Norwegian School of Economics

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# Empirical Evidence of Lead-Lag Relation between the Norwegian CDS and Stock Markets

*Using Vector Autoregression with Exogenous Variables (VARX) and Structured Regularization for Large Vector Autoregressions with Exogenous Variables (VARX-L) Framework*

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Master thesis, MSc in Economics and Business administration,

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NORWEGIAN SCHOOL OF ECONOMICS

# Contents

# Abstract

The master thesis studies the lead-lag relation between the Norwegian CDS and stock markets with daily observations from June 24, 2010 to May 5, 2017 of three Norwegian firms, DNB Bank ASA, Telenor ASA, and Statoil ASA. I use vector autoregression with exogenous variables models (VARX) on firm level where stock returns and credit default swap spread changes are endogenous variables, and exchange rate (NOK/Euro) change and 10-year Norwegian government bond yield change are exogenous variables. The CDS samples are drawn on senior unsecured debt with modified-modified restructuring type, Euro settlement currency, 30-year and 5-year maturity.

The results of VARX suggest that the lagged equity returns predict the CDS returns while the lagged CDS spread changes do not predict the stock returns. Combined with the fact that the Norwegian stock market is more liquid than the Norwegian CDS market, one hypothesis is that CDS market is slow to reflect information due to the liquidity problem. I also use the VARX-L framework, Structured Regularization for Large Vector Autoregressions with Exogenous Variables. It implements penalty structures to the conventional VARX models. After allowing for more heterogeneity and flexible lag structure in the VARX-L models, the analysis reveals that large lags of CDS spread changes can predict stock returns.

The thesis contributes to the literature in two ways. First, to the best of my knowledge, the thesis is the first to study this question in the context of Norwegian financial markets. The current literature claims that the 5-year maturity CDS is most popular and liquid contract. However, in the Norwegian CDS market, maturity seems to positively correlate with liquidity, so I also include 30-year CDS in the analysis. Secondly, the thesis adds a machine learning component to the traditional VAR analysis which allows to show that large lags of CDS spread changes can predict stock returns.

# 1. Introduction

In Norway, the bondholders use credit default swap (CDS) contracts to mitigate the default risk of the bond issuers (Norges Bank, 2018). The reference entities can be either government or companies. The reference obligation of a CDS contract is bond, and the bond issuer is called *reference entity* in the CDS contract. The protection buyer pays a fixed CDS spread to the seller periodically (usually quarterly) until the maturity of the bond or a credit event[1] is triggered. If a credit event is triggered, the protection buyer receives compensation from the protection seller for the loss and the proprietorship of the bond becomes the protection seller (if it is physical settlement). Thus, the CDS contract transfers the risk and yield on an underlying bond from the protection buyer to the protection seller.

The CDS contracts are credit insurance, the protection sellers are credit insurance companies in Norway (Norges Bank, 2018). There is another kind of protection seller who wants to have credit exposure to a company, but it cannot afford the bonds (Bomfim, 2015). It sells a CDS contract so that it is exposed to the credit risk. For hedging purposes, the protection buyer holds the underlying bond and is exposed to the default risk. For speculation purpose, the investor can buy a CDS contract without holding the underlying bond, which is equivalent to short selling the underlying bond.[2] According to Norges Bank (2018), the largest bondholders in the Norwegian bond market are large institutions, including life insurance companies, banks, pension funds, and mutual funds. Finally, market makers are another important type of trader in the CDS market. They provide live quotes of bid spread and ask spread, hence make the transactions go quicker. Without market makers, it may take longer for the sellers and buyers to find counterparties. However, the CDS bid-ask spread[3] is rather wide, thus the CDS percentage bid-ask spread[4] is much higher than the stock percentage bid-ask spread[5] of the same company. For example, on May 26th, 2021, the CDS percentage bid-ask spread and stock percentage bid-ask spread of DNB Bank ASA are 16% and 4% respectively; the CDS

[1] The credit event is briefly described in section 3.1.3. ISDA (2003) fully explained the definition of credit events.

[2] The pros and cons of shortselling are not the scope of the thesis. Here I only introduce the protection buyers who are actually bondholders.

[3] CDS bid-ask spread is ask spread minus bid spread.

[4] CDS percentage bid-ask spread is calculated by dividing CDS bid-ask spread by CDS spread.

[5] Stock percentage bid-ask spread is calculated by dividing bid-ask spread by stock price.

percentage bid-ask spread and stock percentage bid-ask spread of Telenor ASA are 20% and 3% respectively.

The market participants have been following the standard contracts and definitions introduced by the International Swaps and Derivatives Association (ISDA), hence the negotiation costs are significantly reduced. Instead of writing a lengthy contract from scratch, the counterparties can just fill in blacks and check the boxes in the standardized template (Bomfim, 2015). CDSs are traded over-the-counter (OTC) bilaterally between buyers and sellers. The OTC trading is not as highly regulated as the stock exchange trading.

In frictionless markets, the stock and CDS market should reflect credit risk of the same reference entity instantly and simultaneously. The stock price and CDS spread of the same reference entity should change at the same time. However, many researchers found evidence that there is a lead-lag relation between the CDS and stock market. They claim one market processes information more efficiently than the other, hence it can price the changing credit risk faster than the other. Acharya and Johnson (2007) explained that since banks have private information on borrowers through their lending relationships, the CDS market can be more vulnerable to insider trading if the participants acquire that information from the lenders. Therefore, they believe that the CDS market reflects credit risk faster than the stock market. On the other hand, the stock market should lead the CDS market according to the market selection theory (Easley et al., 1997), informed traders select market partially according to the transaction costs. For transaction cost considerations, informed traders are deterred from trading in the CDS market due to high spreads (Norden and Weber, 2009), thus they choose to trade only in the stock market. As a result, there are more informed traders in the stock market than the CDS market.

On a more personal note, I worked in the credit reporting company Experian before and have been interested in credit risk management for many years. In 2019, I learned about credit default swaps in the derivatives course during my exchange semester in the University of Mannheim. I chose to write the thesis about CDS to gain a deeper understanding about it. After reading the current literature about CDS, I found out that there is no consensus among researchers regarding the lead-lag relation between the CDS and stock markets in reflecting credit risk. Thus, I would like to contribute to the unsettled debate myself. Furthermore, to the best of my knowledge, there are no prior studies addressing this question in the context of Norwegian financial markets and using Norwegian companies' data. I am studying in Norway and will work in Norway after graduation, I hope to gain a better knowledge about Norwegian financial system in the process of studying the Norwegian CDS and stock markets.

The thesis uses daily data from June 24th, 2010 to May 5th, 2017 on CDS spread changes and stock returns to examine whether credit risk is priced equally fast by the CDS and stock markets. The final sample includes three Norwegian companies, DNB Bank ASA, Telenor ASA, and Statoil ASA. I use vector autoregression with exogenous variables models (VARX) to study the question and further supplement the analysis by novel machine learning tools that allow for more flexibility in selecting the right lag order and set of exogenous predictors (referred to as the VARX-L[6] model, see Nicholson et al., 2017). The results of the VARX models show that unconditionally, stock returns predominantly lead CDS spread changes. However, after allowing for more heterogeneity and flexible lag structure in the VARX-L models, the analysis reveals that large lags of CDS spread changes can predict stock returns.

The thesis makes two key contributions to the literature. First, the paper adds to the literature by using Norwegian companies' data. Second, the paper extends the set of methods used to study related problems by adding a regularization component to the VARX analysis within the VARX-L framework.

The rest of the paper is organized in four sections. Section two provides a brief literature review. Section three focuses on the explanation of the data. Section four addresses the empirical analysis and the last section contains concluding remarks.

[6] An acronym for Structured Regularization for Large Vector Autoregressions with Exogenous Variables

# 2. Literature Review

In the study of the lead-lag relationship between the credit default swap (CDS) and stock market, some researchers found out that credit pricing information flows from CDS to stocks. Acharya and Johnson (2007) used a sample of 79 North American single-name CDS over the period January 2001 through October 2004 and found information flow from the CDS market to the stock market. They explained that informed banks have non-public information on borrowers through their lending relationships, thus CDS markets can utilize this information on underlying firms through the banks. This insider trading theory is verified by Berndt and Ostrovnaya (2007) with a bigger sample (144 U.S. firms from nine industries). They found a significant information flow from credit to equity markets, especially for highly volatile firms. In more recent research, Castellano and Scaccia (2014) used not only U.S. sample but also European sample which covers the period from 2004 to 2010. They used CDS index instead of single-name CDSs and found that the CDS indexes volatility tent to increase several months before the stock market volatility. Except for the insider trading theory, there is another explanation given by Eyssell et al. (2013), which found that China sovereign CDS spread changes leaded stock returns due to the inefficient of Chinese stock market. There were market impediments in the Chinese stock market while there are fewer restrictions in the CDS market.

