and the Jarque-Bera statistic test for EW-7. As we can see, the histogram has skewness to the left, implying that the residuals deviate from normality, but the p-value (0.10) of the residuals do not deviate significantly from normality.

Figure 4.13 Normality Test for VIX on Event Window 7

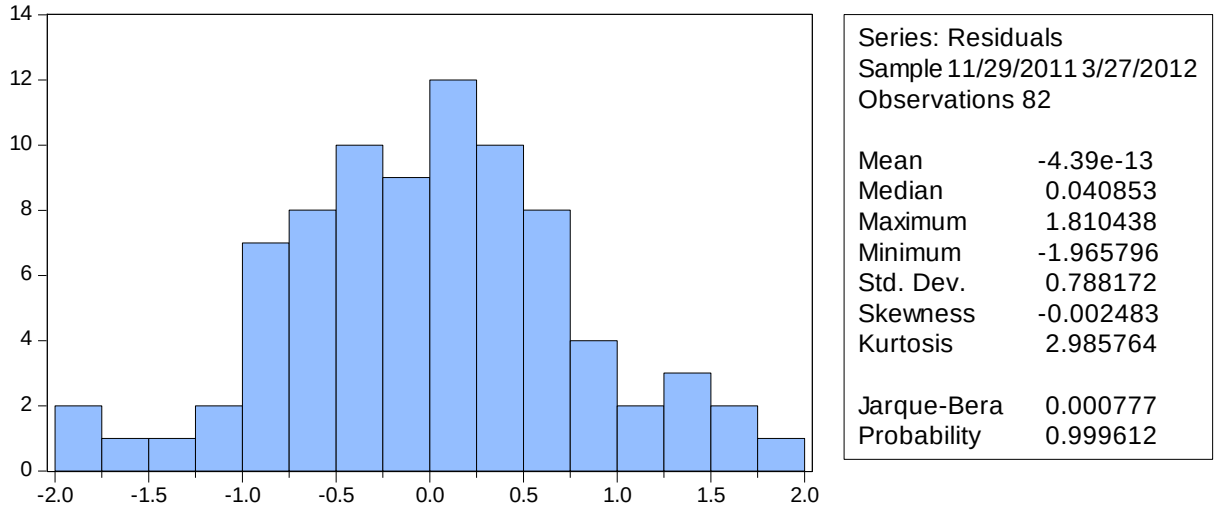
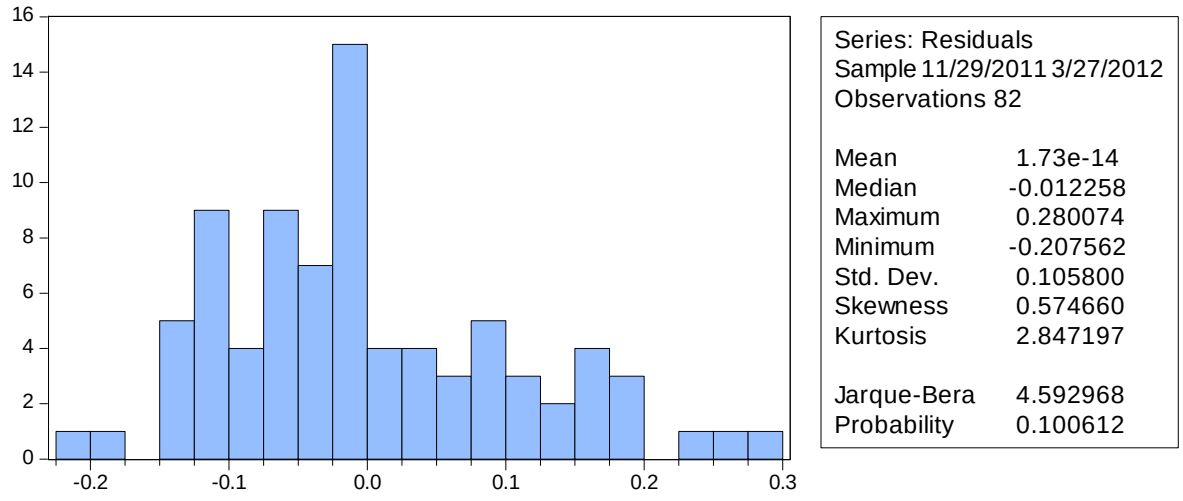


Figure 4.14 Normality Test for PCR on Event Window 7



4.3.2 Independence Assumption

As mentioned on Chapter 3 the Independence Assumption was tested on the residuals using the Breusch-Godfrey Lagrange Multiplier (LM). This test takes the residuals of the model and makes a regression analysis in order to validate it. For this study a 5% significance level was used. If the p-value of the test statistics is below that percent then the assumption will not be

validated. The tests on the residuals of both sentiment proxies (VIX and PCR) for all event windows were made with two lags.

4.3.2.1 Event Window 1 (September, 2007) Results

Each of the sentiment proxies residuals were tested for the Independence Assumption on EW-1. Tables 4.8 and Table 4.9 present the results of the Breusch-Godfrey Lagrange Multiplier test for the residuals of the VIX and PCR respectively on EW-1. As we can see, the Independence Assumption is validated for the residuals of the VIX with a p-value of 0.95, and the residuals of the PCR, with a p-value of 0.52. This means there is no serial correlation among the error terms.

Table 4.8 - Independence Test for VIX on Event Window 1

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.042648	Prob. F(2,77)	0.9583
Obs*R-squared	**0.094054**	**Prob. Chi-Square(2)**	**0.9541**

Table 4.9 - Independence Test for PCR on Event Window 1

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.600434	Prob. F(2,77)	0.5511
Obs*R-squared	**1.305278**	**Prob. Chi-Square(2)**	**0.5207**

4.3.2.2 Event Window 2 (July, 2008) Results

The sentiment proxies (VIX and PCR) residuals were tested for independence on EW-2 using the Breusch-Godfrey Lagrange Multiplier test. In tables 4.10 and 4.11 the results of the test for the residuals of the VIX and PCR are presented for EW-2. The independence assumption holds for the residuals of the VIX and the PCR with p-values at 0.72 and 0.42, respectively.

Table 4.10 - Independence Test for VIX on Event Window 2

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.260119	Prob. F(2,35)	0.7724
Obs*R-squared	**0.629788**	**Prob. Chi-Square(2)**	**0.7299**

Table 4.11 - Independence Test for PCR on Event Window 2

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.716757	Prob. F(2,35)	0.4954
Obs*R-squared	**1.691879**	**Prob. Chi-Square(2)**	**0.4292**

4.3.2.3 Event Window 3 (October, 2008) Results

The VIX and PCR residuals were tested using the Breusch-Godfrey Lagrange Multiplier for the independence assumption on EW-3, and the results are displayed in Tables 4.12 and Table 4.13. The results presented a p-value of 0.32 for the residuals of the VIX, and a p-value of 0.98 for the residuals of the PCR. According to these values we can conclude that the residual errors are independent from each other for both sentiment proxies in EW-3.

Table 4.12 - Independence Test for VIX on Event Window 3

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.972286	Prob. F(2,35)	0.3882
Obs*R-squared	**2.263299**	**Prob. Chi-Square(2)**	**0.3225**

Table 4.13 - Independence Test for PCR on Event Window 3

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.012869	Prob. F(2,35)	0.9872
Obs*R-squared	**0.031597**	**Prob. Chi-Square(2)**	**0.9843**

4.3.2.4 Event Window 4 (February, 2009) Results

In tables 4.14 and 4.15 the results are presented for the Independence Assumption test of the VIX and PCR residuals for EW-4. The VIX residuals presented a p-value of 0.37 and the PCR residuals a p-value of 0.51. This means that the independence assumption holds for both sentiment proxies' residuals.

