Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Economics and Management
Dept. of Industrial Economics and Technology Management

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Johannes Høva Bøhler

How have quantitative easing influenced the credit risk of commercial banks in the US? Evidence from the CDS market.

Master's thesis in Industrial Economics and Technology Management
Supervisor: Rita Pimentel
Co-supervisor: Sjur Westgaard
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Problem Description

In this paper, we investigate how determinants of credit risk in the US banking sector change over time on a macroeconomic level. The main goal is to examine the effect of quantitative easing using a continuous proxy variable.

Preface

This paper is written as a master thesis for the course TIØ 4900 - Master Thesis in Financial Engineering at the Norwegian University of Science and Technology (NTNU) during the spring of 2021. The course is part of the master program Industrial Economics and Technology Management and is mandatory for students choosing the Financial Engineering specialization.

The effects and consequences of quantitative easing are of great interest to us. It was meant as a temporary solution to stimulate the economy during the Great Recession of 2008. Now, 13 years later, the Federal Reserve's balance sheet is still increasing, and no one knows how it will affect the economy in the long run. We appreciate being able to do a deep dive into such a fascinating topic and cherish all we have learned.

We would like to thank our supervisors, Rita Pimentel and Sjur Westgaard, for their valuable guidance. They have been available throughout the semester and given us detailed feedback on our work and process. We are very grateful.

Trondheim, June 11th, 2021

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Abstract

This article analyzes the effect of quantitative easing (QE) on credit risk in the United States (US) banking sector. During the Great Recession of 2008 interest rates was lowered to close to zero. Therefore, the Federal Reserve (FED) had to find a new tool to reverse the recession. The answer was QE which consists of the FED entering the open market and buying large amounts high-grade bonds. In this paper, we investigate how FED's purchases of mortgage-backed securities (MBS) affects credit risk in the US banking sector. We implement a rolling regression model with a 104-week window on observations from January 2009 to April 2021. The regression model uses the North American Banks 5 year CDS Index as a proxy for credit risk and includes a set of macroeconomic and market-based control variables. The main conclusion is that QE successfully lowered credit risk in the US banking sector. Additionally, we find that most variables change in value and significance over time, and not only in the transition between the time of crisis and no crisis. Finally, we discuss the potential negative consequences of FED's large-scale purchases.

Sammendrag

Denne artikkelen analyserer effekten av kvantitative lettelser på kredittrisiko i den amerikanske banksektoren. Under finanskrisen i 2008 var renten nær null og Federal Reserve (FED) trengte et nytt verktøy for å motvirke resesjonen i økonomien. Deres løsning var å entre markedet og kjøpe store mengder obligasjoner, en prosedyre kalt kvantitative lettelser. I denne artikkelen undersøker vi hvordan FEDs kjøp av lånsbaserte verdipapirer, mortgage-backed securities, påvirker kredittrisiko i den amerikanske banksektoren. Vi analyserer effekten av kjøpene ved bruk av en rullerende regresjonsmodell. Modellen har et regresjonsvindu på 104 uker som starter på første observasjon i januar 2009 og beveger seg en og en uke frem i tiden helt til april 2021. I tillegg til variabelen for kvantitative lettelser bruker regresjonsmodellen et sett med makroøkonomiske og markedsbaserte kontrollvariabler. Hovedkonklusjonen er at kvantitative lettelser senket kredittrisiko i den amerikanske banksektoren over lengre perioder. I tillegg fremheves det at forklaringsevnen til majoriteten av kontrollvariablene endrer seg over tid, både i styrke og i fortegn. Endringen bevises å være kontinuerlig over hele regresjonsperioden. Til slutt diskuterer vi de potensielle negative konsekvensene av FEDs kvantitative lettelser.

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Chapter 1

Introduction

"I want to say that under the Federal Reserve act we are never again going to see a financial panic like the panic of 1907" declared Charles Hamlin, the first head of the Federal Reserve (FED) in 1915[1]. The 1907 "Bankers Crisis" had left the stock market down more than 50% compared to the high the previous year. Several state and local banks throughout the United States (US) went bankrupt due to a lack of liquidity. The new central bank founded in 1913 in the United States was going to be a lender of last resort for the commercial banks, thereby avoiding future financial and credit crises like the ones in 1873, 1893, and 1907 (Bordo and Roberds, 2013).

Fast forward 108 years and the United States and Europe regularly find themselves in the middle of financial panics. Since the beginning of the 21st century four major financial waves of panic have occurred. First the dotcom bubble in 2000, second the Great Recession of 2008, third the European sovereign debt crisis, and last the Covid-19 pandemic. Each wave of panic caused big stock market declines, increased volatility, and tighter credit markets.

One of the significant developments in central bank policy during this period was the emergence of a new central bank tool called Quantitative Easing (QE). The new tool was a response to interest rates already being set close to zero. Japan is credited as the first country that started implementing QE in 2001, but it was not until the financial crisis of 2008 that central banks of western nations started using QE regularly (Hausken, 2013). Quantitative easing is an unorthodox way of pumping money into the economy and aiming to lower the long-term interest rates to combat a recession (Hausken, 2013). The goal is to stimulate the economy, increase bank lending, and encourage spending. Another name for quantitative easing is Large Scale Asset Purchases (LSAPs) because the policy consists of central banks doing large purchases of assets in the money markets. LSAPs have varied significantly in the type of assets purchased by central banks, from Treasurys and government-guaranteed Mortgage-Backed Securities (MBS) in the U.S. to Exchange-Traded Funds and corporate bonds in Japan (Di Maggio, Kermani, and Palmer, 2020). Critics of the programs say the central banks are temporarily saving the banks with more liquidity, only to create a bigger credit problem later on. In January of 2009, then Chairman of the FED Ben Bernanke responded that the programs would be reversed once credit markets stabilized; "However, at some point, when credit markets and the economy have begun to recover, the Federal Reserve will have to unwind its various lending programs[...] As lending programs are scaled back, the size of the Federal Reserve's balance sheet will decline, implying a reduction in excess reserves and the monetary base"[2]. However, 12 years later the balance sheet has only increased.

[1]https://fraser.stlouisfed.org/title/statements-speeches-charles-s-hamlin-443/federal-reserve-act-7601

[2]https://www.federalreserve.gov/newsevents/speech/bernanke20090113a.htm

The four recent waves of panic are different in nature, but all of them increased the credit risk of corporations and led to major losses in the stock market. The dotcom bubble was driven by speculators bidding up the price of internet stocks and initial public offerings (Matias Gama, 2017). When the market understood that the discounted cash flow of companies did not justify the high quotes, the bubble burst. The Great Recession, receiving its name for being the worst financial crisis since the Great Depression, was primarily caused by a bubble in the housing market (Whalen, 2008). Low interest rates since the dotcom bubble made credit for borrowers cheap. In addition, risky loans were gathered together in new derivative products and sold with high credit ratings. Investors rushed out of these products as their quality got known, causing the stock market to fall and the credit market to tighten severely. As a response, the FED cut interest rates further, saved some of the most important financial institutions, and started their quantitative easing programs. These tools helped gain confidence in the American stock and credit market, and by early 2013 the Dow Jones Industrial Average was back above the high before the Great Recession. On the other side of the Atlantic, Europe struggled much more to recover from the crisis (Lane, 2012). Large amounts of sovereign debt and bank debt in countries such as Portugal, Italy, Greece, and Spain led these and other European countries into a severe recession. The recession had a major impact on southern European countries' labor market, credit market, and stock markets. The latest financial panic, on the other hand, was caused by an event outside of the financial markets. Whereas some investors such as Warren "Oracle of Omaha" Buffett expressed his concerns about the valuations before the dotcom bubble burst, the pandemic was much harder to predict. In early 2020 the stock market fell sharply and many businesses all over the world were forced to shut down while workers were laid off. The energy and tourism sectors were particularly hit because of travel restrictions. Once again, the central banks around the world increased their quantitative easing programs to improve liquidity in the credit market and keep funding cheap. In addition, most sovereign nations took several measures to save businesses from going bankrupt. By the spring of 2021, the US stock market had rallied back and made new highs.

In this paper, we use credit default swap (CDS) spreads as the measure for credit risk. The CDS presents a way for bondholders to hedge their credit risk by acting as insurance in the case of default of the underlying asset. The outstanding size of the CDS market rose greatly in the 2000s exceeding $60 trillion. Since then the market has steadily decreased to a current amount of $10 trillion. Despite the recent decline, the literature shows advantages of using CDS spreads as a proxy for credit risk instead of bond spread. The CDS spread is, inter alia, more responsive to changes in credit conditions. While investigating the relationship between corporate bonds and CDS spreads, Zhu (2006) found both to move together in the long run, yet in the short run, the CDS spreads responded significantly faster to the market.

In this paper, we contribute to the existing literature by examining the effect of QE on the credit risk of the banking sector. QE continues to gain interest from financial media and investors as the balance sheet of the FED grows to new records. Assets held have almost doubled from January 2020 until May 2021, signaling how aggressively the FED has tried to stabilize the credit markets during the Covid-19 pandemic. With this new data, we have the opportunity to investigate the importance of QE and control variables on US banks' credit risk in the last decade. Previous studies on credit risk in the US mostly investigate the effect of the early QE programs in 2008 and 2009. Furthermore, a majority of them performed event studies on important FED announcements. We, on the other hand, use the MBS held by the

FED as a proxy for QE. We contribute to existing literature in two ways: Firstly, the MBS variable is continuous which means that we can perform a rolling regression on observations from the beginning of MBS purchases in 2009 until the Covid-19 pandemic. The corresponding results illustrate if, when, and how variables' explanatory power change over time. Secondly, to our knowledge no other paper isolated the effect of the riskier parts of the asset purchases, and studied its effect on credit risk over time. Krishnamurthy and Vissing-Jorgensen (2011) suggested in their paper that the MBS purchases had a greater effect on credit risk than the Treasury purchases in the early days of QE. However, they only studied the effect of a few announcements made by the FED regarding QE. Furthermore, we chose the banking sector because the commercial banks are directly involved in the QE programs. That is; they buy, hold and sell large amounts of high-grade bonds. Therefore, they are the first to receive increased liquidity from the programs.

Chapter 2

Literature review

To investigate determinants of US banks' credit risk one must decide on what type of factors to include and what type of model to implement. A common approach is the use of panel regression (Kajurova, 2015; Di Febo and Angelini, 2018). The model is particularly popular for exploring the explanatory power of firm-specific variables and idiosyncratic risk drivers in bond and CDS spreads. However, most papers investigating these factors find residuals to still contain variation indicating that explanatory power from systematic risk drivers is missing (Collin-Dufresne, Goldstein, and Martin, 2001). In this article, one of the goals is to examine how determinants change over time. We do so by implementing a rolling regression model with a specified regression window. The approach has previously been used on bank CDS in Europe (Annaert et al., 2013). As we are mostly interested in systematic risk drivers of the banking sector as a whole we decide to only include macroeconomic and market-based variables. Removing firm-specific factors significantly lowers the complexity of the model, albeit at the loss of their corresponding explanatory power.