However, there is a widespread view in the literature that the credit pricing information flows from stocks to CDSs, and not vice versa. One dominating explanation is market selection theory, which means informed traders select market partially according to the transaction costs. For transaction cost considerations, informed traders are deterred from trading in the CDS market due to the high spreads (Norden & Weber, 2009), thus choose to trade only in stock market. As a result, there are more informed traders in the stock market than the CDS market. The market selection theory is supported by Norden and Weber (2009) with a sample of 58 European and US companies and Hilscher et al. (2015) with a sample of almost 800 firms. Another explanation of why stock market leads CDS market is that CDS market is inefficient in processing information (Byström, 2005). The results of Tolikas and Topaloglou (2017) is compatible with the explanation that stock market leads the CDS market in the price discovery process. They found same results among a sample throughout four geographical regions (i.e., North America, Europe, the UK, and Asia) over the period from January 1, 2008, to June 30, 2014. The dominance of stock market in the lead–lag relationships between the stock market and the CDS market is also supported by Trutwein and Scheireck (2011), Narayan et al. (2014), Forte and Peña (2009), Kiesel et al. (2016), and Ehlers et al. (2010).

Unlike the above literature which found a clear-cut evidence that the CDS market leads the stock market or the other way round. Norden and Weber (2004) and Flannery et al. (2010) found that the CDS and stock markets are generally equally efficient and it is hard to say which market leads consistently.

What's more, several researchers found out the lead-lag relationships between the stock market and the CDS market is dynamic. Which market leads the other market depends on other factors as explained below.

The main factor researchers discovered is the economy condition. On one hand, Forte and Lovreta (2015), Coudert and Gex (2010), Alexander and Kaeck (2008) found that the stock market is informationally dominant compared to the CDS market during periods of financial distress and the CDS market dominants during non-crisis periods. On the other hand, the results of Giannikos et al. (2013) showed that the stock market is leading the single-name CDS market in the price discovery process during stable periods while the single-name CDS market is informationally dominant during the crisis. This is supported by Santamaría et al. (2014), which used the sample of sovereign CDSs, sovereign bonds and equity for 13 European countries. Santamaría et al. (2014) found that sovereign CDS markets led the price discovery process during the 2010 sovereign debt crisis.

Marsh and Wagner (2016) stated that the lead-lag relationship between the stock market and the CDS market depends on the type of new information the markets are processing. They used a sample of 193 reference entities, from January 1, 2004 to October 14, 2008 and found that the stock market is quicker in processing macro information and common risk factors while the single-name CDS market reflects reference entity-specific information quicker. Marsh and Wagner (2016) gave a potential explanation that institutional investors with hedging demands in the CDS market are well informed about the reference entity-specific news, and may behave passively to macro news.

# 3. Data

This section details the construction of the final dataset used in the empirical part of the thesis. I first explain my choices of the set of companies, types of CDS contracts and time window. Then I look at some descriptive statistics and provide basic analysis of the time series.

I extract stock prices from Bloomberg Terminal and credit default swap spreads from Thomson Reuters DataStream, respectively. The Bloomberg Terminal provides real-time data on financial markets including but not limited to equities, foreign exchange, fixed income, commodities, and derivatives. Thomson Reuters DataStream provides worldwide historical data of over 93,000 active CDSs and 8,000 inactive CDSs as of May 2018 (Thomson Reuters, n.d.). It also provides all kinds of other financial data, such as bonds, exchange rates, equities.

## 3.1 CDS Sample Selection

This section explains the process of selecting 6 CDS contracts from the initial 591 CDS contracts in the Norwegian CDS market. I also briefly discuss the essential CDS contractual terms. The final sample are on three reference entities, DNB Bank ASA, Telenor ASA, and Statoil ASA. The time period of the final sample is from June 24th, 2010 to May 5th, 2017.

### 3.1.1 Reference Entities

By searching the Norwegian CDS contracts from Thomson Reuters DataStream during the period from January 1st, 2010, to December 31st, 2019. There are 591 CDS contracts, 566 of which are active. The reference entities are shown in table 1. In Norway, the public limited liability company put ASA in its name while the private limited liability company put AS in the company name (Norges Bank, 2018).

As the thesis focuses on corporate level, all the sovereign CDS contracts are excluded. Since CMTSU Liquidation is a foreign company and the thesis focuses on the Norwegian market, it is excluded from the sample. The Norwegian bond market attracts foreign issuers because the bond issue regulations in Norway is more concise and standardised than many other countries (Norges Bank, 2018). The CDS contracts are based on the underlying bonds, so there are CDSs with foreign reference entities.

In order to analyse the relation between the CDS and stock market, the samples must be public company, thus, Lock Lower AS and Lock Topco AS are eliminated from the sample. The IPO of Norske Skog happened only on the $18^{th}$ of October 2019, I exclude it from the sample since the time series on stock returns are too short for credible inference.

With the funds financed from the Norwegian bond market and the international capital markets, Eksportfinans ASA has been providing loans to Norwegian exporting companies until 2011 (Norges Bank, 2018). Since 2012, the Norwegian government established a new company, Eksportkreditt Norge AS, to take the function of export financing. Therefore, Eksportfinans gradually phased out the existing loans and stopped new borrowing and lending. Furthermore, the CDS spread data of Eksportfinans ASA is not available on the Thomson Reuters DataStream. Thus, Eksportfinans ASA is also excluded from the sample.

The daily CDS spread time series data of Yara International ASA and Storebrand ASA are shown in figure 1. The CDS spreads remained unchanged for months or years. Because these time series are very illiquid, they are not selected as the final sample. Regarding the meanings of CDS names "SNR MM14 5Y $" and "SNR MR14 5Y $", I explain in the sections 3.1.2-3.1.5. They are the four most essential CDS contractual terms, which are seniority level, restructuring clauses, contract maturity, and settlement currency.

*Table 1: The reference entities of Norwegian CDS contracts*

| Reference Entity | Active CDSs Number[7] | Type |
|---|---|---|
| CMTSU Liquidation | 50 | Foreign Company |
| Kingdom of Norway | 36 | Sovereign |
| Lock Lower AS | 16 | Private Limited Company |
| Lock Topco AS | 5 | |
| DNB Bank ASA | 184 | Public Limited Company |
| Telenor ASA | 71 | |
| Statoil ASA | 81 | |
| Eksportfinans ASA | 16 | |
| Norske Skog ASA | 71 | |
| Storebrand ASA | 26 | |
| Yara International ASA | 10 | |
| Total | 566 | |

[7] In the period from January 1st, 2010 to December 31st, 2019.

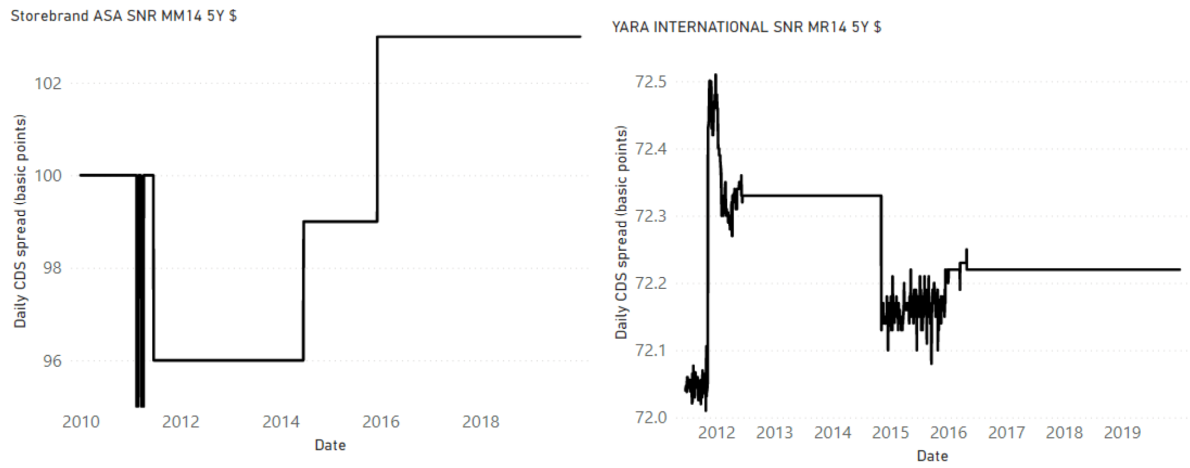


*Figure 1: CDS spreads of Storebrand ASA and Yara International ASA*

This leaves me with 3 companies out of 11 reference entities in the Norwegian CDS market, representing three different sectors of the economy: DNB Bank ASA (Banking sector), Telenor ASA (Telecommunications sector), and Statoil ASA[8] (Oil and Gas Producers).