Table 4.14 - Independence Test for VIX on Event Window 4

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.824219	Prob. F(2,32)	0.4477
Obs*R-squared	**1.959602**	**Prob. Chi-Square(2)**	**0.3754**

Table 4.15 - Independence Test for PCR on Event Window 4

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.548870	Prob. F(2,32)	0.5829
Obs*R-squared	**1.326664**	**Prob. Chi-Square(2)**	**0.5151**

4.3.2.5 Event Window 5 (December, 2009 and February, 2010) Results

The sentiment proxies (VIX and PCR) residuals were tested for the Independence Assumption on EW-5 using the Breusch-Godfrey Lagrange Multiplier test. In tables 4.16 and 4.17 presents the results of the test for the residuals of the VIX and the PCR on EW-5. The Independence Assumption is confirmed for the residuals of the VIX and the PCR with p-values at 0.08 and 0.06, respectively.

Table 4.16 - Independence Test for VIX on Event Window 5

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	2.143292	Prob. F(2,57)	0.1266
Obs*R-squared	**4.825316**	**Prob. Chi-Square(2)**	**0.0896**

Table 4.17 - Independence Test for PCR on Event Window 5

Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	2.584049	Prob. F(2,63)	0.0834
Obs*R-squared	**5.382796**	**Prob. Chi-Square(2)**	**0.0678**

4.3.2.6 Event Window 6 (August and September, 2011) Results

Each of the sentiment proxies (VIX and PCR) residuals were tested for the Independence Assumption on EW-6. Tables 4.18 and Table 4.19 present the results of the Breusch-Godfrey Lagrange Multiplier test for the residuals of the VIX and PCR, respectively, on EW-6. As we can see, the Independence Assumption is validated for the residuals of the VIX with a p-value of 0.80, and the residuals of the PCR, with a p-value of 0.19.

Table 4.18 - Independence Test for VIX on Event Window6

Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	0.207193	Prob. F(2,112)	0.8132
Obs*R-squared	**0.442348**	**Prob. Chi-Square(2)**	**0.8016**

Table 4.19 - Independence Test for PCR on Event Window 6

Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	1.546653	Prob. F(2,112)	0.2175
Obs*R-squared	**3.225180**	**Prob. Chi-Square(2)**	**0.1994**

4.3.2.7 Event Window 7 (January, 2012) Results

The VIX and PCR residuals were tested using the Breusch-Godfrey Lagrange Multiplier for the Independence Assumption on EW-7, and the results are displayed in Tables 4.20 and Table 4.21. The results presented a p-value of 0.38 for the residuals of the VIX and a p-value of

0.71 for the residuals of the PCR. According to these values it can be concluded that the residual errors are independent from each other for both sentiment proxies in EW-7.

Table 4.20 - Independence Test for VIX on Event Window 7

Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	0.886946	Prob. F(2,74)	0.4162
Obs*R-squared	**1.919647**	**Prob. Chi-Square(2)**	**0.3830**

Table 4.21 - Independence Test for PCR on Event Window 7

Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	0.310994	Prob. F(2,74)	0.7337
Obs*R-squared	**0.683484**	**Prob. Chi-Square(2)**	**0.7105**

4.3.3 Linearity Assumption

The linearity assumption tests the dependent variables and the independent variables to see if the relationship between them is linear. In order to examine the linearity assumption a Variance Inflator Factor (VIF) test was performed. As explained in Chaper 3, the VIF look for linear relationships among independent variables. The R^2 is the measure that describes the degree to which a linear regression model can explain the variability of the response variable.

The results will present two calculations of the VIF: uncentered and centered. For the purpose of this study the centered VIF is used to validate the linearity assumption because contrary to the uncentered VIF the latter includes a constant in the calculation. The rule of thumb of 10 was used in this research, meaning that if the VIF is less than 10, then the relationship among the variables examined has a low collinearity. The test on each sentiment proxy (VIX and OCR) for each event window will be presented in the following sections.

4.3.3.1 Event Window 1 (September, 2007) Results

In Table 4.22 and Table 4.23 the results of the VIF test for each of the two sentiment proxies (VIX and PCR) are presented for EW-1. The explanatory variables (*CFSI_INDEX*, *EPU_INDEX*, *LNDEBT* and *LNWILL5000*) showed values below 10, therefore we can conclude they have a low collinearity.

Table 4.22 - Linearity Test for VIX on Event Window 1

Variance Inflation Factors
Sample: 7/30/2007 11/28/2007
Included observations: 85

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	32255.67	157542.9	NA
CFSI_INDEX	1.353751	5.487883	1.317630
EPU_INDEX	6.91E-06	1.372314	1.176487
LNDEBT	45.04000	196743.0	1.597686
LNWILL5000	111.4679	50472.44	1.748146
AR(1)	0.005699	1.318512	1.200461

Table 4.23 - Linearity Test for PCR on Event Window 1

Variance Inflation Factors
Sample: 7/30/2007 11/28/2007
Included observations: 85

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	132.4817	516062.5	NA
CFSI_INDEX	0.003132	8.390340	1.778478
EPU_INDEX	2.40E-07	5.659749	1.140836
LNDEBT	0.271950	945317.6	2.134184
LNWILL5000	0.686565	247786.0	2.227177
AR(1)	0.012960	1.204727	1.186983

4.3.3.2 Event Window 2 (July, 2008) Results

This event window also presented values below 10 when the VIF test was performed on the dependent variables and the independent variables. Tables 4.24 and 4.25 present the results for the VIX and the PCR respectively for EW-2. According to the rule of thumb of 10, if the VIF is less than 10, then the relationship among the variables has a low collinearity.

Table 4.24 - Linearity Test for VIX on Event Window 2

Variance Inflation Factors
Sample: 6/30/2008 8/29/2008
Included observations: 43

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	18584.10	87140.89	NA
CFSI_INDEX	9.894041	117.7009	1.601926
EPU_INDEX	2.15E-06	1.185995	1.162139
LNDEBT	22.66805	95508.94	1.220581
LNWILL5000	59.54836	25005.63	1.342491
AR(1)	0.012035	1.700165	1.608263

Table 4.25 - Linearity Test for PCR on Event Window 2

Variance Inflation Factors
Sample: 6/30/2008 8/29/2008
Included observations: 43

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	928.2933	1305641.	NA
CFSI_INDEX	0.113515	438.7602	3.272991
EPU_INDEX	3.90E-08	2.240000	1.333255
LNDEBT	1.004177	1267611.	3.225276
LNWILL5000	1.192654	150396.3	1.550022
AR(1)	0.015192	1.252973	1.160596

4.3.3.3 Event Window 3 (October, 2008) Results

The linear relationship between the explanatory variables and the dependent variables were tested using the VIF for EW-3. As we can see in tables 4.26 and 4.27, the results are values below 10 on all the explanatory variables for each sentiment proxy, which means that they have a low collinearity among them.