2.1 Credit default swap spreads

This article uses CDS spread as a proxy for credit risk. A CDS spread is the rate at which an underlying asset may be insured in case of a credit event. Thus, it reflects the market perceptions about the financial health of the underlying asset. Since we are investigating the US banking sector as a whole, we decide to use the North American Banks 5 year CDS Index as a proxy. Sector-specific CDS indices are common proxies in studies investigating macroeconomic variables (Malhotra and Corelli, 2018). Several papers have studied the change of CDS determinants in the transitions between a time of crisis and no crisis. Benbouzid, Mallick, and Pilbeam (2018) analyze the short-run effect of the UK housing prices on the UK banks' CDS premiums before, during, and after the Great Recession. Malhotra and Corelli (2018) study the relationship between different sector CDS Index spreads and a set of macroeconomic variables in the US and in Europe. They analyze how the determinants differ in a time of crisis by doing two regressions; one on data during the Great Recession and one on data after. A similar approach is implemented by Samaniego-Medina et al. (2016) who analyze the determinants of CDS spreads of 45 listed European banks before and during the Great Recession. Our approach differs from these in several ways. Firstly, we build our regression model on data from 2009 to 2021. This means that we can analyze how determinants change from the Great Recession, through the European debt crisis, and into the Covid-19 pandemic. Secondly, we implement a rolling regression model. In this approach, we avoid having to divide the data in times of crisis and times of no crisis which is difficult to define accurately. Annaert et al. (2013) used the method on data pre and during the Great

Recession to investigate whether credit risk was correctly priced at the time. Lastly, we include a proxy for quantitative easing.

2.2 Quantitative easing

The literature on unconventional monetary policies has grown fast during the last two decades. The majority of the early papers investigated the impact of QE programs on long-term interest rates. Spiegel (2001) takes a theoretical approach and concludes that there is little evidence that the early asset purchases of the Bank of Japan (BOJ) affected long-term government bond yields. A theoretical study by Bernanke, Reinhart, and Sack (2004) presented three ways of stimulating the economy without lowering interest rates; i) shaping the expectations of the public about future settings of the policy rate ii) increasing the size of the central bank's balance sheet beyond the level needed to set the short-term policy rate at zero (quantitative easing) iii) shifting the composition of the central bank's balance sheet in order to affect the relative supplies of securities held by the public. Odo and Ueda (2007) use a macro-finance model and do not find a significant effect of the BOJs quantitative easing policy on long-term interest rates.

It was only after the FED and the European Central Bank (ECB) also started using quantitative easing as a response to the Great Recession that interest in the topic greatly increased. The studies thereafter investigate one of three areas: the effectiveness in lowering government bond and corporate bond yields, the effectiveness in encouraging bank lending, and the effect on the real economy. Krishnamurthy and Vissing-Jorgensen (2011) study the effect of both the QE1 and the QE2 program of the FED[1]. Firstly, they conclude like Gagnon et al. (2011) that the Treasury bond purchases of the FED successfully lowered long-term Treasury yields. Secondly, they find that QE1 was successful in lowering mortgage rates and corporate bond yields, in contrast to QE2. They find that QE1 was successful in lowering riskier bond yields because it included purchases of Mortage Backed Securities (MBSs), whereas the FED only bought Treasurys in QE2. Thus, they conclude that lower Treasury yields alone are insufficient to stabilize the credit market and encourage lending. Beirne et al. (2011) find that the ECB achieved its goal with the covered bond purchase program (CBPP) during the financial crisis. Covered bonds are similar to MBS and asset backed-securities (ABS) in the US. The study shows that the CBPP lowered market term rates in the primary and secondary market, improved liquidity, and encouraged bank lending. Markmann and Zietz (2017) later confirm the effectiveness of the first CBPP program. However, they conclude that the two next CBPP programs from the ECB were less effective. The reason, according to them, was because the credit market was healthier and already anticipated the programs before they were announced. Schenkelberg and Watzka (2013) were one of the first to investigate the BOJ's unconventional monetary policy effect on the real economy. Using a Structural VAR-based approach, they find that a QE-shock which raises banks reserves by about 7% significantly raises industrial production by 0.4% after about two years. However, they find that these effects are much smaller in magnitude compared to an interest rate shock in normal times. In contrast to several earlier studies they also find that interest rates went down significantly as a result of the BOJ's quantitative easing policy.

[1]QE1 is the name of the first round of QE by the FED. QE2 is the name given to the second round from November 2010 to June 2011. Source: https://www.newyorkfed.org/markets/programs-archive/large-scale-asset-purchases

There are limited studies about the effect of QE on the credit risk of corporations. To the best of our knowledge, there are no studies on how QE from the FED affects the CDS spreads of US banks. Most papers that investigate the effect of QE on credit risk explore the credit risk of sovereign nations in Europe. Albu et al. (2014) study the effect of the ECB's quantitative easing program on CDS spreads of several central and eastern European countries with data from before the Great Recession until June of 2013. Using an ARMA-GARCH approach, they find the announcements of ECB's quantitative easing programs to significantly affect the spreads. However, they did not find a consistent directional effect on the countries' spread. One of the most similar papers to ours, Afonso et al. (2018), analyzes the link between monetary policy, banking risk, and bond pricing regimes in Europe on data from January 1999 to July 2016. It is the only paper that uses assets on the balance sheet of the central bank (in this case the ECB) as a proxy for the QE variable. They find that the sovereign bond purchases by the ECB lowered sovereign bond yields and lowered credit risk in the European banking crisis. Their results show that the purchases improved expectations by signaling that the ECB stands ready to prevent the collapse of sovereign bond markets due to existing fiscal liabilities. In addition, the purchases helped recapitalize European banks that held sovereign bonds. Thus, the program had a profound effect on improving the simultaneous European sovereign debt crisis and the European banking crisis. Martins, Batista, and Ferreira-Lopes (2019) analyze the impact of unconventional monetary policies in the Eurozone on bank lending from 2008 to 2016. This period includes various ECB QE programs, e.g. purchases of asset-backed securities and government bonds. They investigate total credit amounts and credit amounts to subgroups, e.g. government and different types of family spending. They find that the impact is greater to the general government at 1.2% per month than to household consumers at 0.2%, and that credit to consumption increased more and took less time to be effective when compared with house purchases.

In addition to Afonso et al. (2018), the most similar study to ours is Krishnamurthy and Vissing-Jorgensen (2011). They used an event study approach to investigate the impact of the first two quantitative easing programs of the FED on corporate CDS spreads. The events they chose were the most important QE announcements in the US from late 2008 until the end of 2010. They grouped companies from several sectors by credit rating before doing their analysis. Thus, they differ from our paper both in methodology and by which CDS spreads they investigate. We implement linear regression to investigate the importance of QE compared to other control variables. By doing rolling regressions, we can investigate how the importance of the QE variable and other variables change throughout different financial periods. Krishnamurthy and Vissing-Jorgensen (2011), on the other hand, only investigated the impact on corporate CDS spreads around a few announcements. Another difference is that we use a continuous variable as proxy for QE, which is the value of FED's MBS assets. A final difference is that we exclusively investigate the CDS spreads of the banking sector. We choose the banking sector as it is the main transmission mechanism between monetary policies and the real economy.

Chapter 3

The determinants of bank CDS spreads

In this chapter, we discuss the different determinants that potentially affect CDS spreads. Each variable will have a theoretical and empirical justification for its inclusion. We divide them into macroeconomic, market-based, and QE variables. In Table A.1 in Appendix A we present articles that have used the variables included in this study.

3.1 Macroeconomic determinants

Treasury Rate

The Treasury rate is highly monitored by investors and financial media for several reasons. Firstly, it is one of the premier funding channels for the US government. If yields rise, it means that investors are reluctant to lend money to the US government which could signal expectations of higher inflation or strong economic growth. As sovereign nations traditionally seldom default on their loan, and they own the printing press of the currency, their debt is denominated in government bonds and is considered "risk-free". Secondly, it is a major component of discounted cash flow estimations. If yields fall, projects with cash flows further into the future are discounted less, thus worth more. Hence, lower yields make capital intensive long-term projects more profitable, which might lead to an eventual overcapacity. Thirdly, the long-term government bond yields function as an anchor for mortgage rates and other commercial loan rates most of the time. If long-term government bond yields fall, commercial loan rates also fall which makes it easier for businesses and families to service their debt and take on more credit. Again, this effect could lead to overcapacity in capital-intensive industries, but it improves liquidity and stimulates the economy in the short term.

Traditionally, most papers have found higher interest rates to decrease credit risk for corporations (Collin-Dufresne, Goldstein, and Martin, 2001). The theory behind this result is that a higher Treasury rate indicates a stronger economy and thus lower credit risk. However, empirical results have been more uncertain in recent years as Treasury rates have remained low. Samaniego-Medina et al. (2016) does not find a significant relationship between 10 year government bond yields and bank CDS spreads in Europe. Benbouzid, Mallick, and Pilbeam (2018) used a VAR approach to conclude that yields greatly affected housing prices which in turn affected CDS spreads. According to them, a policy of low Treasury rates would typically lead to increased borrowing which will have to be matched by increased housing supply to keep house prices stable. If any element in the chain is not satisfied, it may give rise to major imbalances that may result in a housing bubble, which in turn can cause another credit crisis.

Thus, we expect the Treasury rate to not have a significant relation to CDS spreads in the short term. However, overcapacity in the housing market and other sectors due to low rates might lead to higher credit risk over time.

Interest Rate

The interest rate in the US is decided by the Federal Open Market Committee which is a part of the FED. The rate has a major impact on markets as it decides the rates commercial banks charge each other for overnight lending. This rate is particularly influential on the economy considering it functions as a floor for the interest rates banks charge on loans to customers. Banks charge a higher rate to customers based on their risk. The difference between the federal funds rate and their rate to customers is their margin. Thus, if the FED funds rate increases customer rates increase as well. This leads to less borrowing and fewer investments which in turn slows down the economy. Additionally, higher rates encourage customers to deposit money in the bank which makes saving money relatively more attractive than spending money. This tends to lower the price of risky assets and slow down spending. As a result, the interest rate is used as a tool against asset and consumer goods inflation. In empirical work, the federal funds rate is shown to have a positive relation with CDS spreads (Szafranek et al., 2020), i.e when interest rate increases, the CDS spreads increases. However, other proxies do produce negative coefficients (Kajurova, 2015; Di Febo and Angelini, 2018). Based on the theory and use of the federal funds rate, we expect the interest rate to have a positive relation with CDS spread in our model.

Slope of the Yield Curve

The difference between the various long-term and short-term government bond yields, illustrated by the yield curve, indicates where the economy is headed. The slope of the yield curve, also referred to as term spread, tells us how the bond market expects short-term Treasury rates to move in the future, based on investors' expectations about future economic activity and inflation.

The slope of the yield curve can roughly take four different patterns; normal slope, steep slope, flat slope, and inverted slope. The normal slope is the most common where bond investors demand higher returns for fixed income longer into the future. The steep slope lies above the normal curve and does not flatten for the longest maturities. It signals high economic growth and high inflation. As inflation leads to less purchasing power of future money, bond investors demand high yields for the long-term maturities. Steep yield curves are theoretically positive for banks because they borrow short-term and lend long-term. The flat slope appears when short and long-term yields are equal. This usually happens at the end of the economic cycle when investors suspect the central bank to cool the economy by raising interest rates. The inverted yield curve is uncommon and often a sign of a coming economic recession. When short-term yields are higher than long-term yields investors do not find long-term bonds attractive as they expect the economy and inflation to decrease compared to future interest rates.

Zhang, Zhou, and Zhu (2009) and Tang and Yan (2017) suggest that there is a negative relation between the slope of the yield curve and credit spreads because term spreads normally are treated as a predictor of future economic activity. Hu et al. (2018) confirm this. They find that term spreads are inversely related to CDS spreads, suggesting that a better status of the economic environment will lead to lower CDS spreads. Then, we expect a larger difference between long and short-term government bond spreads to have a decreasing effect on banks' CDS spread.