### 3.1.2 Seniority Level

In the Norwegian bond market, covered bonds[9] have preferred claims on mortgages of mortgage companies and secured bonds are backed by collateral (Norges Bank, 2018). These bonds have higher priority of repayment and have lower credit risk compared to unsecured bonds. In the Norwegian CDS market, bondholders usually do not buy CDS contract for these bonds.

Unsecured bonds are not backed by collateral; hence they have higher credit risk. Unsecured bonds are further classified as senior unsecured bonds and subordinated unsecured bonds. The former has higher priority for repayment than the latter. If a bond issuer goes bankrupt, the covered bonds and secured bonds are repaid first, then senior unsecured bonds, at last subordinated unsecured bonds. In the Norwegian CDS market. 494 of the 566 active CDS contracts are drawn on senior unsecured bond, while only 72 are drawn on subordinated unsecured bond. The full name of CDS only contains “senior” or “subordinated” to identify

[8] Statoil is now known as Equinor (Equinor, 2018).

[9] In Norway, covered bonds are issued by mortgages companies and are backed by mortgages (Norges Bank, 2018).

the seniority. In order to avoid lengthy name, the short name of CDS uses “SNR” or “SEN” to represent senior unsecured and “SUB” for subordinated unsecured.

In the current literature analysing the relationship between stocks and single-name CDSs, many researchers (Acharya and Johnson, 2007; Berndt and Ostrovnaya, 2007; Norden and Weber, 2009; Kiesel et al., 2016; Flannery et al., 2010; Norden and Weber, 2004) used CDS contracts drawn on senior unsecured debt. In line with the prior research, I also choose the CDS contracts on senior unsecured debt.

### 3.1.3 Restructuring Clauses

The CDS contract specifies which events trigger the protection payment. The event that triggers protection payment is called credit event. If none of the credit events occur before the CDS contract expires, they protection seller doesn’t need to make any payment to the protection buyer. The International Swaps and Derivatives Association (ISDA) defined the credit event in the 2003 Credit Derivatives Definitions. If the reference entity happens one or more of bankruptcy, failure to pay, obligation acceleration, obligation default, repudiation/moratorium or restructuring (ISDA, 2003: 30), the credit event triggers. In brief, restructuring means that the terms of a reference obligation change in a way that is disadvantageous to creditors, such as reducing the interest rate, reducing the principal amount, postponing interest or principal payment, changing payment priority or changing payment currency (ISDA, 2003: 32).

The CDS market have evolved four different contractual clauses for restructuring events in CDS contracts: 1) No restructuring. Credit events do not include any restructuring events; 2) Full restructuring. All restructuring events are included in the credit events. It was the standard contractual clause according to the 1999 ISDA credit derivatives definitions; 3) Modified restructuring. ISDA modified the restructuring clause in 2001. Restructuring events except for restructuring of bilateral loans are included in the credit events. Furthermore, the restructuring event only triggers to the CDS contract with a maturity of 30 months or less after the termination of the CDS contract (Packer & Zhu, 2005); 4) Modified-modified restructuring. Because some market participants especially European market participants thought the modified restructuring clause was too strict. ISDA further modified the modified restructuring clause. The maturity of underlying assets after the termination of the CDS contract must be shorter than 60 months for restructured obligations and 30 months for all other obligations.

Since the CDS transactions contain several contractual clauses, the CDS market developed a series of codes to represent the clauses. As in section 3.1.2, "SEN" and "SNR" represent senior unsecured while "SUB" means subordinated unsecured. Regarding restructuring clauses, the codes are 1) XR: No restructuring; 2) CR: Old/Full restructuring; 3) MR: Modified restructuring; 4) MM: Modified-modified restructuring (ISDA, 2014).

In 2014, ISDA published the 2014 Credit Derivatives Definitions, which became the new standard for CDS contracts. The 2014 definitions not only apply to new CDS contracts but also encourage existing contracts to adjust accordingly. In order to identify if the CDSs are following the 2014 definitions, the codes with "14" represent the CDSs under the 2014 definition. The new codes are shown in table 2. The active CDS number of each type in the Norwegian CDS market is also listed in the table. In regards to ISDA definitions, there are 140 CDSs following the 2003 definitions and 426 CDSs under the 2014 definitions. Regarding restructuring type, there are 265 MM, 171 XR, 100 CR, and 30 MR.

Kiesel et al. (2016) used modified-modified restructuring clause for European firms because it is common for European CDS contracts, which is confirmed in the Norwegian CDS market. Furthermore, the modified-modified restructuring was introduced mostly by the requests of European participants, so I choose CDS contracts with modified-modified restructuring.

*Table 2: Codes for ISDA Definitions and Restructuring Types*

| ISDA Definitions | Restructuring Type | Code | Active CDSs Number[10] |
|---|---|---|---|
| 2003 | No restructuring | XR | 0 |
| 2003 | Old /Full restructuring | CR | 60 |
| 2003 | Modified restructuring | MR | 10 |
| 2003 | Modified-modified restructuring | MM | 70 |
| 2014 | No restructuring | XR 14 | 171 |
| 2014 | Old /Full restructuring | CR 14 | 40 |
| 2014 | Modified restructuring | MR 14 | 20 |
| 2014 | Modified-modified restructuring | MM 14 | 195 |
| | | Total | 566 |

[10] In the period from January 1st, 2010 to December 31st, 2019.

### 3.1.4 Settlement Currency

By the end of 2017, around half of the outstanding bond funding in the Norway bond market is in foreign currencies (Norges Bank, 2018), which are mostly in Euro, also in United States Dollar, Swedish Krona, British Pound and others. The reference obligation of Norwegian CDS contracts is a bond, so the settlement currency is also mostly in Euro, 305 of the 566 active CDS contracts. The other currencies are United States Dollar (181 out of 566), United Kingdom Pound (20 out of 566), Canadian Dollar (15 out of 566), Japanese Yen (10 out of 566), Norwegian Krone (10 out of 566), Swedish Krona (10 out of 566), and Australian Dollar (10 out of 566).

In the current literature, Norden and Weber (2009), Forte and Peña (2009), Coudert and Gex (2010) chose the European CDSs sample with Euro as the settlement currency. In line with the prior research, I select the Euro settlement currency as well. The short names of CDSs usually use “EUR” or “E” to represent Euro, such as “DNB BANK SNR MM14 30Y EUR” and “TELENOR ASA SNR MM14 6M E”.

### 3.1.5 Contract Maturity

After selecting the reference entities, seniority level, restructuring clauses, and settlement currency, the number of CDS contracts reduced from 566 to 50. There are 10 CDS contracts on the reference entity Telenor ASA, 10 CDS contracts are on the reference entity Statoil ASA, and 30 CDSs are on the reference entity DNB Bank ASA.

Figure 2 shows the time series of CDS spreads on reference entity Telenor ASA, senior unsecured, modified-modified restructuring, 2014 definitions, Euro as settlement currency. The CDS spread is the daily closing midpoint (unit: basic points). The only difference among them is the maturity terms, which include 30-year, 20-year, 10-year, 7-year, 5-year, 4-year, 3-year, 2-year, 1-year, and 6-month. Most Norwegian bonds have one to ten years maturities, but some have up to 20 to 30 years (Norges Bank, 2018). Since the CDS contract maturity does not have to match the maturity of the reference obligation (Bomfim, 2015), all these CDS contracts have the same reference obligation. The time series follow the similar pattern. The longer the maturity, the higher the default probability, hence the higher the CDS spread. The volatility of the CDS spread seems to rise with maturity too.