Table 4.26 - Linearity Test for VIX on Event Window 3

Variance Inflation Factors
Sample: 9/03/2008 11/03/2008
Included observations: 43

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	891185.3	5289427.	NA
CFSI_INDEX	36.41775	537.8554	1.355803
EPU_INDEX	2.37E-05	7.638527	1.432188
LNDEBT	851.8630	4551907.	3.554715
LNWILL5000	70.64133	36722.14	3.786515
AR(1)	0.032801	1.328117	1.324306

Table 4.27 - Linearity Test for PCR on Event Window 3

Variance Inflation Factors
Sample: 9/03/2008 11/03/2008
Included observations: 43

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	7522.504	2948986.	NA
CFSI_INDEX	0.168464	144.3394	1.820760
EPU_INDEX	5.43E-08	2.474903	1.219338
LNDEBT	7.567605	2676006.	3.857083
LNWILL5000	0.295731	9954.243	2.972205
AR(1)	0.026948	1.645856	1.631329

4.3.3.4 Event Window 4 (February, 2009) Results

For this event window, the VIF test results also showed that the variables have a low collinearity among them, because the values were below 10. Tables 4.28 and 4.29 present the results of the VIF test on each sentiment proxy for the EW-4.

Table 4.28 - Linearity Test for VIX on Event Window 4

Variance Inflation Factors
Sample: 1/16/2009 3/17/2009
Included observations: 40

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	207770.0	8324.748	NA
CFSI_INDEX	80.84692	11.26454	1.235939
EPU_INDEX	4.43E-06	1.940381	1.833931
LNDEBT	128.1611	5032.166	5.364662
LNWILL5000	203.8875	540.7775	4.230457
AR(1)	0.000876	14.55756	1.141783

Table 4.29 - Linearity Test for PCR on Event Window 4

Variance Inflation Factors
Sample: 1/16/2009 3/17/2009
Included observations: 40

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	207770.0	8324.748	NA
CFSI_INDEX	80.84692	11.26454	1.235939
EPU_INDEX	4.43E-06	1.940381	1.833931
LNDEBT	128.1611	5032.166	5.364662
LNWILL5000	203.8875	540.7775	4.230457
AR(1)	0.000876	14.55756	1.141783

4.3.3.5 Event Window 5 (December, 2009 and February, 2010) Results

In Table 4.30 and Table 4.31 the results of the VIF test for each of the two sentiment proxies are presented for EW-5. The explanatory variables showed values below 10, therefore we can conclude they have a low collinearity among them according to the rule of thumb of 10.

Table 4.30 - Linearity Test for VIX on Event Window5

Variance Inflation Factors
Sample: 11/27/2009 3/12/2010
Included observations: 69

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	7.308550	3632137.	NA
CFSI_INDEX	0.000314	3.595625	2.835055
EPU_INDEX	2.25E-09	25.03906	2.790653
LNDEBT	0.002528	1144994.	2.455666
LNWILL5000	0.037460	1627621.	2.720844
AR(1)	0.026937	3.884336	3.883764
AR(2)	0.034625	4.068799	4.033419
AR(3)	0.033354	2.691327	2.589551
MA(4)	0.000656	1.508736	1.365901
MA(5)	0.001830	2.498177	2.421748

Table 4.31 - Linearity Test for PCR on Event Window5

Variance Inflation Factors
Sample: 11/27/2009 3/12/2010
Included observations: 71

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	107.0049	843992.1	NA
CFSI_INDEX	0.004562	3.235399	3.063333
EPU_INDEX	6.80E-08	10.49099	1.269848
LNDEBT	0.031629	227338.1	1.240996
LNWILL5000	0.690493	476702.6	2.890528
AR(1)	0.014608	1.113136	1.086295

4.3.3.6 Event Window 6 (August and September, 2011) Results

The linear relationship between the explanatory variables and the dependent variables were tested using the VIF for EW-6. As we can see in tables 4.32 and 4.33, the results are values below 10 on all the explanatory variables for each sentiment proxy, which means that they have a low collinearity among them.

Table 4.32 - Linearity Test for VIX on Event Window 6

Variance Inflation Factors
Sample: 6/02/2011 11/21/2011
Included observations: 120

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	6004.573	746464.8	NA
CFSI_INDEX	0.031048	9.116645	2.276253
EPU_INDEX	3.16E-08	1.554295	1.502411
LNDEBT	6.151634	703154.5	2.149622
LNWILL5000	0.785961	8788.142	1.537212
AR(1)	0.001567	1.102052	1.073906

Table 4.33 - Linearity Test for PCR on Event Window 6

Variance Inflation Factors
Sample: 6/02/2011 11/21/2011
Included observations: 120

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	1269.144	4868130.	NA
CFSI_INDEX	0.002049	19.06093	4.370272
EPU_INDEX	1.98E-08	3.820019	1.226940
LNDEBT	1.313149	4630338.	3.556099
LNWILL5000	0.189970	65404.52	2.711580
AR(1)	0.006415	1.157218	1.151727

4.3.2.7 Event Window 7 (January, 2012) Results

This event window also presented values below 10 when the VIF test was performed on the dependent variables and the independent variables. Tables 4.34 and 4.35 present the results for the VIX and the PCR respectively for EW-7. According to the rule of thumb of 10, if the VIF is less than 10, then the relationship among the variables has a low collinearity.

Table 4.34 - Linearity Test for VIX on Event Window 7

Variance Inflation Factors
Sample: 11/28/2011 3/27/2012
Included observations: 82

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	51391.51	171285.9	NA
CFSI_INDEX	1.321063	9.886586	1.183842
EPU_INDEX	3.98E-06	1.353062	1.169038
LNDEBT	59.86412	184430.6	1.155070
LNWILL5000	85.43750	26055.53	1.324370
AR(1)	0.004408	1.193010	1.154603

Table 4.35 - Linearity Test for PCR on Event Window 7

Variance Inflation Factors
Sample: 11/28/2011 3/27/2012
Included observations: 82

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	387.7223	1649978.	NA
CFSI_INDEX	0.004479	47.17930	2.708813
EPU_INDEX	9.62E-08	7.899556	1.392224
LNDEBT	0.660184	2594873.	4.122692
LNWILL5000	0.665465	257541.1	6.183527
AR(1)	0.012448	1.029521	1.028700

4.3.4 Homoscedasticity Assumption

As mentioned in Chapter 3 the homoscedasticity assumption means that the residuals for the model have constant variance. For this study, the null hypothesis of no heteroscedasticity is rejected when p-values of the Chi-Square distribution are lower than the significance level of 5%. Each of the sentiment proxies (VIX and PCR) were tested using the Heteroskedasticity White Test for each event window.

4.3.4.1 Event Window 1 (September, 2007) Results

The results of the Heteroskedasticity White Test on each sentiment proxy for EW-1 are expressed in tables 4.36 and 4.37. As we can see, for the VIX the calculated p-value is 0.12 and for the PCR is 0.13. This means that we fail to reject the null hypothesis because there is no statistically significant heteroscedasticity at a 0.05 significance level.

Table 4.36 - Heteroskedasticity White Test for VIX on Event Window 1

F-statistic	1.527474	Prob. F(18,66)	0.1086
Obs*R-squared	***24.99649***	***Prob. Chi-Square(18)***	***0.1250***
Scaled explained SS	28.38177	Prob. Chi-Square(18)	0.0565

Table 4.37 - Heteroskedasticity White Test for PCR on Event Window 1

F-statistic	1.509420	Prob. F(17,67)	0.1184
Obs*R-squared	***23.53883***	***Prob. Chi-Square(17)***	***0.1325***
Scaled explained SS	14.33536	Prob. Chi-Square(17)	0.6432

4.3.4.2 Event Window 2 (July, 2008) Results

In Table 4.38 and Table 4.39 the results of Heteroskedasticity White Test for each of the two sentiment proxies are presented for EW-2. The calculated p-value for the VIX is 0.86 and for

the PCR is 0.80. According to the p-values the homoscedasticity assumption is not violated, because we fail to reject the null hypothesis of no-heteroscedasticity.