TED Spread

The TED spread is the difference between the three-month London Interbank Offered Rate (LIBOR) rate and three months US Bill rate. The LIBOR is a benchmark interest rate at which global banks lend to each other short-term. A high TED spread indicates higher credit risk due to US Bills being considered risk-free. The TED spread is thus representing the risk in the international banking sector. In empirical research, the TED spread rate is used as a proxy for the funding cost of financial institutions (X. Wang, Xu, and Zhong, 2019). Its explanatory power on CDS spreads shows varied results depending on an economic policy uncertainty variable present in the model. Additionally, a benchmark result finds no statistical evidence for it to be considered significant. As the empirical work is unclear on the effect of the TED spread rate, we follow the theory and expect it to have a positive coefficient in our regression model, if statistically significant.

3.2 Market determinants

Market volatility

Market volatility is widely used as a proxy for market uncertainty (Annaert et al., 2013; Kajurova, 2015; Samaniego-Medina et al., 2016; X. Wang, Xu, and Zhong, 2019; Di Febo and Angelini, 2018; Greatrex, 2008; Galil et al., 2014; Drago, Tommaso, and Thornton, 2017). Increased volatility could lead to a chain of margin calls due to too much leverage in the market. This chain of margin calls and defaults might be contained by the central banks, policymakers, and market participants, or it could snowball into a financial panic. Authorities have used many tools in recent years to prevent volatility to snowball out of control by lowering rates, guaranteeing debt, bailouts, and expansionary monetary policies. The empirical work agrees on the explanatory power of this variable as most papers find increased market volatility to increase CDS spreads.

Market return

In theory, a higher market return indicates healthier companies with larger profits. However, investors may drive markets too high as they want to take part in asset appreciations. One example is the dotcom bubble in 2000.

The market return is widely used when investigating determinants for CDS spreads (Annaert et al., 2013; Malhotra and Corelli, 2018; Kajurova, 2015; Samaniego-Medina et al., 2016; Di Febo and Angelini, 2018; Greatrex, 2008; Drago, Tommaso, and Thornton, 2017). There is a general consensus in empirical work that market return has a positive relation with CDS spreads.

Gold price

Gold is seen as a safe investment when there is turmoil in the market. Therefore, it often increases in price in times of financial panics. Additionally, gold is considered as a protector of wealth in periods where real interest rates, i.e. nominal rate minus inflation rate, are negative. Thus, movements in the gold price can be an important determinant of credit risk in the market and the banking sector.

An interesting note is that gold tends to initially decrease in price as a liquidity crisis happens. Investors want liquidity to meet their margin calls to be able to maintain their assets. This is especially true for a deflationary crisis. However, later in a financial panic, the gold price tends to increase as investors replace their riskier assets with gold. In empirical work, the gold price is shown to be non-significant during a period of crisis and has a positive relation to CDS spreads after (Malhotra and Corelli, 2018). Therefore, we expect the gold to be negative in times of financial panic and positive afterward.

Oil price

In general, oil and energy represent significant costs for corporations, consumers, and the public sector. As the United States has traditionally been an importer of oil, low oil prices have lowered costs for the government and businesses. However, the US became a net exporter of oil in 2019. This was mostly due to the new shale oil technology which made the US oil sector boom from 2014. Thus, lower prices became less important than before. In empirical work, the explanatory power of the oil price on the CDS spreads varies between sectors, e.g. no significance in the banking sector, a positive coefficient in other financial companies, and a negative coefficient in the transportation sector (Malhotra and Corelli, 2018). Overall, we expect higher oil prices to increase bank CDS spreads in the US. Especially, since the country was a net importer for most of the time included in our data set.

3.3 The QE determinant

The value of FED's Mortgage Backed Securities

One possible proxy for QE is the value of FED's balance sheet. After FED issues new currency, it buys assets in the primary and secondary market. This injects liquidity into the market, as assets are traded for currency. The assets the FED has bought since the Great Recession are US Treasurys, MBS, and other investment-grade assets. The institutions that hold these securities are mostly commercial banks, hedge funds, and pension funds.

However, instead of using the total value of the FED's balance sheet as a proxy for QE, we use the total value of only the MBS held by the FED. We choose this proxy due to the findings of Krishnamurthy and Vissing-Jorgensen (2011). They show that the first round of QE by the FED that included MBSs was more effective in lowering credit spreads than the next round that mainly consisted of Treasurys. Since MBSs are riskier than Treasurys, it is reasonable to assume that demand for MBSs is more relevant to stabilize the banking sector than demand for low-risk Treasurys.

The risk of overcapacity because of low rates also applies to asset purchases. When the FED buys securities in Treasury auctions and the secondary market, it can lead to artificially low yields which may make financing easier and thus create overcapacity. Another long-term risk of large-scale asset purchases is that investors and banks might take on more risk as they expect the FED to enter the market with more liquidity in case of a financial panic.

We expect MBS purchases by the FED to decrease bank CDS spreads. More liquidity in the banking sectors should lower the probability of default for the banks, at least short-term.

Chapter 4

Data Analysis

The data set used in this study contains weekly values of the North American Banks 5 year CDS Index spread, and nine macroeconomic and market-based variables (see Table 4.1). The observations are from 14.01.2009 to 07.04.2021 and there are no missing values. The QE data was collected from Federal Reserve Economic Data (FRED)[1] and the remaining variables were fetched from Refinitiv Eikon. Before we estimate the regression models, we investigate the variables through exploratory data analysis to better understand their distribution, correlation, and relation with each other. In the descriptive statistics table, we observe that the scale of the variables varies. Particularly QE contains large values resulting in a greater standard deviation compared to the others. When explanatory variables have different scales it may affect the value of the regression parameters making it more difficult to compare them with one another. We solve the problem by standardizing the data. Then, the variables will be on the same scale and thus facilitate comparison between their corresponding regression coefficients.

Time series

We compare the time series of each explanatory variable and CDS spread within the considered period. These are presented in Figure A.1 in Appendix A. We are especially interested in the QE variable whose time series is depicted in Figure 4.1. The graph illustrates several periods where the two variables move simultaneously, i.e. reacting to the same signals though mostly in opposite direction. The indications are promising regarding our expectation of QE being a significant and negative determinant for the CDS spread. Among the control variables, we observe that market return and slope of the yield curve move opposite to CDS spread while market volatility and TED spread rate show signs of moving in parallel to it. However, the remaining variables present a less clear relation.

Box plots

[1]https://fred.stlouisfed.org/series/WSHOMCB

Variable	Number of observations	Mean	Standard deviation	min	25% quartile	50% quartile	75% quartile	max
CDS Index	639	103.210	60.412	22.260	62.125	83.534	125.850	421.566
QE	639	1390646	455319.8	5634	970027.5	1575433	1744811	2234807
Treasury Rate	639	2.319	0.734	0.543	1.847	2.322	2.831	3.934
Slope of Yield Curve	639	1.426	0.822	-0.036	0.766	1.433	2.141	2.883
Market Volatility	639	19.109	8.207	9.150	13.420	16.700	22.215	76.450
Market Return	639	0.125	0.151	-0.452	0.060	0.147	0.204	0.686
TED Spread Rate	639	31.350	17.333	-18.950	20.640	27.000	40.435	114.000
Interest Rate	639	0.545	0.722	0.040	0.090	0.150	0.660	2.450
Gold Price	639	1362.109	241.513	812.050	1211.790	1298.070	1539.260	2047.550
Oil Price	639	68.650	22.489	12.030	49.575	64.610	90.250	112.760

TABLE 4.1: Descriptive statistics of the data set.

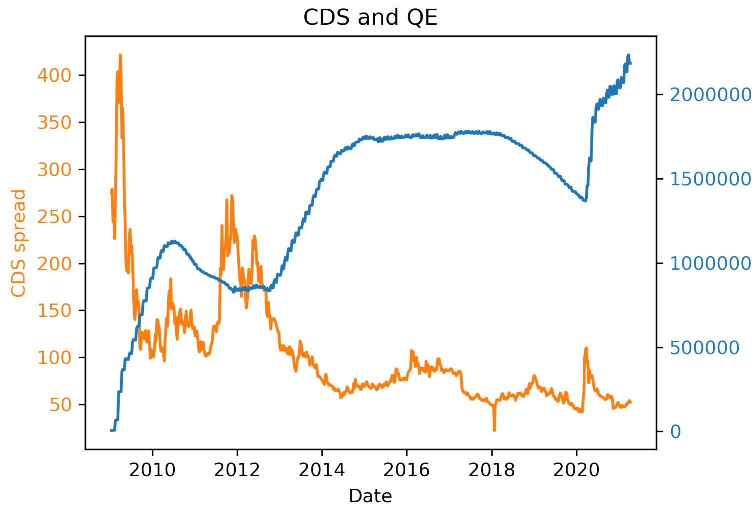

FIGURE 4.1: Time series plot of QE and CDS.

We create box plots of each variable, presented in Figure A.2 in Appendix A, to determine whether they contain outliers. In a box plot, an outlier is defined as a data point located outside the whiskers of the box plot, i.e. outside 1.5 times the interquartile range above the upper quartile and below the lower quartile. We notice that CDS, market volatility, market return, TED spread, and interest rate all show signs of having outliers. Nonetheless, this phenomenon is not uncommon for financial data. Several times through history the stock market has declined significantly in a single day, e.g. Black Monday in October 1987 where the US stock market declined by more than 20%. Outliers may have a significant impact on the performance of a regression model by affecting the slope of the regression line. Removing them is a viable solution in regression models where the regression periods are specified. However, in a rolling regression model removing observations may alter the window within which the regression is estimated. Therefore, we decide to let the outliers be and accept the potential downsides they bring to the model.

Heatmap

The heatmap, presented in Figure 4.2, shows the correlation between variables. Those between the target and the explanatory variables, i.e. top row or leftmost column, give an indication of what results we might expect from the regression model. Most noticeably there is a very strong negative correlation between QE and CDS at -0.84. Next, we see the TED spread rate, market volatility, and market return with similar absolute values of about 0.56. All with the expected sign. As we move closer to zero absolute correlation we find slope of yield curve, interest rate, oil price, Treasury rate, and gold price, respectively. Both interest rate and slope of yield curve have opposite sign of what we expect. The rolling regression will be able to show in what period the unexpected correlations arise.