It is common practice in the literature to study 5-year maturity CDS contracts because the researchers (e.g., Finnerty et al., 2013; Norden & Weber,2004; Trutwein & Schiereck, 2011) have found out that 5-year maturity CDS contracts are most popular and liquid among all maturity terms. In order to verify this statement, I count the percent of zero daily changes in each time series. A zero daily change usually means there is no transaction on the day. During the period from 1 January, 2010 to 31 December, 2019, there are 2608 observations on level data and 2607 observations on daily changes series. 7% of the daily changes in the 30-year maturity CDS are zero, 8% in 20-year maturity CDS, 10% in 10-year and 7-year maturity CDSs, 11% in 5-year maturity CDS, 14% in 4-year maturity CDS, 18% in 3-year maturity CDS, 22% in 2-year maturity CDS, 26% in 1-year maturity CDS, and 29% in 6-month maturity CDS. Therefore, generally speaking, in the Norwegian CDS market, the longer the maturity, the more liquid the CDS, while holding the others the same.

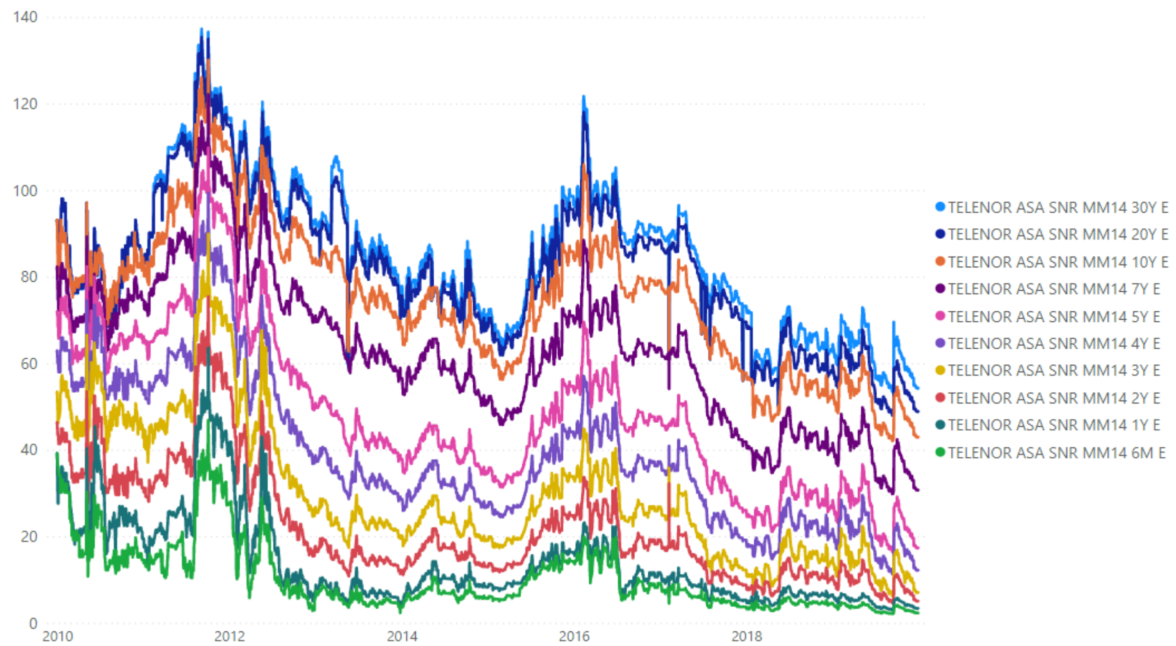


*Figure 2: Time series of CDS spreads on reference entity Telenor ASA*

Figure 3 shows the time series of CDS spreads on reference entity Statoil ASA, senior unsecured, modified-modified restructuring, 2003 definitions, Euro as settlement currency. These time series start from June 24, 2010 because Statoil ASA changed name from StatoilHydro ASA to Statoil ASA on November 2nd, 2009 (Equinor, 2009). The old CDS contracts were on the reference entity StatoilHydro ASA. The bonds issued after November

2nd, 2009 became the reference obligation of CDS contracts on reference entity Statoil ASA. These time series end on May 5, 2017 because the bonds matured in 2017. Furthermore, Statoil ASA changed name to Equinor ASA on March 15th, 2018 (Equinor, 2018). The bonds issued afterwards are the reference obligation of new CDS contracts on reference entity Equinor ASA.

During the period from June 24th, 2010 to May 5th, 2017, there are 1792 observations on level data and 1791 observations on daily changes series. 6% of the daily changes in the 30-year maturity CDS are zero, 8% in 20-year maturity CDS, 10% in 10-year maturity CDS, 11% in 7-year maturity CDS, 13% in 5-year maturity CDS, 14% in 4-year maturity CDS, 16% in 3-year maturity CDS, 18% in 2-year maturity CDS, 22% in 1-year maturity CDS, and 25% in 6-month maturity CDS. It confirms the conclusion from earlier that the longer the maturity, the more liquid the CDS, while holding the others the same.

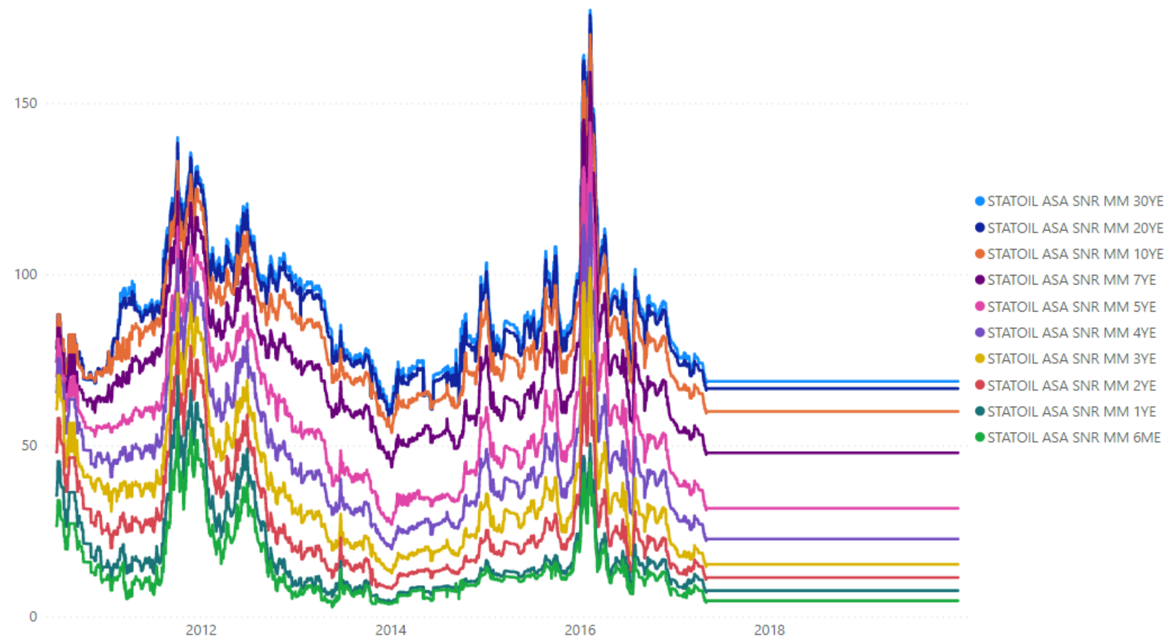


*Figure 3: Time series of CDS spreads on reference entity Statoil ASA*

Figure 4 shows the time series of CDS spreads on reference entity DnB Nor Bank ASA, senior unsecured, modified-modified restructuring, 2014 definitions, Euro as settlement currency. These time series end in 2013 because the bonds matured in 2013. Furthermore, DnB Nor Bank ASA changed name to DNB Bank ASA on November 11th, 2011 (DNB, 2011). The bonds issued afterwards are the reference obligation of new CDS contracts on reference entity DNB Bank ASA. When all other maturities' CDS contracts stopped transactions on March 13, 2013, the 5-year maturity CDS continued transactions until December 12, 2013. It confirms the finding of the current literature that the 5-year maturity CDS is most popular among all maturity terms.