Table 4.38 - Heteroskedasticity White Test for VIX on Event Window2

F-statistic	0.495875	Prob. F(17,25)	0.9310
Obs*R-squared	***10.84314***	***Prob. Chi-Square(17)***	***0.8646***
Scaled explained SS	8.118814	Prob. Chi-Square(17)	0.9639

Table 4.39 - Heteroskedasticity White Test for PCR on Event Window2

F-statistic	0.564110	Prob. F(16,26)	0.8825
Obs*R-squared	***11.08064***	***Prob. Chi-Square(16)***	***0.8045***
Scaled explained SS	6.271431	Prob. Chi-Square(16)	0.9849

4.3.3.3 Event Window 3 (October, 2008) Results

For this event window, the Heteroskedasticity White Test results displayed in tables 4.40 and 4.41 also showed that there is no presence of heteroscedasticity among the residuals in the model. The calculated p-value for the VIX is 0.58 and for the PCR is 0.49, which means that we failed to reject the null hypothesis because the p-values were greater than the significance level of 5%.

Table 4.40 - Heteroskedasticity White Test for VIX on Event Window 3

F-statistic	0.794215	Prob. F(18,24)	0.6886
Obs*R-squared	***16.05193***	***Prob. Chi-Square(18)***	***0.5889***
Scaled explained SS	17.13415	Prob. Chi-Square(18)	0.5139

Table 4.41 - Heteroskedasticity White Test for PCR on Event Window 3

F-statistic	0.911751	Prob. F(18,24)	0.5735
Obs*R-squared	***17.46273***	***Prob. Chi-Square(18)***	***0.4915***
Scaled explained SS	19.04523	Prob. Chi-Square(18)	0.3890

4.3.4.4 Event Window 4 (February, 2009) Results

Tables 4.42 and 4.43 present the results for the Heteroskedasticity White Test performed on the VIX and the PCR for EW-4. The p-value for the VIX is 0.10 and the p-value of the PCR is 0.13, which is higher than the significance level of 5%, therefore the assumption of homoscedasticity is not violated.

Table 4.42 - Heteroskedasticity White Test for VIX on Event Window4

F-statistic	2.155001	Prob. F(19,20)	0.0482
Obs*R-squared	***26.87341***	***Prob. Chi-Square(19)***	***0.1076***
Scaled explained SS	26.60157	Prob. Chi-Square(19)	0.1143

Table 4.43 - Heteroskedasticity White Test for PCR on Event Window4

F-statistic	1.868652	Prob. F(18,21)	0.0853
Obs*R-squared	***24.62545***	***Prob. Chi-Square(18)***	***0.1356***
Scaled explained SS	21.47329	Prob. Chi-Square(18)	0.2562

4.3.4.5 Event Window 5 (December, 2009 and February, 2010) Results

The results of the Heteroskedasticity White Test on each sentiment proxy (VIX and PCR) for EW-5 are expressed in tables 4.44 and 4.45. As we can see, for the VIX the calculated p-value is 0.27 and for the PCR is 0.85. This means that null hypothesis was not rejected because the values were greater than the significance level of 5%.

Table 4.44 - Heteroskedasticity White Test for VIX on Event Window 5

Heteroskedasticity Test: White

F-statistic	2.536457	Prob. F(59,9)	0.0669
Obs*R-squared	***65.08575***	***Prob. Chi-Square(59)***	***0.2733***
Scaled explained SS	63.92884	Prob. Chi-Square(59)	0.3076

Table 4.45 - Heteroskedasticity White Test for PCR on Event Window5

Heteroskedasticity Test: White

F-statistic	0.575836	Prob. F(17,53)	0.8949
Obs*R-squared	**11.06932**	**Prob. Chi-Square(17)**	**0.8529**
Scaled explained SS	6.662798	Prob. Chi-Square(17)	0.9875

4.3.3.6 Event Window 6 (August and September, 2011) Results

For this event window, the Heteroskedasticity Harvey Test results performed on the VIX is displayed in table 4.46, while the results of the White Test for the PCR is shown table 4.47. The p-value for the VIX is 0.10 which is above the significance level of 5%. This means that for the VIX we fail to reject the null hypothesis of no heteroscedasticity. Similarly, the p-value of the White test for the PCR is 0.58, which is higher than the significance level of 5%; therefore we fail to reject the null hypothesis of no heteroscedasticity.

Table 4.46 - Heteroskedasticity Harvey Test for VIX on Event Window 6

Heteroskedasticity Test: Harvey

F-statistic	1.959832	Prob. F(4,115)	0.1053
Obs*R-squared	***7.658127***	***Prob. Chi-Square(4)***	***0.1049***
Scaled explained SS	8.189301	Prob. Chi-Square(4)	0.0849

Table 4.47 - Heteroskedasticity White Test for PCR on Event Window 6

Heteroskedasticity Test: White

F-statistic	0.862399	Prob. F(17,102)	0.6185
Obs*R-squared	***15.08043***	***Prob. Chi-Square(17)***	***0.5897***
Scaled explained SS	12.08254	Prob. Chi-Square(17)	0.7951

4.3.2.7 Event Window 7 (January, 2012) Results

In Table 4.48 and Table 4.49 the results of Heteroskedasticity White Test for each of the two sentiment proxies are presented for EW-7. The calculated p-value for the VIX is 0.20 and for the PCR is 0.68. Therefore we fail to reject the null hypothesis is rejected because the p-values were greater than the significance level of 5%.

Table 4.48 - Heteroskedasticity White Test for VIX on Event Window 7

Heteroskedasticity Test: White

F-statistic	1.341638	Prob. F(18,63)	0.1942
Obs*R-squared	***22.72254***	***Prob. Chi-Square(18)***	***0.2015***
Scaled explained SS	19.38001	Prob. Chi-Square(18)	0.3688

Table 4.49 - Heteroskedasticity White Test for PCR on Event Window 7

Heteroskedasticity Test: White

F-statistic	0.762355	Prob. F(17,64)	0.7272
Obs*R-squared	***13.80876***	***Prob. Chi-Square(17)***	***0.6806***
Scaled explained SS	10.95563	Prob. Chi-Square(17)	0.8589

4.4 OLS Results

The following sections will present the results and discussion for the examination of the VIX and the PCR using the OLS for each event window. Each table has a summary of the OLS statistics for both dependent variables in order to facilitate their comparison. The final OLS model looks like:

$$SP_{EW^i} = \beta_0 + \beta_1 CFSI_{INDEX} + \beta_2 EPU_{INDEX} + \beta_3 LNDEBT + \beta_4 LNWILL5000 + AR(1) + \epsilon_i, \quad (4.1)$$

where, SP_{EW_i} represents the dependent variable Sentiment Proxy (VIX or PCR) for each event window $(EW)_i$. The independent variables are: the Cleveland Financial Stress Index (*CFSI_INDEX*), Economic Policy Uncertainty (*EPU_INDEX*), the natural log of the statutory debt limit (*LNDEBT*) and the natural log of the Wilshire 5000 Index prices (*LNWILL5000*). AR (1) is a first-order autoregressive autocorrelation disturbance term. The first order means that values are auto correlated with one lag (Dougherty, 2002).