The correlation value between explanatory variables indicates potential collinearity. If collinearity is present in the regression model they will explain some of the same variances in the target variable which in turn reduces their statistical significance. The highest correlation between explanatory variables in this data set is the one between interest rate and slope of the yield curve at -0.72. Although the correlation is quite high, it is not higher than 0.80, which is the commonly recommended

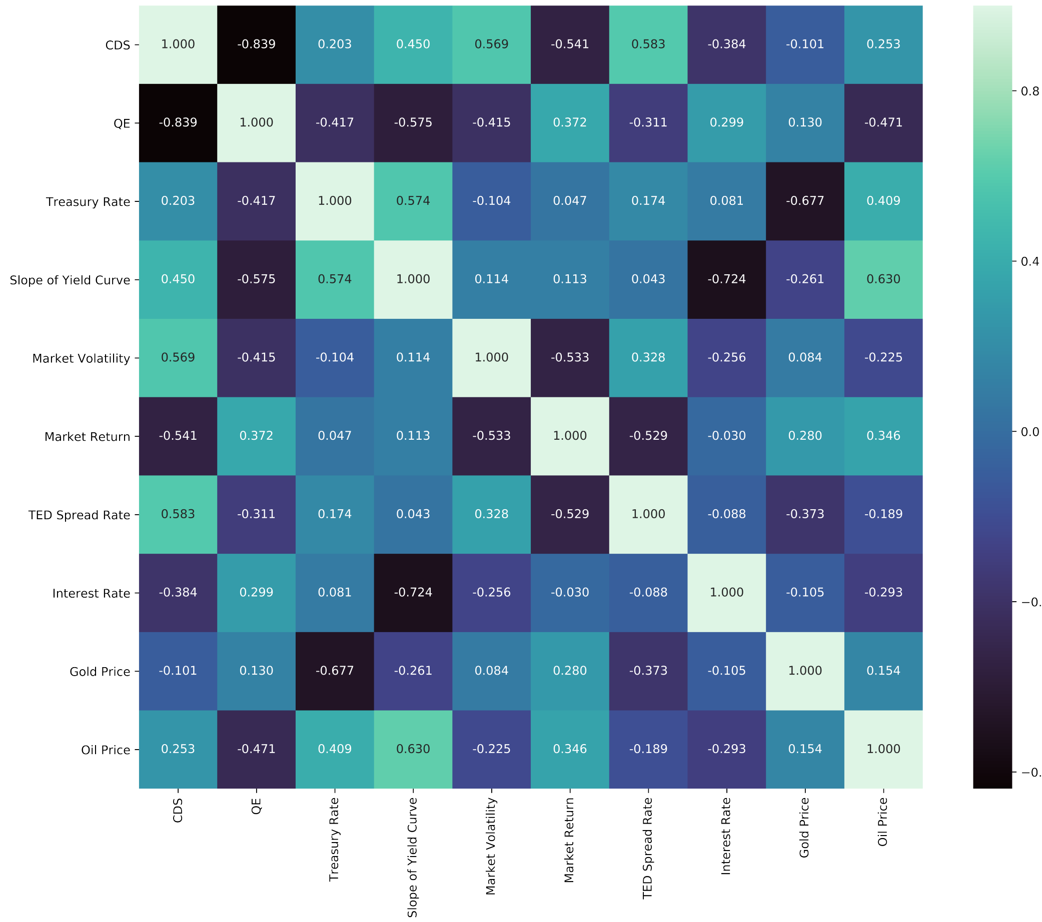

FIGURE 4.2: Heatmap of the data set.

value to remove one of the variables or to consider a transformation of the two variables. Therefore, we keep all variables in our study.

Q-Q plots and pairplot

To investigate the distribution of each variable we create Q-Q plots. Q-Q plots, i.e. quantile-quantile plots, are probability plots that help identify skewness and kurtosis, and thus the distribution of the data. When the data points in a Q-Q plot follow a straight line they can be considered normally distributed. Figure A.3 in Appendix A presents the Q-Q plots of all variables in this article's data set. We recognize that no variable is considered normally distributed which a Shapiro-Wilk test confirms.

Pairplot visualizes the relationship between variables. It is a matrix of scatter plots where the distribution of single variables follows the diagonal. The full pairplot is presented in Figure A.5 in Appendix A. However, we are mostly interested in the scatter plots between the dependent and independent variables, i.e. top row, illustrated in Figure 4.3. We notice that several scatter plots show signs of an exponential function. These include QE, market return, TED spread rate, interest rate, and gold price. The only plot illustrating a relationship which is more similar to linear is market volatility while Treasury rate, slope of yield curve, and oil price look more like large clusters. In an attempt to highlight linear relationships, we apply log transformations to some variables. Additionally, transforming the variables with the

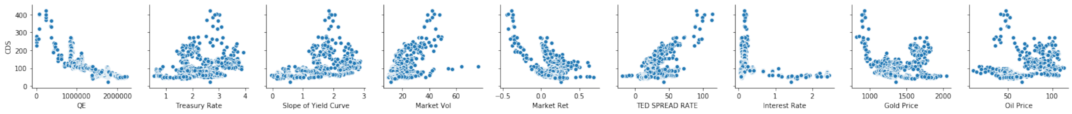

FIGURE 4.3: Scatter plot between the dependent variable and each independent variable.

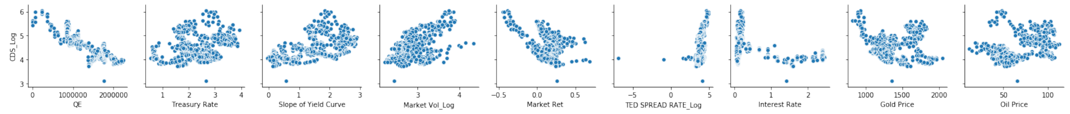

FIGURE 4.4: Scatter plot between the dependent variable and each independent variable after the log transformation of CDS, market volatility and TED spread rate.

natural logarithm may shift their distribution towards a normal one, e.g. CDS, market volatility and TED spread, as seen on Q-Q plots in on Figure A.4 in Appendix A. Through trial and error while observing the pairplot we find that the log transformation of CDS, market volatility, and TED spread rate makes the relationship between the dependent and independent variables closer to linear (see Figure 4.4). For this reason, we decide to use these log transformations in the regression models. Using the natural logarithm of independent and dependent variables in CDS regression models is fairly common (Hu et al., 2018; X. Wang, Xu, and Zhong, 2019). Nonetheless, it demands caution when interpreting the parameters of the regression models.

Chapter 5

Methodology

To determine which factors are important to explain the CDS banking index we implement a structural approach using regression analysis. The approach is widely used in papers where CDS determinants are explored (Malhotra and Corelli, 2018; Greatrex, 2008; Samaniego-Medina et al., 2016; Liu, Qiu, and T. Wang, 2021; Di Febo and Angelini, 2018).

Before performing each regression, all variables are standardized, i.e. for each variable,

$$z_i = \frac{x_i - \mu}{s} \tag{5.1}$$

where x_i is the i^{th} observation, μ is mean of the observations, and s is the standard deviation. The re-scaling sets every variable to have a mean of 0 and a standard deviation of 1. When the variables in a data set contain values of different scales the standard deviations may vary significantly running the risk of dominating one another. Standardization re-scales the variables to have equal magnitude.

Benchmark results are estimated by running a regression on the full data set. The estimation is performed using the following formula:

$$\begin{aligned} ln(CDS)_t =& \alpha + \beta_1 QE_t + \beta_2 TRate_t + \beta_3 SLOPE_t + \beta_4 ln(VOL)_t + \beta_5 RET_t \\ &+ \beta_6 ln(TED)_t + \beta_7 INTEREST_t + \beta_8 GOLD_t + \beta_9 OIL_t + \epsilon \end{aligned} \tag{5.2}$$

with date/week t and variables described in Table 5.1. From the results, we determine whether there are non-significant variables in the model and remove them. We re-estimate the coefficients in the model and repeat the process until the model is exclusively built on significant variables. The benchmark results highlight the variables which are significant in the 12 years from January 2009 until April 2021.

The majority of papers that analyze determinants of CDS spreads divide the observations into sub-periods and estimate the models with a formula similar to Equation (5.2) to determine how they change. The approach presents generalized variable coefficients of the specific sub-periods but disregards the evolution of the variables

Variable	Description	Proxy	Expected coefficient sign
$ln(CDS)$	Natural logarithm of CDS index spread	NA Banks 5 year CDS Index	
QE	Quantitative easing	Value of MBS held by FED	-
$TRate$	Treasury Rate	US Treasury 10 year bond	+
$SLOPE$	Slope of the Yield Curve	Difference between the 10 year and 2 year Treasury bonds	-
$ln(VOL)$	Natural logarithm of Market Volatility	CBOE VIX Index	+
RET	Market Return	Trailing twelve months of the S&P 500	-
$ln(TED)$	Natural logarithm of TED Spread Rate	TED spread rate	+
$INTEREST$	Interest rate	US federal funds rate	+
$GOLD$	Gold Price	LBMA Gold Price	-
OIL	Oil Price	Crude Oil WTO	+

TABLE 5.1: Variables of the regression model.

over time. To capture this evolution we implement a rolling regression model that is specified by a regression window. The window defines the time frame in which the regression is estimated and moves one week ahead for every regression until the last observation. In light of recent crises and to ensure a considerable number of observations for each regression we set the window to 104 weeks, i.e. two years. Therefore, the total number of regressions is 535, i.e. the total number of observations minus the regression window. The rolling regression model uses the following formula:

$$\begin{aligned} ln(CDS)_{t\to t+p} =& \alpha + \beta_1 QE_{t\to t+p} + \beta_2 TRate_{t\to t+p} + \beta_3 SLOPE_{t\to t+p} \\ &+ \beta_4 ln(VOL)_{t\to t+p} + \beta_5 RET_{t\to t+p} + \beta_6 ln(TED)_{t\to t+p} \\ &+ \beta_7 INTEREST_{t\to t+p} + \beta_8 GOLD_{t\to t+p} + \beta_9 OIL_{t\to t+p} + \epsilon \end{aligned} \tag{5.3}$$

where $t \in \{0, 1, 2, ..., 535\}$ and p signify date/week and regression window, respectively. In our study we are mostly considering $p = 104$. The parameters are estimated with ordinary least squares (OLS) method. Similarly to the benchmark approach we remove the non significant variables in each regression and re-estimate until the models are exclusively built on significant variables.

The performance of the regression models is measured by adjusted R squared. While both R squared and adjusted R squared represent the explanatory power of a regression model, the adjusted R squared also takes into consideration the number of predictors. In the rolling regression model, we estimate 535 different regressions where the number of predictors ranges from 1 to 9[1]. The adjusted R squared allows us to compare them with each other and with similar studies. Other studies that also use the adjusted R squared as a measure of performance include Greatrex (2008), Collin-Dufresne, Goldstein, and Martin (2001) and Galil et al. (2014) among others.

[1]If no predictors are considered significant, then we do not consider a regression for that window, and the adjusted R squared will be set to zero

Chapter 6

Results and Discussion

6.1 Full Period Regression

We apply a regression on the entire data set to establish benchmark results, presented in Tables 6.1 and 6.2. Our first observation is the significant factors. The regression model based on data from January 2009 until April 2021 estimate QE, logarithm of market volatility, market Return, logarithm of TED spread rate, interest rate, and oil price coefficients as significant. Secondly, the results substantiate our main hypothesis of QE being an important factor in explaining changes in logarithm of CDS. The corresponding coefficient is negative, in accordance with our expectation, and has an absolute coefficient value of 0.310, which is greater than the others. As we analyze the remaining significant variables we note that all, except interest rate, meet our sign expectation. To investigate this we will examine the variable further in the rolling regression.