For the sake of brevity, I calculate the percent of zero daily changes for all series in the same period. During the period from January 1st, 2010 to March 13th, 2013, there are 834 observations on level data and 833 observations on daily changes series. 18% of the daily changes in the 30-year and 20-year maturity CDSs are zero, 20% in 10-year maturity CDS, 21% in 7-year maturity CDS, 23% in 5-year maturity CDS, 25% in 4-year and 3-year maturity CDSs, 27% in 2-year maturity CDS, 30% in 1-year maturity CDS, and 31% in 6-month maturity CDS. It draws the same conclusion that the longer the maturity, the more liquid the CDS, while holding the others the same.

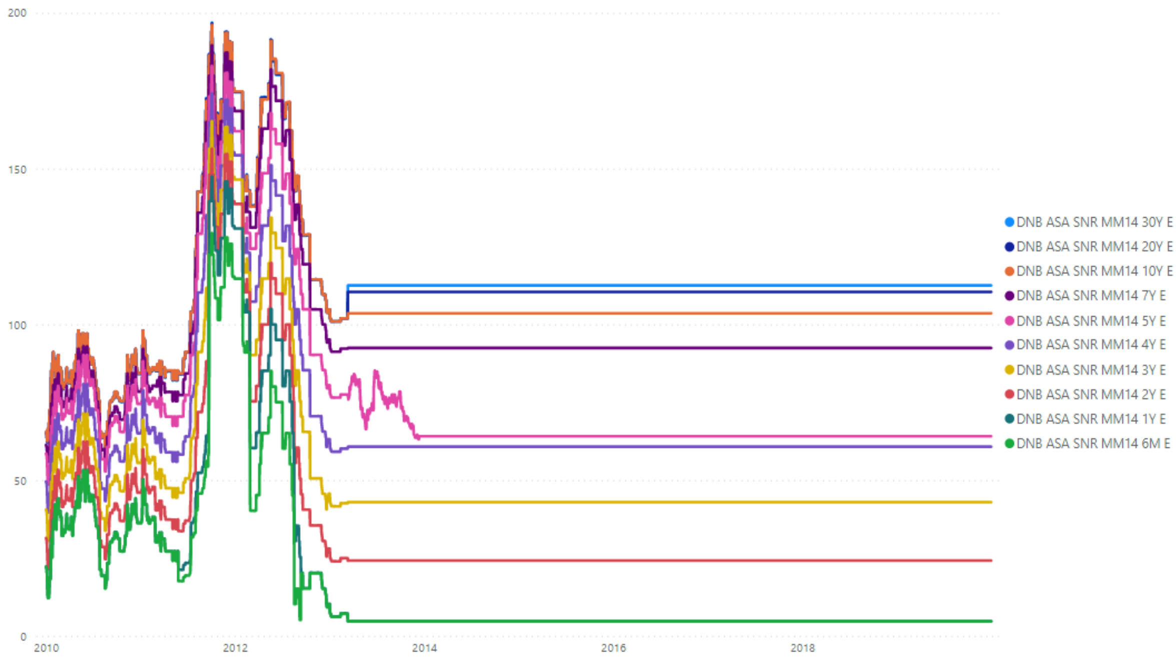


*Figure 4: Time series of CDS spreads on reference entity DnB Nor Bank ASA*

Figure 5 shows the time series of CDS spreads on reference entity DNB Bank ASA, senior unsecured, modified-modified restructuring, 2014 definitions, Euro as settlement currency. These time series start after November 11th, 2011 because DnB Nor Bank ASA changed name to DNB Bank ASA on November 11th, 2011. The old CDS contracts were on the reference entity DnB Nor Bank ASA, which are described above. The 5-year maturity CDS contract entered the market first on January 12th, 2012. Then the 30-year, 20-year, 10-year, and 7-year maturity CDSs entered on March 14th, 2013. The 4-year, 3-year, 2-year, and 1-year maturity CDSs started transactions on May 7th, 2015. Finally, the 6-month maturity CDS contracted entered the market on July 17th, 2015.

For the sake of brevity, I calculate the percent of zero daily changes for all series in the same period. During the period from July 17th, 2015 to December 31st, 2019, there are 1163 observations on level data and 1162 observations on daily changes series. 46% of the daily changes in the 30-year maturity CDS are zero, 48% in 20-year, 5-year, 4-year, and 3-year maturity CDSs, 49% in 7-year and 2-year maturity CDSs, 51% in 1-year and 6-month maturity CDS, and 52% in the 10-year maturity CDS. These series are very illiquid after December 5, 2018, therefore almost half of daily changes are zero.

Because all the contractual terms of the CDSs in figure 4 and 5 are the same, they are different CDS contracts due to the rename of the reference entity, I think it makes sense to merge the series with same maturity in figure 4 and 5 to get a series with longer time period. The CDS series on DnB Nor Bank ASA that ends on March 13th, 2013 and the CDS series on DNB Bank ASA that starts on March 14th, 2013 can be merged to be a longer series from January 1st, 2010 to December 31st, 2019.


*Figure 5: Time series of CDS spreads on reference entity DNB Bank ASA (2014 definitions)*

Figure 6 shows the time series of CDS spreads on reference entity DNB Bank ASA, senior unsecured, modified-modified restructuring, 2003 definitions, Euro as settlement currency. Since I choose the CDS contracts following 2014 definitions for DNB Bank ASA, these series are not selected in the final sample. It also confirms that year-5 maturity CDS entered the market first, and the longer the maturity, the higher the CDS spread.

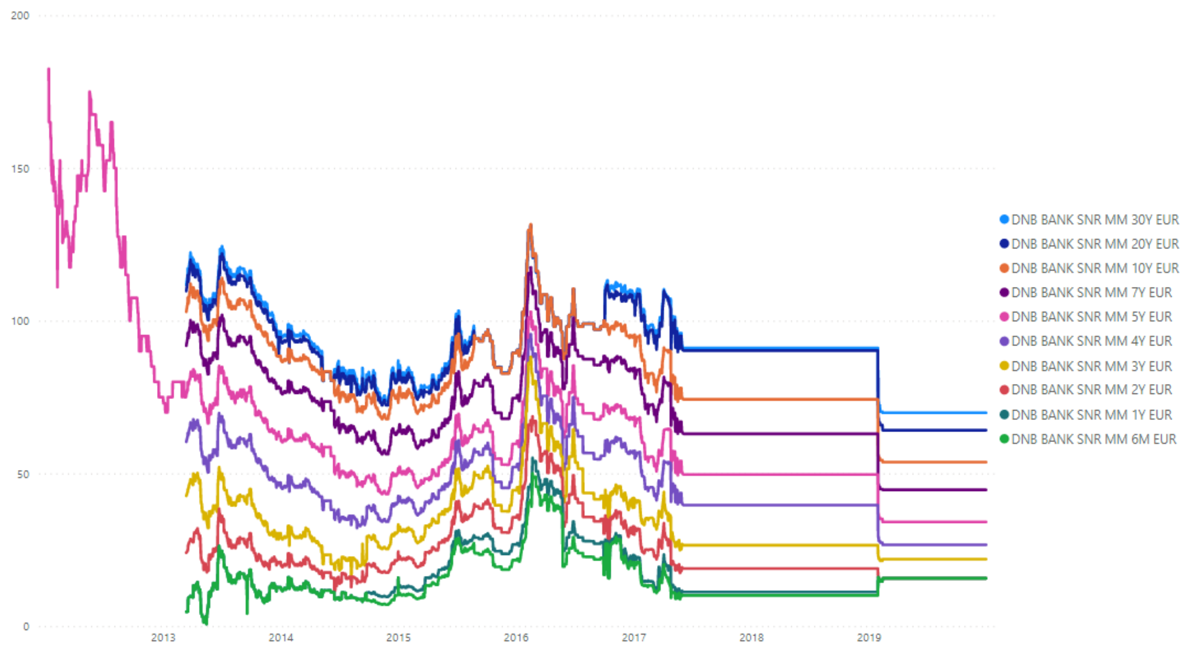


*Figure 6: Time series of CDS spreads on reference entity DNB Bank ASA (2003 definitions)*

In general, the longer the maturity, the more liquid the Norwegian CDS, remain other contractual terms the same. 5-year maturity CDS is most popular, it enters the CDS market no later than the other maturities and exits no sooner than the other maturities.