4.4.1 OLS Results for Event Window 1

Table 4.50 shows the results summary of the OLS performed on the VIX and PCR for EW-1. According to the adjusted R^2, 93.03% of the variation in the VIX can be explained jointly by the independent variables (*CFSI_INDEX*, *EPU_INDEX*, *LNDEBT* and *LNWILL5000*). And, the level of significance for the F-statistic test for the whole model was below 1%, which means that the independent variables jointly can influence the VIX.

However, only *LNDEBT* and *LNWILL5000* are significant at the 1% level, which means that the coefficients are statistically significant different to zero. Therefore an increase in *LNDEBT* would result in a significant increase in the VIX, and an increase in *LNWILL5000* would result in a significant decrease in the VIX. According to Bandopadhyaya & Jones (2008)

when the VIX is high, investor sentiment is presumed to be low because investors are assumed to be risk averse.

Table 4.50 OLS results for Event Window 1

Variable	VIX	PC Ratio
C	754.6479*** (179.5986)	26.88978** (11.51007)
CFSI_INDEX	-1.373500 (1.163508)	-0.133828** (0.55962)
EPU_INDEX	0.000224 (0.002629)	0.000195 (0.000490)
LNDEBT	24.04281*** (6.711185)	0.692717 (0.521488)
LNWILL5000	-150.6405*** (10.55783)	-4.830522*** (-5.829795)
AR(1)	0.792975*** (0.075490)	0.183651 (0.113844)
Observations	85	85
R-squared	0.934473	0.474849
Adjusted R-squared	0.930326	0.441611
F-statistic	225.3236	14.28657
Prob (F-statistic)	0.000000	0.000000
Note: White heteroskedasticity-consistent standard errors & covariance Standard errors are shown in parentheses. ***, **, * represents significance at 1%, 5%, and 10%, respectively		

The adjusted R^2 for the PCR is 0.44, which means that only 44.16% of the variations in the dependent variable can be explained by the independent variables. The F-statistic test level of significance for the model was below 1%, meaning that the independent variables can influence the PCR. Both *CFSI_INDEX* and *LNWILL5000* seemed to influence the PCR, increases in these variables decreases the PCR significantly. If the PCR decreases, optimists in the market would

increase over the pessimists. For this event window we can say that a change in debt has a direct and significant effect on the VIX, but it has no effect on the PCR as an explanatory variable.

4.4.2 OLS Results for Event Window 2

A summary of results of the OLS regression performed on the VIX and PCR for EW-2 is displayed in Table 4.51. The adjusted R^2 for the VIX is 0.94 and for the PCR is 0.45, which implies that the variation in the sentiment proxies can be explained jointly by the independent variables by 94.07 and 45.85% respectively. The level of significance of the F-statistic test for the whole model was below 1%, which means that the independent variables jointly can influence each of the sentiment proxies. For EW-2, *EPU_INDEX* and *LNWILL5000* are significant for the VIX model. Therefore, increases in *EPU_INDEX* and in *LNWILL5000* resulted in a significant decrease in the VIX. The *EPU_INDEX* variable did not behave as expected (positive relation) with the VIX on this event window.

Meanwhile for the PCR, only the *LNWILL5000* variable has a p-value lower than at least 5% of the significance level. When the variable *LNWILL5000* increase, the PCR decreases significantly.

For EW-2 we can conclude that a change in debt limit does not have a significant effect on the VIX or the PCR. Meanwhile, the *EPU_INDEX* did not behaved as expected in relation to the VIX, because when the level of uncertainty increases the implied volatility should increase also. The explanatory variable *LNWILL5000* behave as expected because the VIX is a contrarian indicator of the market. High levels of the VIX reflect a potential drop in the stock market (Whaley, 2009).

Table 4.51 OLS results for Event Window 2

Variable	VIX	PC Ratio
C	716.8403*** (136.3235)	27.33455 (30.46791)
CFSI_INDEX	5.230352 (3.145480)	-0.089815 (0.336920)
EPU_INDEX	-0.003645** (0.001465)	-0.000152 (0.000198)
LNDEBT	3.669173 (4.761098)	1.261141 (1.002087)
LNWILL5000	-85.82555*** (7.716759)	-6.757071*** (1.092087)
AR(1)	0.809108*** (0.109703)	0.565735*** (0.123254)
Observations	43	43
R-squared	0.947784	0.522978
Adjusted R-squared	0.940728	0.458516
F-statistic	134.3187	8.112919
Prob (F-statistic)	0.000000	0.000030
Note: White heteroskedasticity-consistent standard errors & covariance. Standard errors are shown in parentheses. ***, **, * represents significance at 1%, 5%, and 10%, respectively		

4.4.3 OLS Results for Event Window 3

Table 4.52 present the results of the OLS estimated on the VIX and PCR for EW-3. The variation in the VIX can be explained by the independent variables jointly in 96.96% according to the adjusted R^2. And, the level of significance of the F-statistic test for the model was below 1%, which means that the independent variables can influence the VIX.

Table 4.52 OLS results for Event Window 3

Variable	VIX	PC Ratio
C	3477.975*** (944.0261)	248.6034*** (86.73237)
CFSI_INDEX	8.957159 (6.034712)	0.347782 (0.4100443)
EPU_INDEX	0.009821* (0.004870)	0.000360 (0.000233)
LNDEBT	-70.79839** (29.18669)	-7.631274*** (2.750928)
LNWILL5000	-142.1534*** (8.404840)	-2.045171*** (0.543811)
AR(1)	0.209784 (0.181112)	0.576898*** (0.164159)
Observations	43	43
R-squared	0.973276	0.366705
Adjusted R-squared	0.969664	0.281124
F-statistic	269.5009	4.284910
Prob (F-statistic)	0.000000	0.003565
Note: White heteroskedasticity-consistent standard errors & covariance. Standard errors are shown in parentheses. ***, **, * represents significance at 1%, 5%, and 10%, respectively		

In this event window, the *EPU_INDEX, LNDEBT* and *LNWILL5000* were significant at different levels. There is a positive relation between the *EPU_INDEX* and the VIX in which an increase in the first would result in a significant increase in the second. The opposite happens with *LNDEBT* and *LNWILL5000,* which presented a negative relation with the VIX. An increase in these variables would result in a significant decrease in the dependent variable.

The PCR has an adjusted $R^2$of 0.28, which means that only 28.11% of the variations in the dependent variable can be explained by the independent variables. The F-statistic test level of significance for the model was below 1%, meaning that the independent variables can influence

the PCR. Only *LNDEBT* and *LNWILL5000* are highly significant. When these variables increase, the PCR decreases significantly.

We can point out that for EW-3 a change in debt limit has a significant negative effect on the VIX and the PCR as an explanatory variable. The relationship between the *LNDEBT* and the dependent variables was not as expected. The positive change in debt limit should increase the VIX and the PCR creating increasing levels of volatility and pessimism respectively. Event window 3 also captures the peak period of the financial crisis of 2008. This might be a factor that contributed more to the investor sentiment than changes in statutory debt limit.

4.4.4 OLS Results for Event Window 4

Table 4.53 shows the results summary of the OLS performed on the VIX and PCR for EW-4. According to the adjusted R^2, 75.75% of the VIX's variation can be explained by the independent variables (*CFSI_INDEX, EPU_INDEX, LNDEBT* and *LNWILL5000*). The level of significance of the F-statistic test for the model was below 1%, which means that the independent variables can influence the VIX.