Variable	Coefficient	p-value
QE	-0.318*** (0.013)	0.000
Treasury Rate	-0.044 (0.028)	0.108
Slope of Yield Curve	0.012 (0.040)	0.775
ln(Market Volatility)	0.059*** (0.012)	0.000
Market Return	-0.064*** (0.012)	0.000
ln(TED Spread Rate)	0.056*** (0.009)	0.000
Interest Rate	-0.085*** (0.030)	0.005
Gold Price	-0.026 (0.017)	0.120
Oil Price	0.043*** (0.016)	0.006
Adjusted R Squared	0.852	

TABLE 6.1: Variable coefficients, p-values and adjusted R squared of the regression on the full period. Standard deviations are reported in parentheses. Significance levels at 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

Variable	Coefficient	p-value
QE	-0.310*** (0.012)	0.000
ln(Market Volatility)	0.052*** (0.010)	0.000
Market Return	-0.076*** (0.010)	0.000
ln(TED Spread Rate)	0.052*** (0.008)	0.000
Interest Rate	-0.104*** (0.008)	0.000
Oil Price	0.029** (0.011)	0.012
Adjusted R Squared	0.852	

TABLE 6.2: Variable coefficients, p-values and adjusted R squared of second regression on the full period where non-significant variables have been removed. Standard deviations are reported in parentheses. Significance levels at 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

6.2 Rolling Regression

To analyze the rolling regression results in Figures 6.1 and 6.2 we use timestamps or general moments in time to reference the regression coefficients and adjusted R squared. One must keep in mind that these regressions are built on the 104 weeks leading up to the points on the graphs. In that way, if it is said that a variable is significant from timestamps 01.01.2011 to 01.01.2012 the complete time period in which the variable stands significant is from 01.01.2009 to 01.01.2012.

Figure 6.1 shows how the adjusted R squared of the rolling regression model evolves over time. At first glance, we observe that the adjusted R squared is high for a large portion of the regression. It generally fluctuates between 0.8 and 0.9 with the exception of a few sub-periods. There are two short dips to just below 0.6 in mid 2011 and mid 2017, before a longer dip occurring in mid 2018 until early 2020. As we compare these periods with the variable coefficients in Figure 6.2 we notice that the largest dips represent regressions where few variables are significant.

In the next part, we will analyze the results in Figure 6.2 by first interpreting the control variables and then moving on to QE. Lastly, we analyze the results in light of different crises during the considered period. Separate graphs for each variable are presented in Figure A.6 in Appendix A to facilitate the interpretation.

At first glance on the graphs in Figure A.6 we see that all variable coefficients change over time. Every variable has some periods where there is no statistical significance, though some more than others. Logarithm of market volatility and logarithm of TED spread rate stand out most noticeably by having constant significance over a large majority of the regressions as well as never changing sign. Both of the variables have positive coefficients which are in accordance with our expectations. The logarithm of TED spread rate graph illustrates decreasing coefficients over time culminating in no explanatory power since early 2019. Inversely, we find market return and gold price to have increasing coefficients and significance throughout the

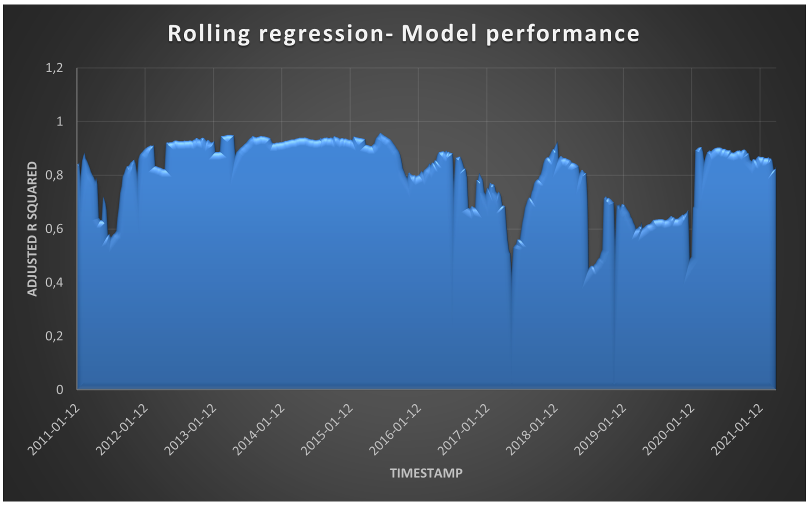

FIGURE 6.1: The adjusted R squared in a rolling regression with a 104-week regression window.

FIGURE 6.2: The coefficient values of significant variables in a rolling regression with a 104-week regression window.

regressions. Market return is for the most part non-significant[1] in the regressions before 2015 and shows very negative coefficients in the years after. However, there is an exception in the period from mid 2017 to late 2018. The gold price shows an interesting path alternating between positive and negative values. However, from 2019 and onward it displays a negative gradient and in 2021 it is at its most negative value. Encouragingly, the sign of market return and gold price is aligned with our expectations about these variables. Treasury rate, slope of yield curve, and interest rate have the fewest regressions in which they are significant. While Treasury rate appears to be mostly negative, slope of the yield curve and interest rate have an unclear relationship with logarithm of CDS as there is no dominant sign throughout the regressions. These findings may be a result of interest rates being set close to zero since the Great Recession. Lastly, we observe that the oil price is mostly negative and has distinct periods of significance. One before 2013, another between 2015 and late 2017 with a short exception from mid to late 2016, and the last period from 2020 to the end. Both Treasury rate and oil price were the only variables to oppose our expectations. When we examine the time series graphs in Figure A.1 in Appendix A we notice that CDS and Treasury rate move simultaneously and in opposite direction during several periods, noticeably from 2009 to late 2012 and from 2013 to 2014. These periods explain protruding negative regression coefficients during the first rolling regressions. The time series of CDS and oil price present certain movements in opposite direction as well. These are particularly distinguishable during spikes, e.g. before 2010, around 2012, around 2016 and around 2020. Presumably, these movements explain the unexpected regression coefficients.

As we compare the rolling regression graphs with the full period regression result we notice a couple of tendencies. Variables with a dominating sign and variables with many regressions where they are significant are also significant in the full period regression. The only exception is the interest rate which exhibits none of the traits above. As the full period regression estimates a negative coefficient for interest rate we would assume that the distinctly negative relation with CSD index spread from mid 2017 until early 2019 has a overshadowing effect. A noticeable contradiction between the results is the oil price. While the full period regression estimates a positive coefficient the rolling regression model estimates it to be mostly negative.

The rolling regression results are promising in regards to earlier studies. A positive significant market volatility and negative significant Treasury rate are common estimates for US and European bank CDS spreads during the Great Recession (Annaert et al., 2013; Malhotra and Corelli, 2018; Samaniego-Medina et al., 2016). Additionally, the Treasury rate turning non-significant in times of no crisis is consistent with their findings too. The estimated coefficient of gold price was mostly non-significant during the Great Recession as was found by Malhotra and Corelli (2018). However, the negative significant Oil price is not consistent with the aforementioned findings where it was estimated to be non-significant both during and after the Great Recession. The slope of the yield curve, though mostly non-significant in the rolling regression, is found to be ill-behaved in many articles. It is either non-significant or its sign rest on the specifications of the regression and the set of independent variables (Avramov, Jostova, and Philipov, 2007). Lastly, a positive significant logarithm of TED spread and a negative significant market return were expected in the regressions before 2016 (X. Wang, Xu, and Zhong, 2019; Drago, Tommaso, and Thornton, 2017; Samaniego-Medina et al., 2016). However, the rolling regression results can

[1] To simplify writing we use the terms non-significance and non-significant with the meaning that there is no statistical evidence to be considered significant

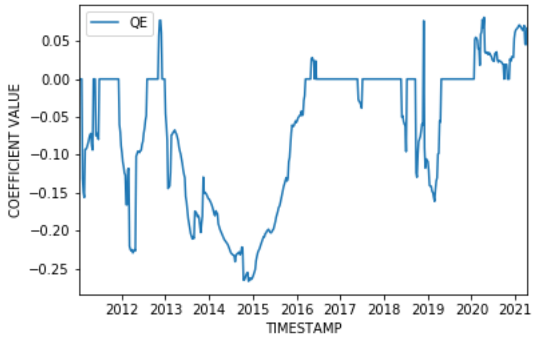

FIGURE 6.3: QE coefficients of rolling regression model.

only support these findings with the TED spread as market return turns negative and significant quite late in the regression period. When examining the time series of CDS and market return in Figure A.1 in Appendix A it looks like they move in opposite direction for almost the entire period. Nonetheless, the movements are not captured by the model.

In summary, the rolling regression highlights an issue that comes with the use of regression models on a full period or large sub-periods. While the existing literature agrees that determinants change over time, the extent to which it changes may sometimes be neglected. Our model clearly show that the explanatory power of variables not only changes in the transition from a time of crisis to no crisis but also within the time of crisis and the time of no crisis. The results suggest that CDS spread predictions based on structural models should be followed with caution.

The main interest of our regression model is the QE variable. While most articles use dummy variables to proxy quantitative easing in regression models, we chose the value of FED's MBSs. This proxy not only provides information on whether the FED is implementing QE but also to what extent. Figure 6.3 shows the importance of the variable throughout the rolling regression. We observe a very negative QE coefficient from the first regression until 2015. We can compare these regression coefficients with the time series of CDS and QE in this specific period (see Figure 6.4). On the graphs, we observe that the negative regression coefficients occur mostly where the value of FED's MBSs is increasing and the CDS index spread is decreasing. Most noticeable are the regressions after 07.01.2013. Additionally, we notice that there are certain regressions where the QE coefficients show no statistical evidence of being significant. These regressions might be explained by the seemingly positive correlation in the time series where both QE and CDS are decreasing, e.g. observations between mid 2010 and early 2011.

As we move further into the regression periods we see a change in value. The QE remains mostly non-significant between early 2016 and early 2018. The time-series graph in Figure 6.5 illustrates this period where the QE for a large part remains almost constant and the CDS fluctuates. From mid 2018 until mid 2019 the QE coefficient once again turns negative. In these regressions, we note the entrance of observations where QE decreases and CDS increases which is presumably the cause. A surprising result is the positive QE from early 2020 to early 2021. We expected a negative value given the evident negative correlation between QE and CDS detected in the time series from early 2020 to early 2021. From late 2019 to early 2020 the time series depicts a period where the FED lowers the value of MBS in their balance while the CDS index decreases. Additionally, both time series spike in parallel

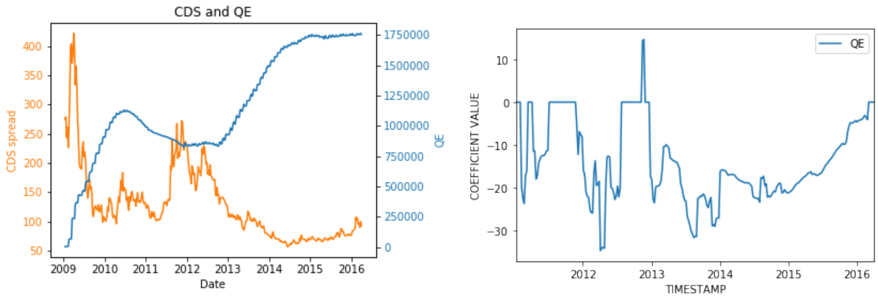

FIGURE 6.4: Time series of QE and CDS observations, and rolling regression QE coefficients for the period 07.01.2009 until 09.03.2016. Note that Date and TIMESTAMP signify date of observation and last date of which the regression is performed, respectively.