The study chooses the most liquid 30-year maturity CDS and also the most popular 5-year maturity CDS for each company. Hence, there are 6 CDS contracts chosen as the final CDS sample. Because the CDSs on Statoil ASA span from June 24$^{th}$, 2010 to May 5$^{th}$, for the sake of brevity, the sample time period for all companies is from June 24$^{th}$, 2010 to May 5$^{th}$.

## 3.2 Stock Prices

Each CDS reference entity is matched to a traded equity. The Norwegian equities are issued and traded on Oslo Børs. The daily closing prices for the stocks are obtained from Bloomberg

Terminal over the time period from June 24th, 2010 to May 5th, 2017. Then the daily returns were calculated as log changes of equity prices. There are very few zero observations in the stock returns time series. The percentage of non-zero observations in the three stock returns time series are 94.9% (Statoil ASA), 95.3% (DNB Bank ASA), and 94.9% (Telenor ASA). Thus, the Norwegian stock market appears to be more liquid than the CDS market. Because the CDS contracts are traded OTC between institutional investors, the CDS market may not be as active as the stock market which is filled with both institutional investors and retail investors.

Figure 7, 8 and 9 show the time series of stock price and return for the three companies respectively. The stock price time series seem to be non-stationary, while the stock returns look stationary. Although the three companies are in different industry, they share some similarities in the long term. They all reached bottom around 2012, then bounced up. Statoil ASA reached peak in the middle of 2014, while the other two companies continued going up until the middle of 2015. The three series touched bottom again in the middle of 2016. Since Norway has an open economy, one assumption is that they are all affected by the global economy and Norwegian economy.

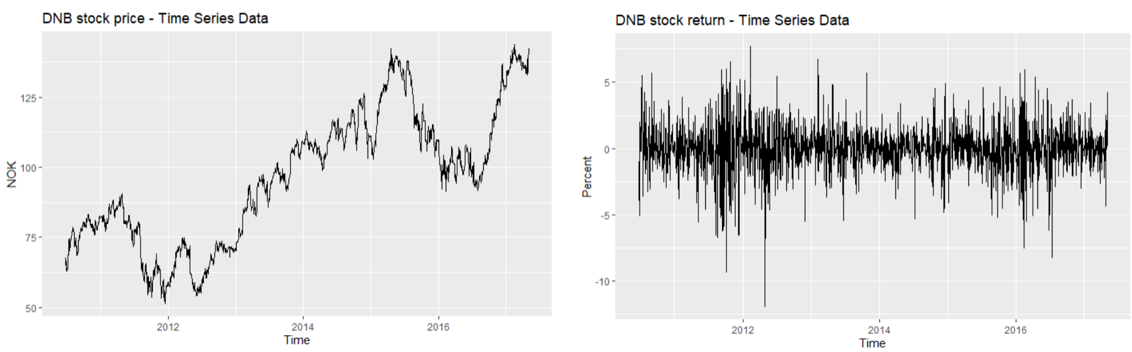


*Figure 7: DNB Bank ASA stock price and stock return*

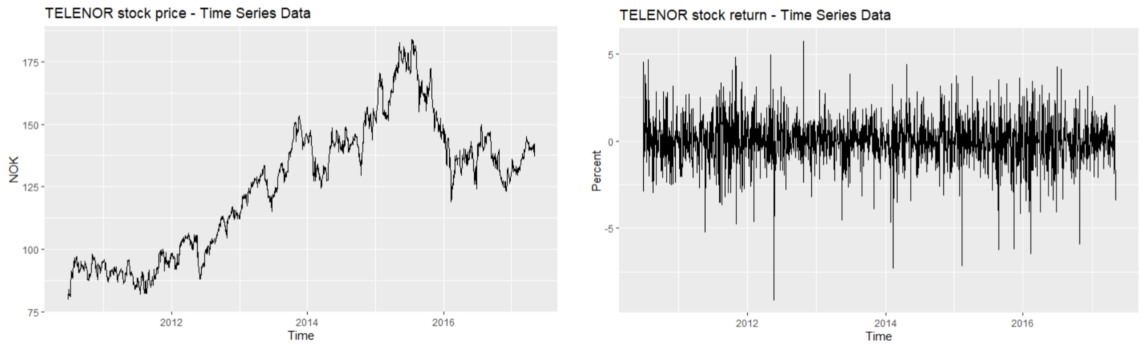


*Figure 8: Telenor ASA stock price and stock return*

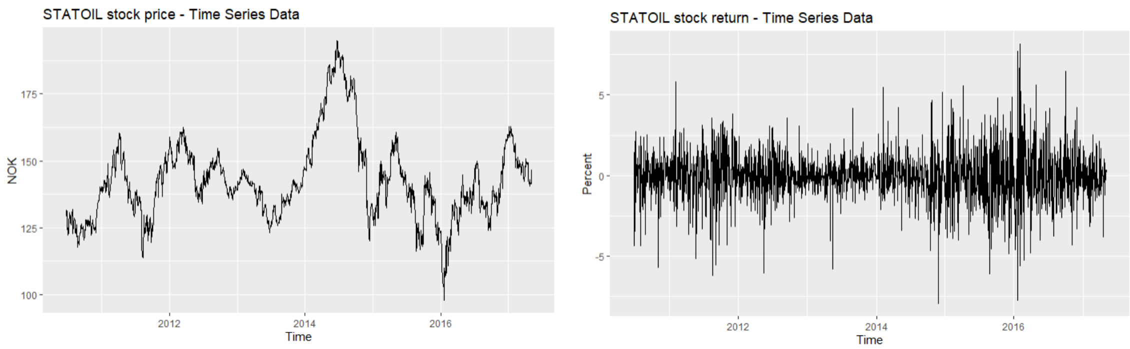


*Figure 9: Statoil ASA stock price and stock return*

## 3.3 Exogenous Variables

The main method used in the analysis is a vector autoregression with exogenous variables model (VARX) where CDS spread changes and stock returns are endogenous variables.

In Norway, government bond yields serve as reference rates for corporate bonds, CDSs and other financial instruments (Norges Bank, 2018). Norwegian government bonds are listed and traded on Oslo Børs (Norges Bank, 2018), so they are liquid enough to act as reference rates. In order to provide reference rates to financial instruments with different maturities, the government bonds have maturities ranging from 3-month to 10-year. Since the samples of the study are 5-year and 30-year maturities CDSs, I choose 10-year maturity government bond yield. Furthermore, the government bond yields are not decided by the credit risk of an individual company, therefore the bond yields seem to be determined outside the model and can be the exogenous variable.

Norway is an open economy, since the exports of goods and services (of GDP) is 38.44% and imports of goods and services (of GDP) is 32.63% (World Integrated Trade Solution, n.d.). Norwegian krone (NOK) floats freely so the NOK/Euro rate changes all the time. NOK/Euro rate measures the unites of Norwegian krone equivalent to one unit of Euro. An increase in the NOK/Euro rate represents the devaluation of Norwegian krone relative to Euro. Priestley and Ødegaard (2002) found evidence that the Norwegian stock market has statistically significant exchange rate exposure. To be specific, Norwegian industries have a negative exposure to the NOK/ECU[11] rate, and the stock prices fall if Norwegian krone depreciates. Therefore, I add the exchange rate shock to the VARX model and choose NOK/Euro rate change as the second exogenous variable.

In summary, I use two exogenous variables obtained from Norges Bank, the Norwegian central bank: lagged changes of the NOK/Euro rate and lagged changes of 10-year Norwegian government bond yield, which are assumed to be determined outside of the system.

## 3.4 Descriptive statistics

Table 3 presents summary statistics for the daily CDS spreads (unit: basis points, 100 basis points is 1%) and daily stock prices (unit: NOK). Table 4 presents summary statistics for daily percentage changes of CDS spread and stock price. 30-year maturity CDS spreads are higher than 5-year maturity CDS spreads for the same reference entity. CDS spreads and changes are both positively skewed. The CDS spread changes have very high kurtosis, which means the values extremely deviate from the mean. CDS spreads and changes have higher standard deviation than stock prices and changes of the same company. The CDS spread changes are more volatile compared to the stock returns with a very wide range between the minimum and maximum. The wide range of daily CDS spread changes is due to the high CDS bid-ask spread. The transaction costs of the CDS market are higher than those of the stock market and deter some traders from entering the CDS market. According to the market selection theory, some informed traders are deterred by the high transaction costs of the CDS market and would choose only the equity market.