However, the independent variables with p-values below the significant level of at least 10% are: the *CFSI_INDEX, EPU_INDEX and LNWILL5000*, which means that the coefficients are statistically significant. The relationship of these three variables with the VIX is a negative one. Therefore, an increase in the variables previously mentioned would result in a significant decrease in the VIX. The *CFSI_INDEX* and the *EPU_INDEX* did not behave as expected resulting in a negative relationship instead of a positive one when regressed with the VIX.

Table 4.53 OLS results for Event Window 4

Variable	VIX	PC Ratio
C	453.2770 (455.8179)	-31.62155 (27.92419)
CFSI_INDEX	-16.27442* (8.991492)	0.525561** (0.248704)
EPU_INDEX	-0.004489** (0.002104)	0.000101 (0.000141)
LNDEBT	18.13740 (11.32083)	1.470317* (0.816290)
LNWILL5000	-104.5419*** (14.27892)	-1.434783** (0.561775)
AR(1)	0.965007*** (0.029592)	0.740201*** (0.146937)
Observations	40	40
R-squared	0.788612	0.520801
Adjusted R-squared	0.757525	0.450330
F-statistic	25.36828	7.390342
Prob (F-statistic)	0.000000	0.000088
Note: White heteroskedasticity-consistent standard errors & covariance. Standard errors are shown in parentheses. ***, **, * represents significance at 1%, 5%, and 10%, respectively		

The adjusted R^2 for the PCR is 0.45, which means that only 45.03% of the variations in the dependent variable can be explained by the independent variables. The F-statistic test level of significance for the model was below 1%, meaning that the independent variables can influence the PCR. But, only the *CFSI_INDEX*, *LNDEBT* and *LNWILL5000* has p-values lower than at least10% of significance. The first two explanatory variables have a positive relation with the PCR and the third one has a negative relationship. When *CFSI_INDEX* and *LNDEBT* increase, the PCR also increases. If the variable*LNWILL5000* increases, then the PCR decreases. This time the variables behave as expected in relation to the PCR. For this event window we can conclude

that a change in debt has a significant positive effect on the PCR, but it has no effect on the VIX as an explanatory variable.

4.4.5 OLS Results for Event Window 5

A summary of results of the OLS regression performed on the VIX and PCR for EW-5 is showed in Table 4.54. The adjusted R^2 for the VIX is 0.95 and for the PCR is 0.37, which implies that the variation in the sentiment proxies can be explained jointly by the independent variables by 95.92% and 37.01% respectively. The level of significance of the F-statistic test for the whole model is below 1%, which means that the independent variables jointly can influence each of the sentiment proxies.

For the VIX, the *CFSI_INDEX*, *EPU_INDEX*, *LNDEBT* and *LNWILL5000* were significant. All except the *EPU_INDEX* have a negative relationship with the VIX. Therefore, an increase in *CFSI_INDEX*, *LNDEBT* or *LNWILL5000* would result in a significant decrease in the VIX, while an increase in the *EPU_INDEX* resulted in a significant increase in the VIX. The *CFSI_INDEX* and the *LNDEBT* did not behave as the expected positive relationship with the VIX for this event window. For the VIX both *EPU_INDEX* and *LNWILL5000* behaved as expected.

For the PCR, only the *CFSI_INDEX* and the *LNWILL5000* have a p-value lower than at least 5% of the significance level. When both independent variables increase, the PCR decreases significantly. The *CFSI_INDEX* also did not behave as the expected positive relationship with the PCR.

For EW-5 we can conclude that a change in debt has a significant negative effect on the VIX, but it has no effect on the PCR as an explanatory variable.

Table 4.54 OLS results for Event Window 5

Variable	VIX	PC Ratio
C	61.30648*** (2.703433)	33.91939*** (10.34432)
CFSI_INDEX	-0.100305*** (1.303161)	-0.148580** (0.067546)
EPU_INDEX	0.000268*** (4.74E-05)	-0.000192 (0.000261)
LNDEBT	-0.331464*** (0.050283)	0.296073 (0.177846)
LNWILL5000	-5.162939*** (0.193547)	-4.485403*** (0.830959)
AR(1)	0.844147*** (0.164124)	0.059613 0.120865
AR(2)	-0.575290*** (0.186079)	
AR(3)	0.319696* (0.182630)	
MA(4)	-0.924302*** (0.025611)	
MA(5)	0.075695* (0.042781)	
Observations	71	71
R-squared	0.964557	0.415166
Adjusted R-squared	0.959150	0.370178
F-statistic	178.4030	9.228512
Prob (F-statistic)	0.000000	0.000001

Note:
White heteroskedasticity-consistent standard errors & covariance.
MA Backcast
Standard errors are shown in parentheses.
***, **, * represents significance at 1%, 5%, and 10%, respectively

4.4.6 OLS Results for Event Window 6

Table 4.55 present the results of the OLS performed on the VIX and PCR for EW-6. The variation in the VIX can be explained by the independent variables jointly in 98.04% according to the adjusted R^2. And, the level of significance of the F-statistic test for the model was below 1%, which means that the independent variables can influence the VIX.

Table 4.55 OLS results for Event Window 6

Variable	VIX	PC Ratio
C	211.5587*** (77.489)	-17.01355 (35.62505)
CFSI_INDEX	0.128960 (0.176205)	-0.099542** (0.045271)
EPU_INDEX	-0.000271 (0.000178)	2.31E-05 (0.000141)
LNDEBT	-2.627207 (2.480249)	1.332768 (1.145927)
LNWILL5000	-13.37318*** (0.886545)	-2.338044*** (0.435856)
AR(1)	0.897502*** (0.039581)	0.272011*** (0.080093)
Observations	120	120
R-squared	0.981300	0.401192
Adjusted R-squared	0.980480	0.374929
F-statistic	1196.436	15.27565
Prob (F-statistic)	0.000000	0.000000
Note: White heteroskedasticity-consistent standard errors & covariance. Standard errors are shown in parentheses. ***, **, * represents significance at 1%, 5%, and 10%, respectively		

In this model only *LNWILL5000* is highly significant. There is a negative relationship between the *LNWILL5000* and the VIX in which an increase in the first would result in a significant decrease in the second.

The PCR has an adjusted R^2 of 0.37, which means that only 37.49% of the variations in the dependent variable can be explained by the explanatory variables. The F-statistic test level of significance for the model was below 1%, meaning that the independent variables can influence the PCR. For this event window, *CFSI_INDEX* and *LNWILL5000* were significant, this means that increases in those variables, decrease the PCR.

During EW-6 occurred the debt crisis of 2011 which was previously explained in Chapter 2. For this window, a change in debt limit has no significant effect on the VIX and the PCR as an explanatory variable, which is not what we expected, due of the extensive public discussion of the debt crisis.

4.4.7 OLS Results for Event Window 7

Table 4.56 shows the results summary of the OLS performed on the VIX and PCR for EW-7. According to the adjusted R^2, 95.80% of the variation in the VIX can be explained jointly by the independent variables (*CFSI_INDEX*, *EPU_INDEX*, *LNDEBT* and *LNWILL5000*). And, the level of significance for the F-statistic test for the model was below 1%, which means that the independent variables jointly can influence the VIX.

However, only the *LNWILL5000* has a p-value below the 1% level of significance, which means that the coefficient is statistically significant different to zero. Therefore, an increase in *LNWILL5000* would result in a significant decrease in the VIX because they have a negative relationship.