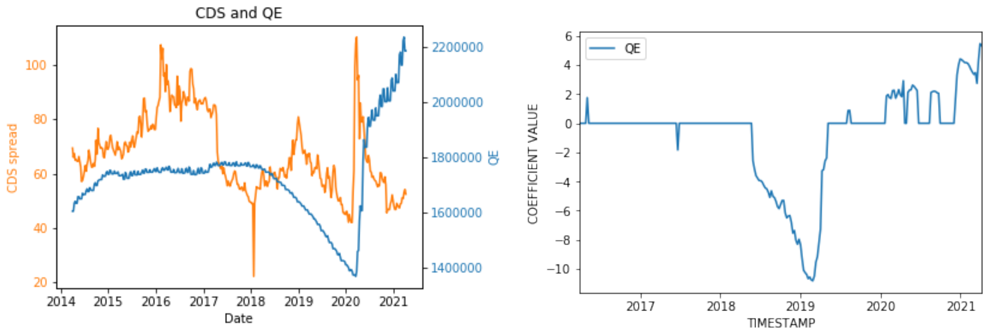

FIGURE 6.5: Time series of QE and CDS observations (left) and rolling regression QE coefficients (right) for the period 05.03.2014 until 07.04.2021.

in early 2020. As all these observations are present in regressions leading up to April 2021, given the 104-week regression window, we end up with a model that incorporates all this different information. To investigate the explanatory variables in 2020 and 2021 further we rerun a rolling regression on observations from 09.10.2019 to 07.04.2021 with a 52-week regression window. Doing so we are able to isolate the observations in 2020 and 2021. The new rolling regression results are presented in Figure 6.6.

We notice a major difference in the values. The QE coefficients, which we depict in Figure 6.7, are almost all significant and negative. This confirms that by using a 52-week rolling regression we can highlight the behaviour observed at the end of the period. Next, we discuss the results and QE variable in light of the major crises.

To compare the determinants of CDS spreads throughout times of crisis we define the period in which they occurred. We consider at the following financial panics: the Great Recession, the European debt crisis, and the Covid-19 pandemic. We acknowledge that the European debt crisis mainly inflicted consequences for the European banks and economies whereas our model utilizes a US bank index. However, as modern economies and financial markets are closely linked we include this crisis in the discussion.

The Federal Reserve Economic Data (FRED) defines the Great Recession from 01.12.2007 to 06.01.2009[2]. However, several articles that have studied CDS spread

[2]https://fredhelp.stlouisfed.org/fred/data/understanding-the-data/recession-bars/

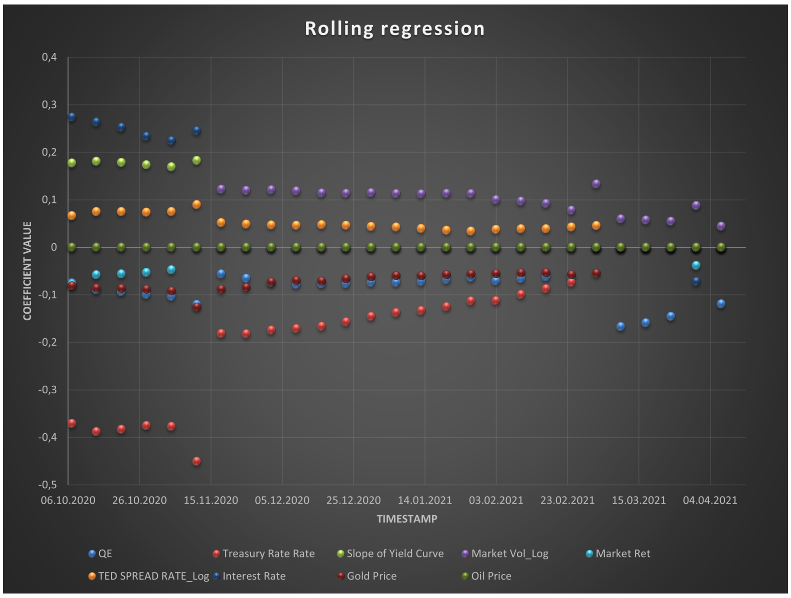

FIGURE 6.6: Variable coefficients of rolling regression model with a 52-week regression window on observations from 10.10.20119 until 07.04.2021.

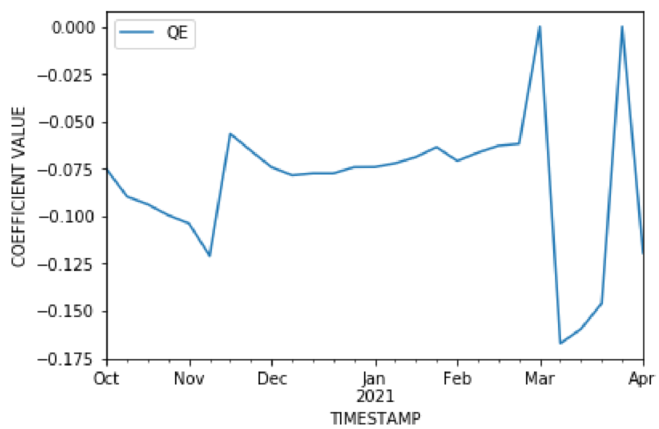

FIGURE 6.7: QE coefficients of rolling regression model with a 52-week regression window.

determinants pre, during, and post the Great Recession have chosen different periods. Among others, Malhotra and Corelli (2018) defines the Great Recession from 14.12.2007 to 31.12.2012 while Di Febo and Angelini (2018) sets it to be between September 2007 and December 2009. We will consider observations between 2007 and 2011, thus rolling regression results from timestamp 12.01.2011 until 04.01.2012. That way we compare the rolling regressions in which 50% of the observations are within the crisis period.

As for the European sovereign debt crisis, we define it by looking at the elevated spikes in the US bank CDS index, i.e. from 01.06.2011 until 01.01.2013. To compare the results from the European sovereign debt crisis we observe the regressions in which more than 50% of the data is during the crisis. Therefore, we look at the regressions from timestamp 06.06.2012 until 01.01.2014.

The Covid-19 pandemic is an ongoing Crisis at the time of writing. We consider its beginning as that defined by FRED, i.e. 02.01.2020. In this crisis, we are considering the rolling regression results with a 52-week regression window.

Great Recession[3]

The Great Recession was in large part caused by a bubble in the housing market. Lenders issued mortgages and passed them on to large banks which overtook the risk of default. Over time the lending standards fell causing an increase in risky loans. The banks repackaged the mortgages into MBSs and collateralized debt obligations (CDO) to make them more attractive to investors. When the mortgages began defaulting and the market noticed the major underlying risk of these derivatives the bubble burst. In an attempt to shield the economy the FED began their first attempts at quantitative easing. The MBSs were among the securities they bought. The rolling regression model estimates a negative coefficient for the QE variable during this period. It signifies that QE, through the buying of MBSs, significantly lowered credit risk in banks. The significance and sign of the variable are in accordance with both our prediction and the results of other studies (Krishnamurthy and Vissing-Jorgensen, 2011).

European debt crisis[4]

It could be argued both for or against whether the European sovereign debt crisis led to a crisis in the banking sectors outside Europe. In Figure 4.1 we observe that the US bank CDS spreads clearly spiked during that time, though not to levels seen during the Great Recession. Nonetheless, there was fear in the market considering recent events, e.g. the Great Recession, and worries that the sovereign debt crisis would spread to the rest of the world. Another element making the period particularly interesting is the lead-up to the crisis where the FED did the first major "tapering" of its balance sheet. Tapering is referred to the process where the FED slows down its asset purchases or even sells assets to shrink the balance sheet. In the period leading up to the European sovereign debt crisis, the FED sold off a considerable amount of MBS for the first time. The rolling regression results corresponding to the crisis period show a negative QE increasing in absolute value which illustrates its importance in lowering credit risk.

A comment should be made about the QE variable in the period after the European Sovereign debt crisis as it remains non-significant for a long time. During this period, from 2014 to 2018, the FED halted its asset purchases. It was also a period

[3] We are considering rolling regression results between timestamps 12.01.2011 and 04.01.2012.
[4] We are considering rolling regression results between timestamps 06.06.2012 and 01.01.2014.

where the US bank CDS spreads were stable at about 70 points, which can be seen in Figure 4.1. A reason for the non-significance might be the minimal change in the QE variable during this period. As there was no change in the QE, the regression may have been unable to determine any relationship between the QE and logarithm of CDS.

Covid-19 pandemic[5]

While the 104-week rolling regression model estimates a positive coefficient for QE during the Covid-19 pandemic the 52-week rolling regression shows different results. The latter model estimates negative coefficients as shown in Figure 6.7. This further strengthens our hypothesis that the unconventional monetary policy functions well at lowering the credit risk of banks. Whereas more liquidity and demand for risky assets were expected to help stabilize the mortgage derivative market in the Great Recession, it was less obvious that it would help stabilize the credit market in the pandemic. There are some reasons to think that the growth of the balance sheet might not be the best proxy for this particular crisis. Firstly, the Covid-19 pandemic was an exogenous event with very particular effects on both the demand and supply side of the economy. For example, the travel and leisure sectors were suddenly hit with severely decreased demand. At the same time, supply chains around the globe were disrupted because of social distancing and travel restrictions for their workers. The dynamic makes the crisis very different from the Great Recession or the European sovereign debt crisis. While the Covid-19 pandemic mostly hit non-financial sectors the two preceding crises hit first and foremost financial institutions. Secondly, the pandemic was "no one's fault". This, in addition to investors being used to help from the central bank, might have caused an expectation that central banks and governments around the world would help businesses from default.

Even though the Covid-19 pandemic was very different from previous crises, the total value of MBS in FED's balance sheet proved to be a significant explanatory variable for the credit risk of banks. This suggests that measuring the actual buying, and not just the expectation of future buying, should be included in literature investigating determinants for bank CDS spreads.

Potential problems caused by the QE programs

Our results suggest that the MBS purchases by the FED have successfully injected liquidity into the banking sector and lowered credit risk. But the consequences of this new policy are still unclear. There are two areas of the market where investors and economists are worried that potential problems can emerge. One is the massive growth in money supply, which in the spring of 2021 caused a major focus on the risk of potential inflation. Another is the big spike in activity of the overnight reverse repurchase agreement market (RRP), which might be a sign of too much cash and too little collateral in the system.

The M2 money supply measures the total amount of cash and checking deposits, as well as "near money" assets like savings deposits, money market securities, mutual funds, and other time deposits. It has grown from 7500 billion dollars at the beginning of the Great Recession to 20 000 billion dollars at the end of April of 2021[6]. In 2020 alone, it rose by 25% as the FED increased liquidity in the financial sector to combat the recession caused by the pandemic. According to FED Chairman Jerome Powell: "The correlation between different aggregates [such as] M2 and inflation is

[5]We are considering the rolling regression results with a 52-week regression window. The model is built on observations from 09.10.2019 until 07.04.2021.

[6]https://fred.stlouisfed.org/series/M2

just very, very low, and you see that now where inflation is at 1.4% for this year. Inflation dynamics evolve over time, but they don't tend to change overnight."[7]. However, inflation, as measured by the Consumer Price Index, rose to 4.2% over the previous year in April 2021. This has caused fear in the market on the potential for persistently high inflation caused by QE[8].

Another potential problem caused by QE is the recent spike in RRP market. The FED's RRP operations let eligible firms, such as banks and money-market mutual-funds, park large amounts of cash overnight at the FED. Institutions do this when the short-term funding rates have fallen to next to nothing making decent options for storing money difficult to find. This was the case in May 2021. The FED had increased their balance sheet significantly during the pandemic, thereby taking many of the high grade bonds off the market and thus injected excess liquidity. This could be a problem as it may lead to a lack of collateral in financial markets, needed for lending. In late May 2021, the volume in the PPR has gone from zero to 500 billion dollars in a short period [9]. The source of the increased demand for collateral is also partly related to the Basel regulations put in place after the Great Recession. Treasurys and MBSs are considered equivalent to cash but earn a higher yield, which leads to excess cash chasing a decreasing amount of bonds. The impact of QE on the RRP market is very interesting to investigate for further research.