[11] ECU is the predecessor of Euro (Priestley & Ødegaard, 2002).

*Table 3: Descriptive statistics for the daily CDS spreads and stock prices*

| Company | Series | N | Mean | Sd | Median | Min | Max | Range | Skew | Kurtosis |
|---|---|---|---|---|---|---|---|---|---|---|
| DNB | 5Y CDS | 1792 | 80.53 | 32.60 | 70.50 | 45.72 | 182.96 | 137.24 | 1.51 | 1.30 |
| | 30Y CDS | 1792 | 106.62 | 29.60 | 98.32 | 60.51 | 196.89 | 136.38 | 1.33 | 0.97 |
| | Stock | 1792 | 96.06 | 23.51 | 97.50 | 51.35 | 143.75 | 92.40 | 0.09 | -0.98 |
| Telenor | 5Y CDS | 1792 | 54.62 | 16.25 | 49.92 | 31.36 | 109.82 | 78.46 | 1.00 | 0.54 |
| | 30Y CDS | 1792 | 91.75 | 14.68 | 90.15 | 58.95 | 137.26 | 78.32 | 0.38 | -0.24 |
| | Stock | 1792 | 125.57 | 25.94 | 130.05 | 80.15 | 183.85 | 103.70 | 0.05 | -0.99 |
| Statoil | 5Y CDS | 1792 | 56.64 | 19.30 | 54.34 | 26.91 | 144.34 | 117.43 | 1.16 | 1.59 |
| | 30Y CDS | 1792 | 89.64 | 17.72 | 87.49 | 57.94 | 177.17 | 119.23 | 1.21 | 2.30 |
| | Stock | 1792 | 142.57 | 15.42 | 140.75 | 97.93 | 194.85 | 96.93 | 0.86 | 1.18 |

*Table 4: Descriptive statistics for daily CDS spread changes and stock returns*

| Company | Series | N | Mean | Sd | Median | Min | Max | Range | Skew | Kurtosis |
|---|---|---|---|---|---|---|---|---|---|---|
| DNB | 5Y CDS | 1791 | 0.00 | 2.22 | 0.00 | -20.76 | 16.93 | 37.68 | 0.13 | 20.16 |
| | 30Y CDS | 1791 | 0.03 | 1.90 | 0.00 | -15.43 | 15.18 | 30.61 | 0.43 | 19.33 |
| | Stock | 1791 | 0.06 | 1.79 | 0.00 | -10.68 | 8.33 | 19.01 | -0.12 | 2.87 |
| Telenor | 5Y CDS | 1791 | -0.01 | 1.71 | 0.00 | -10.78 | 15.40 | 26.18 | 1.05 | 10.20 |
| | 30Y CDS | 1791 | 0.04 | 2.85 | 0.00 | -37.48 | 47.51 | 84.99 | 2.60 | 94.70 |
| | Stock | 1791 | 0.04 | 1.38 | 0.00 | -8.36 | 6.08 | 14.44 | -0.23 | 2.79 |
| Statoil | 5Y CDS | 1791 | -0.02 | 2.34 | 0.00 | -13.09 | 15.46 | 28.55 | 0.69 | 7.83 |
| | 30Y CDS | 1791 | 0.02 | 2.51 | 0.00 | -16.33 | 19.51 | 35.84 | 0.74 | 16.07 |
| | Stock | 1791 | 0.02 | 1.60 | 0.00 | -7.38 | 8.89 | 16.26 | 0.20 | 2.76 |

*Table 5: Correlation between daily CDS spread (changes) and stock prices (changes)*

| Correlation | Stock price | Correlation | Stock return |
|---|---|---|---|
| DNB | | DNB | |
| 5Y CDS spread | -0.7634(<0.001) | 5Y CDS spread change | -0.1521(<0.001) |
| 30Y CDS spread | -0.5998(<0.001) | 30Y CDS spread change | -0.1407(<0.001) |
| TELENOR | | TELENOR | |
| 5Y CDS spread | -0.8051(<0.001) | 5Y CDS spread change | -0.2053(<0.001) |
| 30Y CDS spread | -0.5997(<0.001) | 30Y CDS spread change | -0.1131(<0.001) |
| STATOIL | | STATOIL | |
| 5Y CDS spread | -0.4134(<0.001) | 5Y CDS spread change | -0.2383(<0.001) |
| 30Y CDS spread | -0.3579(<0.001) | 30Y CDS spread change | -0.1737(<0.001) |

Left panel of table 5 shows the pairwise correlation coefficients between the daily CDS spreads and stock prices. Right panel of table 5 presents the same measures between the daily CDS spread changes and the daily stock returns. The p-values are in parentheses. There are spurious relationships between the two variables both in level data and in changes data. The estimates indicate a fairly strong negative correlation, which is consistent with Norden & Weber (2009), Fung et al. (2008), and Byström (2008).

# 4. Analysis

This section presents the main results of the thesis. I begin with studying the key statistical properties of the time series (stationarity and presence of cointegrating relationships). Consistent with those results, I then formulate standard VARX models to examine the lag-lead relationship between the CDS and stock markets. Finally, I provide additional insights to the baseline findings by estimating regularized VARX models, which use machine learning techniques to allow for more flexible lag structures.

## 4.1 Stationarity Test

It is important to examine stationarity of the individual time series because the VAR model is no longer applicable if time series are nonstationary. The augmented Dickey-Fuller (ADF) unit root test results show that the level time-series (stock prices, CDS spreads, bond yield, and exchange rate) are nonstationary. All daily time-series of stock returns, CDS spread changes, bond yield change, and exchange rate change are stationary and ready for the subsequent analyses. The corresponding number of lags in the ADF Tests are selected according to the Akaike Information Criterion. Table 6 summarizes the results of the tests.

*Table 6: Unit Root Tests*

| Variable | Test-statistic | Critical Values | | | Null hypothesis | Conclusion |
|---|---|---|---|---|---|---|
| | | 1% | 5% | 10% | | |
| DNB 5Y CDS spread | -1.658 | -3.96 | -3.41 | -3.12 | Unit root | Unit root |
| DNB 30Y CDS spread | -1.745 | | | | | |
| Telenor 5Y CDS spread | -1.850 | | | | | |
| Telenor 30Y CDS spread | -3.009 | | | | | |
| Statoil 5Y CDS spread | -2.486 | | | | | |
| Statoil 30Y CDS spread | -2.657 | | | | | |
| DNB Stock price | -2.236 | | | | | |
| Telenor Stock price | -2.111 | | | | | |
| Statoil Stock price | -3.063 | | | | | |
| Exchange rate | -2.599 | | | | | |
| Bond yield | -2.305 | | | | | |
| DNB 5Y CDS spread change | -29.507 | -2.58 | -1.95 | -1.62 | Unit root | Stationary |
| DNB 30Y CDS spread change | -30.320 | | | | | |
| Telenor 5Y CDS spread change | -27.609 | | | | | |

| Variable | Test-statistic | Critical Values | | | Null hypothesis | Conclusion |
|---|---|---|---|---|---|---|
| | | 1% | 5% | 10% | | |
| Telenor 30Y CDS spread change | -35.014 | | | | | |
| Statoil 5Y CDS spread change | -25.325 | | | | | |
| Statoil 30Y CDS spread change | -31.221 | | | | | |
| DNB Stock return | -31.320 | | | | | |
| Telenor Stock return | -30.685 | | | | | |
| Statoil Stock return | -31.855 | | | | | |
| Exchange rate change | -29.679 | | | | | |
| Bond yield change | -27.840 | | | | | |

## 4.2 Cointegration Test

Using Johansen's cointegration test to examine the presence of a cointegrating relationship between stock prices and CDS spreads, the results in table 7 show no evidence of cointegration at the 5% significance level. Therefore, there is no statistical evidence that Norwegian stock market and CDS market have a long-run equilibrium relationship.