The adjusted R^2 for the PCR is 0.19, which means that only 19.62% of the variations in the dependent variable can be explained by the independent variables. This regression has a poor correlation between the PCR and the explanatory variables. The F-statistic test level of significance for the model was below 1%, meaning that the independent variables can influence the PCR. Only *CFSI_INDEX* and *LNWILL5000* has p-values lower than at 5% of the significance level. When both explanatory variables previously mentioned increase, the PCR decreases significantly.

For this event window, we can conclude that a change in debt has no significant effect on the VIX and the PCR as an explanatory variable. The *CFSI_INDEX* does not behave like expected because high values of this variable indicates high systemic financial stress (Federal Reserve Bank of Cleveland, 2014), which would compare to high values of the PCR where pessimists outweigh the optimists (Bandopadhyaya & Jones, 2008).

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Table 4.56 OLS results for Event Window 7

Variable	VIX	PC Ratio
C	601.1521*** (226.6970)	-12.06542 (19.69066)
CFSI_INDEX	0.397467 (1.149375)	-0.175564** (0.066926)
EPU_INDEX	-0.001272 (0.001995)	-0.000363 (0.000310)
LNDEBT	3.233227 (7.737191)	1.317681 (0.812517)
LNWILL5000	-71.29313*** (9.243241)	-2.803883*** (0.815760)
AR(1)	0.853773*** (0.066392)	0.213149* (0.111571)
Observations	82	82
R-squared	0.960672	0.245850
Adjusted R-squared	0.958084	0.196235
F-statistic	371.2885	4.955149
Prob (F-statistic)	0.000000	0.000558
Note: White heteroskedasticity-consistent standard errors & covariance. Standard errors are shown in parentheses. ***, **, * represents significance at 1%, 5%, and 10%, respectively		

4.5 Summary

This chapter presented an analysis of the results from the Ordinary Least Squares Regression performed on two sentiment proxies (VIX and PCR) for each of the seven event windows in order to study whether investor sentiment is affected by changes in the statutory limit of U.S. federal debt. The descriptive statistics were presented first, then the results and analysis of the OLS assumptions, and finally the OLS interpretation of the output data used in this research. Table 4.57 presents a summary of the independent variables that showed a significant relationship with the metrics of investor sentiment

Table 4.57 - Summary of Relationships between Independent and Dependent Variables

Dependent Variable	Independent Variables	EW-1	EW-2	EW-3	EW-4	EW-5	EW-6	EW-7
VIX	*CFSI_INDEX*				X	X		
	EPU_INDEX		X	X	X	X		
	LNDEBT	X		X		X		
	LNWILL5000	X	X	X	X	X	X	X
PCR	*CFSI_INDEX*	X			X	X	X	X
	EPU_INDEX							
	LNDEBT			X	X			
	LNWILL5000	X	X	X	X	X	X	X

Note: An (X) mark denotes a positive relationship with the dependent variable, while a (X) mark presents a negative relationship.

Chapter 5: Conclusions and Recommendations

5.1 Conclusions

The main objective of this research was to analyze whether the investor sentiment is affected by changes in the US Federal Government debt limit. In order to examine this, an Ordinary Least Squares (OLS) regression model was used on four independent variables (*CFSI_INDEX, EPU_INDEX, LNDEBT* and *LNWILL5000*) and two dependent variables (VIX and PCR) for seven event windows containing nine US debt limit changes. The results from the OLS were inconsistent and differ from the expected.

According to Tetlock (2007) investor sentiment can be described as wild movements in the stock market that are seemingly unjustified by fundamentals. For this research, the debt crisis of 2011 was taken as an event that could have affected the stock markets and therefore investor sentiment. That is why a change in investor sentiment was expected from this type of event (change in US debt limit). A positive relationship was also expected between the independent variable *LNDEBT* and both sentiment proxies.

The results from the OLS showed us that the variations in the sentiment proxies were better explained for the VIX rather than the PCR in relation with the explanatory variables jointly. But only in EW-3 the changes in debt limit had a statistically significant negative effect on both dependent variables (VIX and PCR).

For EW-1 and EW-5 the changes in debt limit had a statistically significant positive and negative effect respectively on the VIX. For EW-4 the changes in debt limit had a statistically significant positive effect on the PCR. Contrary to expectations the relationship between the *LNDEBT* and the sentiment proxies was not precise. Only in two event windows presented a

direct relationship with a sentiment proxy. The explanatory variable *LNWILL5000* had a statistically significant negative effect on the PCR and the VIX on all EW's.

The inconsistencies among the results will not allow the researcher to conclude that there is in fact a statistically significant effect with respect to the relationship between the changes in debt limit and the investor sentiment proxies. We can conclude that the best variable that explains the variation on the sentiment proxies is the *LNWILL5000* (which represents the overall market).

5.2 Recommendations

In order to see if changes of the statutory debt limit could affect investor sentiment other variables should be considered in a future research. For example, other explanatory variables that could have an impact on the stock market such as the Gross Domestic Product (GDP), Unemployment Rate, Inflation Rate, and Interest Rate. Also, the analysis should include other sentiment proxies, like investor surveys and trading volume turnover, in order to have a combination of measures of investor sentiment as recommended by Baker & Wurgler (2007) in their research.

Another perspective for a future research is to see the effect that the changes of the statutory debt limit would have in a specific sector, such as the real estate or the automotive industry. In order to measure this, an event study can be performed, in which abnormal returns are calculated using the estimated returns as a benchmark.

Bibliography

Akhtari, M. (2011). Reassessment of the Weather Effect: Stock Prices and Wall Street Weather. *Michigan Journal of Business , 4* (1), 51-70.

Arghyrou, M. G., & Tsoukalas, J. D. (2010). *The Greek Debt Crisis: Likely Causes, Mechanics and Outcomes.* Working paper No. 3266, CESifo.

Austin, A. (2008). *The Debt Limit: History and Recent Increases.* Congressional Resarch Service Report for Congress, US Congress, Congressional Resarch Service.

Austin, A., & Levit, M. (2011). *The Debt Limit: History and Recent Increases.* Congressional Resarch Service Report for Congress, US Congress, Congressional Resarch Service.

Baker, M., & Stein, J. C. (2004). Market liquidity as a sentiment indicator. *Journal of Financial Markets , 7*, 271-299.

Baker, M., & Wurgler, J. (2007). Investor Sentiment in the Stock Market. *Journal of Economic Perspectives , 21* (2), 129-151.

Baker, S. R., Bloom, N., & Davis, S. J. (2013, May 19). Retrieved February 25, 2014, from Economic Policy Uncertainty Web site: http://www.policyuncertainty.com/index.html

Bandopadhyaya, A., & Jones, A. L. (2008). Measures Of Investor Sentiment:A Comparative Analysis Put-Call Ratio Vs. Volatility Index. *Journal of Business & Economics Research , 6* (8), 27-34.

Barber, B. M., Odean, T., & Zhu, N. (2009). Do Retail Trades Move Markets? *The Review of Financial Studies* , 151-186.

Benoit, K. (2011, March 17). Linear Regression Models with Logarithmic Transformations. London School of Economics.

Ben-Rephael, A., Kandel, S., & Wohl, A. (2012). Measuring investor sentiment with mutual fund flows. *Journal of Financial Economics* , 363-382.

Bernile, G., & Lyandres, E. (2011). Understanding Investor Sentiment: The Case of Soccer. *Financial Management , 40* (2), 357-380.

Billingsley, R. S., & Chance, D. M. (1988). Put-call ratios and market timing effectiveness. *Financial Analysts Journal* , 25-28.