[7]https://www.kitco.com/news/2021-02-24/Jerome-Powell-says-money-printing-doesn-t-lead-to-inflation.html

[8]https://www.cnbc.com/2021/05/21/the-federal-reserves-so-called-taper-talk-could-keep-markets-on-edge-through-the-summer.html

[9]https://fred.stlouisfed.org/series/RRPONTSYD

Chapter 7

Conclusion

Much focus in media and financial literature is put on the unconventional monetary policies used by the world's central banks in recent years. As interest rates in most developed countries reached the zero level during the Great Recession, new tools to control the market were needed. In this paper, we contribute to the growing financial literature on the topic by analyzing the relationship between credit risk in the US banking sector and the purchases of MBS by the FED. We include control variables and monitor their change in value and significance over time. Our proxy for credit risk in the US banking sector is North American Banks CDS Index. We run a rolling regression from 2009 to 2021 with a 104-week regression window to analyze how determinants of credit risk in the banking sector behave over time. For each regression, we remove non-significant variables and rerun the regression until only significant variables remain.

Our regression results point to two main findings. Firstly, the QE variable presents several periods of negative significant coefficients in the 104 week regressions, suggesting that the FED's MBS purchases succeeded in lowering the credit risk of US banks. Secondly, the coefficients of bank CDS index determinants change over time. While certain variables are fairly consistently significant over the regressions, such as the logarithm of market volatility, most variables go through short periods of significance. Additionally, we notice that several of the variables with short periods of significance are the most important determinants during these times.

The results met our expectation by indicating that the purchase of MBS successfully lowered US bank CDS spreads during the Great Recession. A crisis rooted in a housing bubble with subprime housing mortgages. However, the results are particularly interesting as they suggest that the buying of MBS worked in later crises as well. Our results show that the MBS purchases significantly helped to lower the heightened credit risk in the banking sector caused by the European Sovereign debt crisis and the Covid-19 pandemic further strengthening the case for the unconventional policy. Therefore, we conclude that a QE variable should be included when investigating determinants of credit risk in the banking sector. We also highlight that the value of MBS in FED's balance is a valid proxy for QE.

There are recent events in the market that might suggest signs of future problems because of QE. For one, it is clear from Figure 4.1 that the Treasury and MBS holdings of the FED is increasing. New crises keep appearing as the FED plans to taper its asset purchases and shrink its balance sheet. This was not intended when they began purchasing assets during the Great Recession. According to FED, the purchases were only meant to stabilize the Great Recession temporarily and to be sold off after the credit markets were stabilized. One effect of the increasing balance sheet is the ever-increasing money supply, which has led to fear of future inflation. Another potential problem is the lack of collateral for banks because of the bond purchases and excess liquidity. This shortage is evidenced by the recent spikes in the RRP market. Both potential problems represent interesting topics for further research.

Appendix A

Appendix

Article	Market volatility	Interest rate	Market return	TED spread rate	Slope of yield curve	Treasury rate	Gold price	Oil price
Annaert et al. (2013)	+/-		-/?		-/?			
Malhotra and Corelli (2018)			-/?			+/?	+/?	+/-/?
Kajurova (2015)	+	-	+		?			
Samaniego-Medina et al. (2016)	+		-			?		
X. Wang, Xu, and Zhong (2019)	+/-/?			+/-				
Di Febo and Angelini (2018)	+	-	-					
Greatrex (2008)	+		-		-	-		
Galil et al. (2014)	+		-		-	-		
Szafranek et al. (2020)		+						
Drago, Tommaso, and Thornton (2017)	+		-		-	?		

TABLE A.1: Macroeconomic and market-based variables used in studies investigating determinants of CDS spreads. The listed variables do not represent the all variables in each article, but the ones we are using in this article.

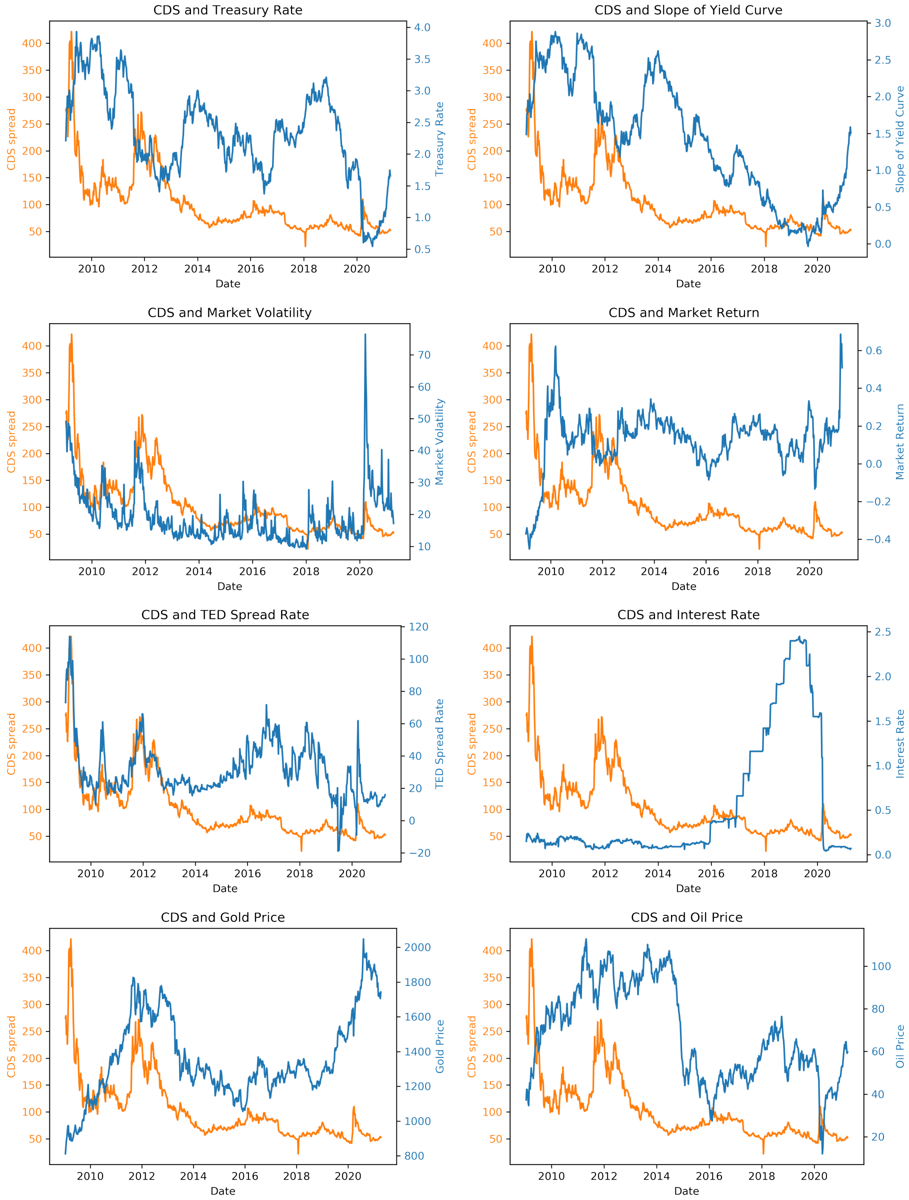

FIGURE A.1: Time series comparison between the CDS bank index and each control variable.

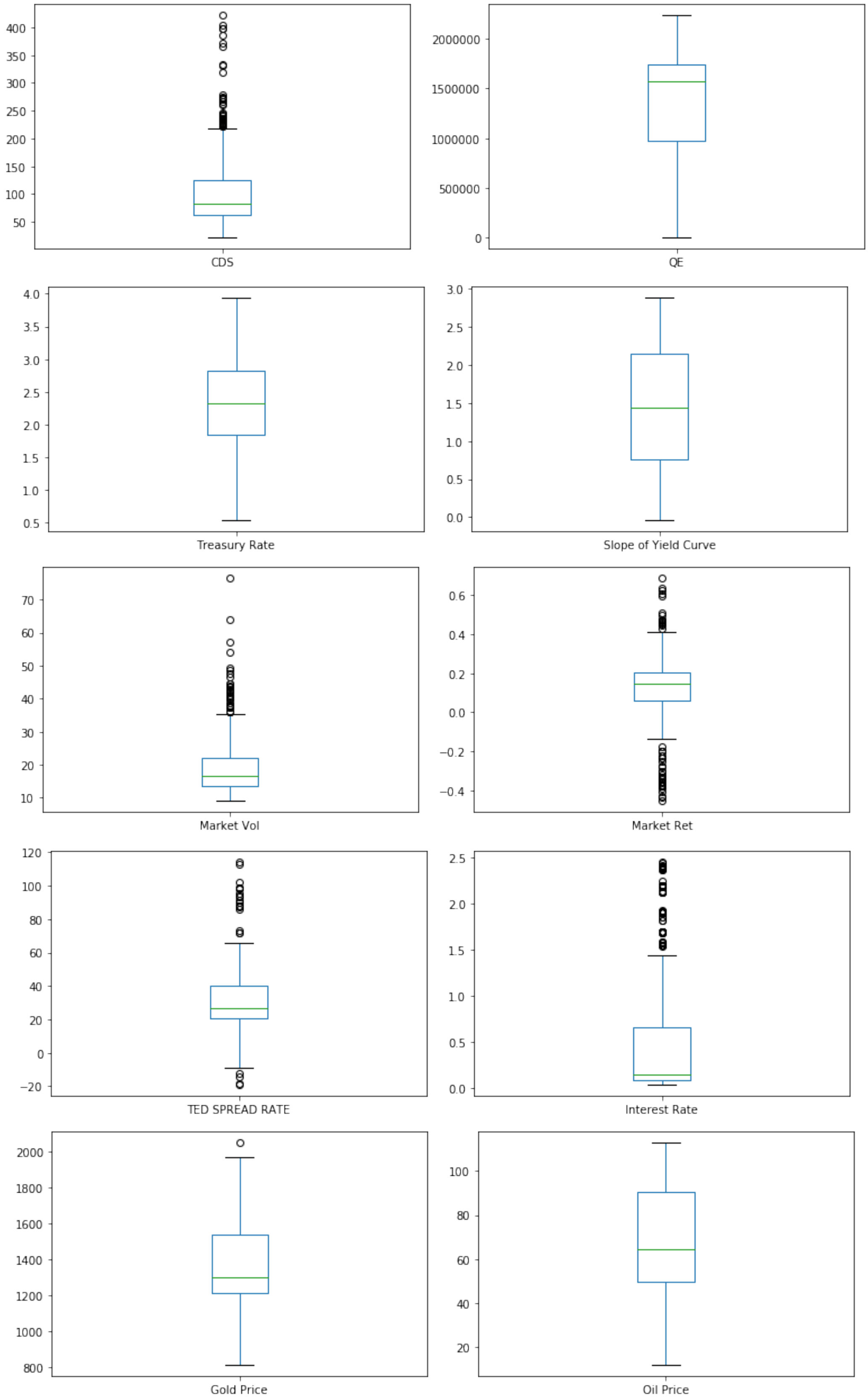

FIGURE A.2: Box plots of each each variable.