Binder, J. (1998). The Event Study Methodology Since 1969. *Review of Quantitative Finance & Accounting , 11* (2), 111-137.

Blanchett, D., & Kaplan, P. D. (2013). Alpha, Beta, and Now … Gamma. *Morningstar Advisor* , 60-63.

Blundell-Wignall, A., & Slovik, P. (2010). A Market Perspective on the European Sovereign Debt and Banking Crisis. *OECD Journal. Financial Market Trends , 2010* (2), 9-36.

Brown, G. W., & Cliff, M. T. (2005). Investor Sentiment and Asset Valuation. *Journal of Business , 78* (2), 405-440.

Corrado, C. (2011). Event studies: A methodology review. *Accounting and Finance , 51* (1), 207-234.

Das, K., & Bhardwaj, U. (2011). Analysing the debt dynamics across countries. *Journal of Corporate Treasury Management , 4* (2), 150-158.

Dennis, P., & Mayhew, S. (2002). Risk-Neutral Skewness: Evidence from Stock Options. *Journal of Financial and Quantitative Analysis , 37* (3), 471-493.

Detrixhe, J. (2011, August 6). *News: Bloomberg*. (D. Liedtka, Editor) Retrieved May 4, 2012, from Bloomberg Web site: http://www.bloomberg.com/news/2011-08-06/u-s-credit-rating-cut-by-s-p-for-first-time-on-deficit-reduction-accord.html

Dodwell, W. J. (2011). *The U.S. Public Debt Crisis: A Catalyst for Fiscal Reform and Economic Growth.* Scholarly Papers, The Public Debt Management Network in Emerging Markets.

Dougherty, C. (2002). *Introduction to Econometrics.* New York: Oxford University Press.

Edmans, A., Garcia, D., & Norli, O. (2007). Sports Sentiment and Stock Returns. *Journal of Finance , 62* (4), 1967-1998.

Eviews 7. (2009). EViews 7 User's Guide. United States of America: Quantitative Micro Software, LLC.

Federal Reserve Bank of Cleveland. (2014). *Research: Federal Reserve Bank of Cleveland*. Retrieved 2014, from Federal Reserve Bank of Cleveland Web site: https://www.clevelandfed.org/research/data/financial_stress_index/about.cfm

Feldman, T. (2010). A More Predictive Index of Market Sentiment. *Journal of Behavioral Finance , 11* (4), 211-223.

Finter, P., Niessen-Ruenzi, A., & Ruenzi, S. (2011). *The Impact of Investor Sentiment on the German Stock Market.* CFR-Working Paper NO. 10-03.

Foucault, T., Sraer, D., & Thesmar, D. (2011). Individual Investors and Volatility. *Journal Of Finance , 66* (4), 1369-1406.

Frazzini, A., & Lamont, O. A. (2008). Dumb money: Mutual fund flows and the cross-section of stock returns. *Journal Of Financial Economics , 88* (2), 299-322.

Greene, W. H. (2002). *Econometric Analysis* (5th Edition ed.). New Jersey: Prentice Hall.

Joseph, K., Babajide Wintoki, M., & Zhang, Z. (2011). Forecasting abnormal stock returns and trading volume using investor sentiment: Evidence from online search. *International Journal Of Forecasting , 27* (4), 1116-1127.

Kamstra, M., Kramer, L., & Levi, M. (2002). *Winter Blues: A SAD Stock Market Cycle.* Working Paper, Federal Reserve Bank of Atlanta.

Kasper, L. (2008). Measuring Investor Sentiment in Mergers and Acquisitions. *Valuation Strategies , 12* (2), 4.

Katsanos, M. (2009). *Intermarket Trading Strategies.* John Wiley & Sons.

Krishnakumar, A. S. (2005). In Defense of the Debt Limit Statute. *Faculty Publications , Paper 62*.

Kumar, A., & Lee, C. (2006). Retail Investor Sentiment and Return Comovements. *Journal Of Finance , 65* (5), 2451-2486.

Lawrence, E. R., McCabe, G., & Prakash, A. J. (2007). Answering Financial Anomalies: Sentiment-Based Stock Pricing. *8* (3), 161–171.

Lei, Y. (2005). *The Trading Volume Trend, Investor Sentiment, and Stock Returns.* Dissertation, Louisiana State University, Business Administration Graduate Program.

Lemmon, M., & Portniaguina, E. (2006). Consumer Confidence and Asset Prices: Some Empirical Evidence. *The Review of Financial Studies , 19* (4), 1499-1529.

Long, J. S., & Ervin, L. H. (1998, September 23). Correcting for Heteroscedasticity with Heteroscedasticity Consistent Standard Errors in the Linear Regression Model: Small Sample Considerations. Bloomington, Indiana: Indiana University.

Longstaff, F. A. (2010). The subprime credit crisis and contagion in financial markets. *Journal of Financial Economics , 97* (3), 436–450.

Mackinlay, C. (1997). Event Studies in Economics and Finance. *Journal of Economic Literature , XXXV,* 13-39.

Masters, J. (2013, October 4). *U.S. Debt Ceiling: Costs and Consequences.* Retrieved February 2014, from Council on Foreign Relations: http://www.cfr.org/budget-debt-and-deficits/us-debt-ceiling-costs-consequences/p24751

O'Brien, R. M. (2007). A Caution Regarding Rules of Thumb for Variance Inflation Factors. *Quality & Quantity , 41,* 673–690.

Office of Management and Budget. (2013). *Impacts and Costs of the October 2013 Federal Government Shutdown.*

Osborne, J. (2002). Notes on the use of data transformations. *Practical Assessment, Research & Evaluation* .

Pan, J., & Poteshman, A. M. (2006). The Information in option volume for future stock prices. *Review of Financial Studies* , 871–908.

Panizza, U., Sturzenegger, F., & Zettelmeyer, J. (2009). The Economics and Law of Sovereign Debt and Default. *Journal of Economic Literature , 47* (3), 1-47.

Qiu, L., & Welch, I. (2005). *Investor Sentiment Measures.* NBER Working Paper , National Bureau of Economic Research.

Singhvi, V. (2001). *Investor Sentiment: Its Measurement and Dimensions.* Dissertation, New York University, Department of International Business and Finance.

Tetlock, P. C. (2007). Giving Content to Investor Sentiment: The Role of Media in the Stock Market. *Journal Of Finance , 62* (3), 1139-1168.

The White House. (2014, May). *Historical Tables: Office of Management and Budget*. Retrieved March 13, 2014, from The White House Website: http://www.whitehouse.gov/omb/budget/Historicals

Tsuji, C. (2009). Are Investment Strategies Exploiting Option Investor Sentiment Profitable? Evidence from Japan. *International Journal of Business and Management , 4* (5), 92-105.

US Department of the Treasury. (2011, August 24). *Debt Limit*. Retrieved October 10, 2011, from US Department of the Treasury Website: http://www.treasury.gov/initiatives/pages/debtlimit.aspx

Wehinger, G. (2010). Sovereign Debt Challenges for Banking Systems and Bond Markets. *OECD Journal. Financial Market Trends* (99), 37-70.

Whaley, R. (2009). Understanding the VIX. *Journal Of Portfolio Management , 35* (3), 98-105.

Wilshire Associates Incorporated. (2010). Retrieved 2014, from Wilshire Web site: http://web.wilshire.com/Indexes/W5000_Methodology_2010_001.pdf

Zhang, C. (2008). *Defining, Modeling, and Measuring Investor Sentiment.* Thesis, University of California, Berkeley, Department of Economics.