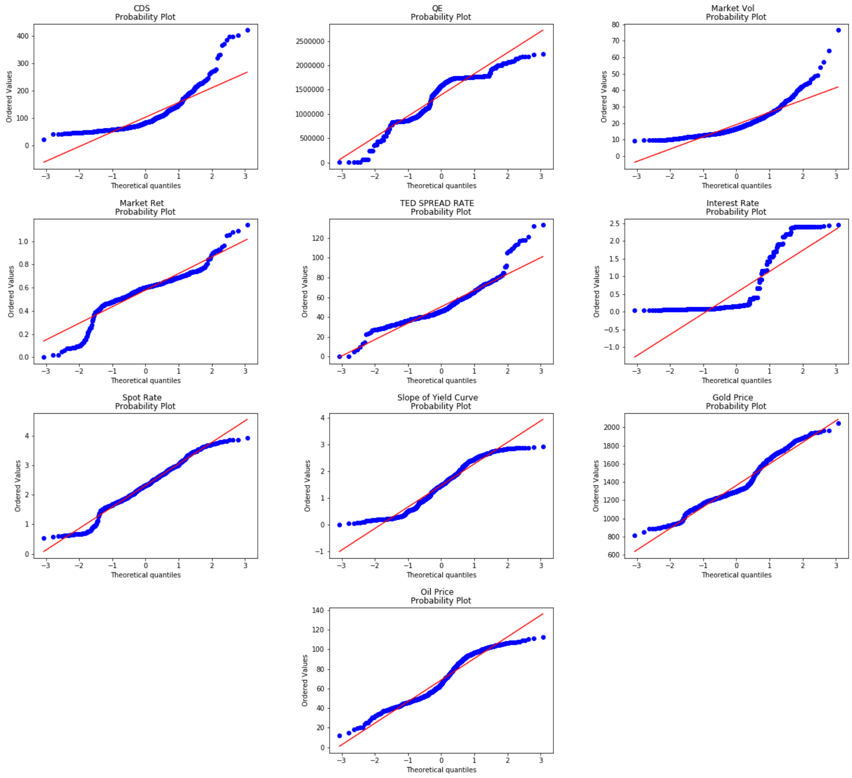

FIGURE A.3: QQ plots of non-transformed variables.

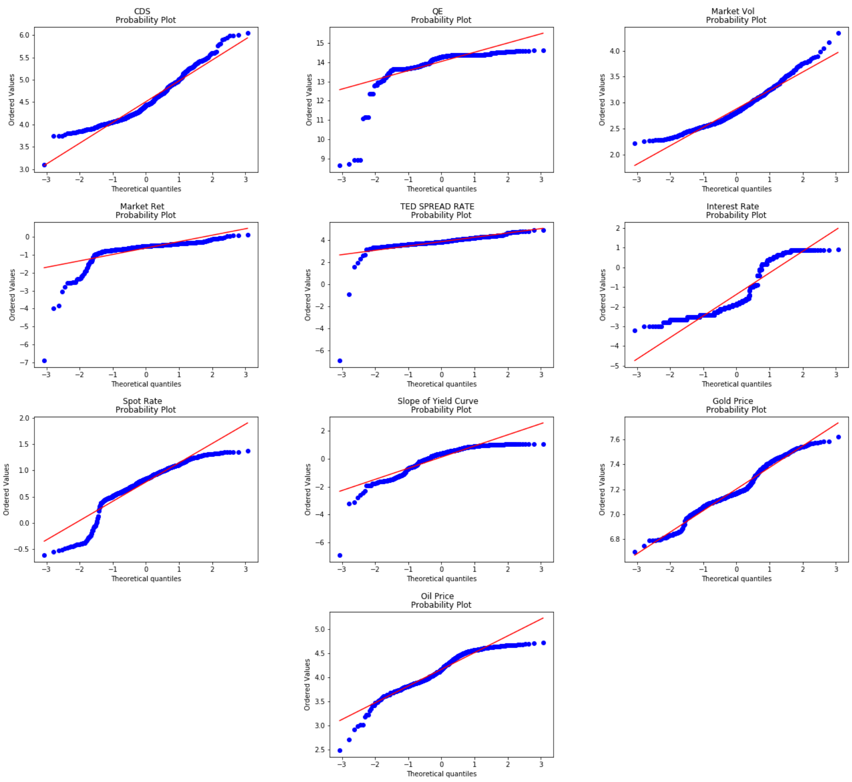

FIGURE A.4: QQ plots of log-transformed variables.

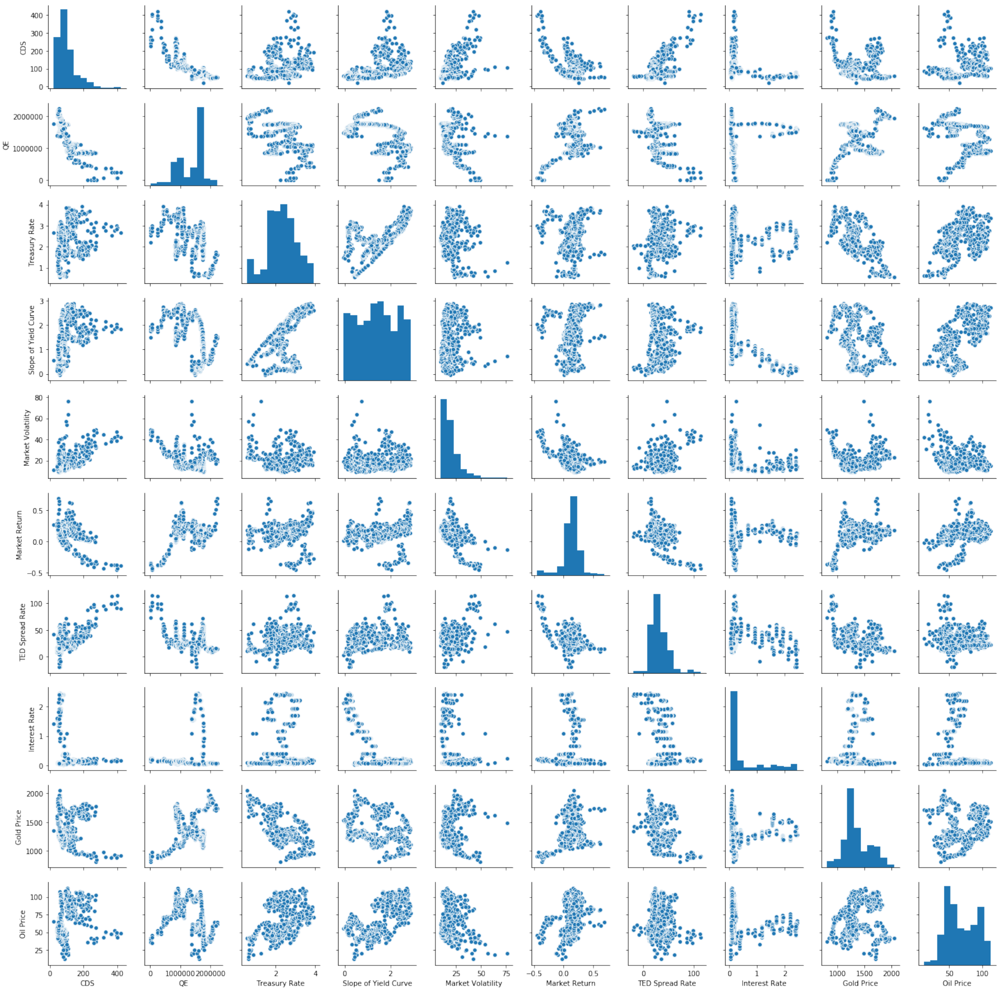

FIGURE A.5: Pairplot of the dataset.

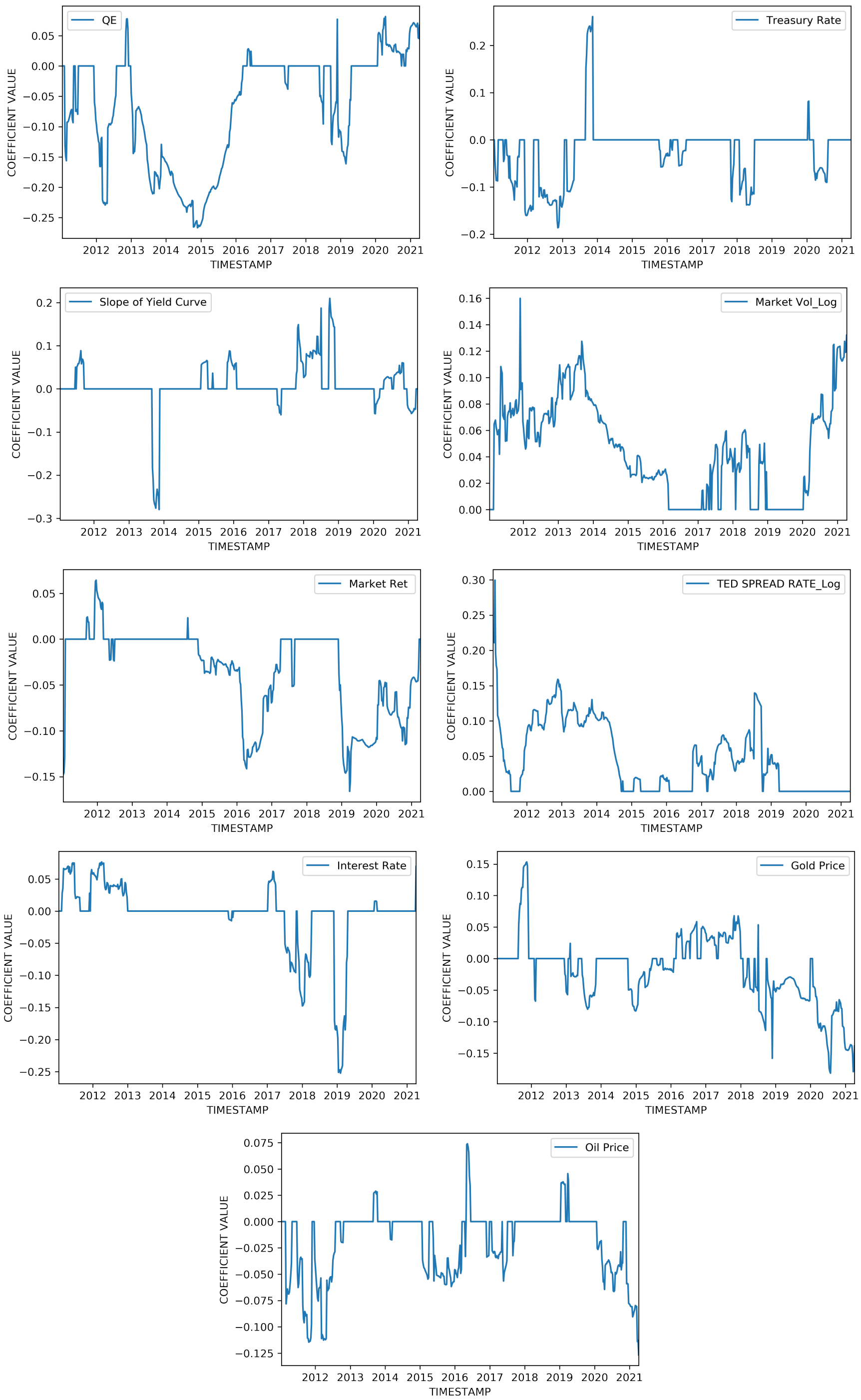

FIGURE A.6: Graphs of coefficients for each variable from rolling regression with 104-week regression window.

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