*Table 7: Johansen's Cointegration Test*

| Variable | Null hypothesis | Test Statistic | Critical Values | | |
|---|---|---|---|---|---|
| | | | 10% | 5% | 1% |
| DNB 5Y CDS spread<br>DNB stock price | r <= 1 | 2.83 | 10.49 | 12.25 | 16.26 |
| | r = 0 | 11.55 | 16.85 | 18.96 | 23.65 |
| DNB 30Y CDS spread<br>DNB stock price | r <= 1 | 3.09 | 10.49 | 12.25 | 16.26 |
| | r = 0 | 9.96 | 16.85 | 18.96 | 23.65 |
| Telenor 5Y CDS spread<br>Telenor stock price | r <= 1 | 3.17 | 10.49 | 12.25 | 16.26 |
| | r = 0 | 9.86 | 16.85 | 18.96 | 23.65 |
| Telenor 30Y CDS spread<br>Telenor stock price | r <= 1 | 4.37 | 10.49 | 12.25 | 16.26 |
| | r = 0 | 16.91 | 16.85 | 18.96 | 23.65 |
| Statoil 5Y CDS spread<br>Statoil stock price | r <= 1 | 6.96 | 10.49 | 12.25 | 16.26 |
| | r = 0 | 9.76 | 16.85 | 18.96 | 23.65 |
| Statoil 30Y CDS spread<br>Statoil stock price | r <= 1 | 8.41 | 10.49 | 12.25 | 16.26 |
| | r = 0 | 11.96 | 16.85 | 18.96 | 23.65 |

## 4.3 VARX Models

### 4.3.1 Methodology

In the literature of lead-lag relationship between the CDS and stock markets, vector autoregression (VAR) models have been widely used as the empirical analysis tool by many researchers, such as Eyssell et al. (2013), Norden & Weber (2009), Hilscher et al. (2015), Trutwein & Scheireck (2011), and Marsh & Wagner (2016). Since the VAR model can reflect the intertemporal co-movement between variables, it is suitable to detect the lead-lag relationship. Furthermore, Norwegian stock market and CDS market do not have a long-run equilibrium relationship, so the standard VAR is more appropriate than a VECM.

In total, I estimate six VARX (X for exogenous variables) models at the firm level. This means there are two separate models for each company, one with 5-year maturity CDS and the other with 30-year maturity CDS. Each VARX model consists of two equations, the first equation with CDS spread change as dependent variable and the second equation with stock return as dependent variable, while lagged bond yield change and lagged exchange rate change are exogenous variables in both equations. The lag order of endogenous variables is selected for each model by AIC. The lag order of exogenous variables is 1. The specification for each model is as below:

$$\begin{pmatrix} \Delta CDS_t \\ \Delta Stock_t \end{pmatrix} = \begin{pmatrix} \alpha_0 \\ \beta_0 \end{pmatrix} + \begin{pmatrix} \sum_{i=1}^{p} \alpha_{1,i} & \sum_{i=1}^{p} \alpha_{2,j} \\ \sum_{i=1}^{p} \beta_{1,i} & \sum_{i=1}^{p} \beta_{2,j} \end{pmatrix} \begin{pmatrix} \Delta Stock_{t-i} \\ \Delta CDS_{t-i} \end{pmatrix} + \begin{pmatrix} \alpha_3 & \alpha_4 \\ \beta_3 & \beta_4 \end{pmatrix} \begin{pmatrix} \Delta IN_{t-1} \\ \Delta EX_{t-1} \end{pmatrix} + \begin{pmatrix} \epsilon_t \\ \varepsilon_t \end{pmatrix} \quad (1)$$

with $\Delta Stock_t$: stock return in t, $\Delta CDS_t$: CDS spread change in t, $\Delta IN_{t-1}$: bond yield change in t-1, $\Delta EX_{t-1}$: exchange rate change in t-1, $p$: lag order, $\varepsilon_t$ and $\epsilon_t$ are the idiosyncratic shocks.

### 4.3.2 Empirical Results

Before fitting the six VARX models, I conduct granger causality tests where the order of lags is selected according to the Akaike Information Criterion. The results in table 8 show that stock returns Granger cause CDS spread changes at 1% significance reveal, while CDS spread changes do not Granger cause stock returns. Granger-causality tests do not infer causality. The results only indicate that the past values of stock returns help to predict the current value of

CDS spread changes. It has to be noted that the correlation may be caused by some other factors that affect both the Norwegian stock and CDS markets.

*Table 8: Granger Causality Tests*

| Company | Null Hypothesis | Lag Order | F-Statistic | Prob. |
|---|---|---|---|---|
| DNB | $\Delta Stock$ doesn't Granger cause 5-year $\Delta CDS$ | 2 | 14.4 | <0.001 *** |
| | 5-year $\Delta CDS$ doesn't Granger cause $\Delta Stock$ | | 0.49 | 0.62 |
| | $\Delta Stock$ doesn't Granger cause 30-year $\Delta CDS$ | 1 | 21.4 | <0.001 *** |
| | 30-year $\Delta CDS$ doesn't Granger cause $\Delta Stock$ | | 0.16 | 0.69 |
| Telenor | $\Delta Stock$ doesn't Granger cause 5-year $\Delta CDS$ | 6 | 4.26 | <0.001 *** |
| | 5-year $\Delta CDS$ doesn't Granger cause $\Delta Stock$ | | 0.82 | 0.56 |
| | $\Delta Stock$ doesn't Granger cause 30-year $\Delta CDS$ | 2 | 16 | <0.001 *** |
| | 30-year $\Delta CDS$ doesn't Granger cause $\Delta Stock$ | | 1.03 | 0.36 |
| Statoil | $\Delta Stock$ doesn't Granger cause 5-year $\Delta CDS$ | 4 | 15.7 | <0.001 *** |
| | 5-year $\Delta CDS$ doesn't Granger cause $\Delta Stock$ | | 0.26 | 0.9 |
| | $\Delta Stock$ doesn't Granger cause 30-year $\Delta CDS$ | 10 | 8.28 | <0.001 *** |
| | 30-year $\Delta CDS$ doesn't Granger cause $\Delta Stock$ | | 0.39 | 0.95 |

The results from the six VARX models are shown in tables 9-14. The estimated coefficients, t-statistics, and p-values are shown in the tables. For each equation, the adjusted $R^2$, F-statistic, and p-value are also shown in the tables. ** and * indicate significance at the 1% and 5% levels respectively.

All the results can be summarized as follows: 1) there is a significantly negative co-movement of stock returns and CDS spread changes, 2) the lagged equity returns significantly predict the CDS returns, 3) the lagged CDS spread changes are never significant in predicting the stock returns. The results of the VARX models with exogenous variables are consistent with the Granger-causality relationships between the stock returns and CDS spread changes. One reason why the stock market reflects new information quicker is that the CDS market cannot reflect information as quick as the stock market due to the liquidity problem.

*Table 9: VARX of DNB 5-year CDS spread change and DNB stock return*

| Dependent Variables / Independent Variables | $\Delta CDS_t$ | | | $\Delta Stock_t$ | | |
|---|---|---|---|---|---|---|
| | Estimate | t-value | Pr(>\|t\|) | Estimate | t-value | Pr(>\|t\|) |
| Constant | 0.0126 | 0.23 | 0.815 | 0.069 | 1.58 | 0.114 |
| $\Delta CDS_{t-1}$ | -0.018 | -0.74 | 0.458 | -0.015 | -0.77 | 0.443 |

| Dependent Variables / Independent Variables | $\Delta CDS_t$ | | | $\Delta Stock_t$ | | |
|---|---|---|---|---|---|---|
| | Estimate | t-value | Pr(>\|t\|) | Estimate | t-value | Pr(>\|t\|) |
| $\Delta Stock_{t-1}$ | **-0.135** | **-4.29** | **<0.001 ***** | -0.041 | -1.60 | 0.109 |
| $\Delta CDS_{t-2}$ | -0.019 | -0.79 | 0.432 | -0.010 | -0.52 | 0.601 |
| $\Delta Stock_{t-2}$ | **-0.076** | **-2.54** | **0.011 *** | -0.043 | -1.75 | 0.079 |
| $\Delta IN_{t-1}$ | -0.021 | -0.84 | 0.399 | 0.022 | 1.08 | 0.282 |
| $\Delta EX_{t-1}$ | 0.022 | 0.21 | 0.837 | -0.077 | -0.86 | 0.389 |
| Adjusted R-squared | 0.0136 | | | 0.000178 | | |
| F-statistic | 4.95 on 6 and 1717 DF | | | 1.05 on 6 and 1717 DF | | |
| P-value | <0.001 | | | 0.39 | | |

*Table 10: VARX of DNB 30-year CDS spread change and DNB stock return*

| Dependent Variables / Independent Variables | $\Delta CDS_t$ | | | $\Delta Stock_t$ | | |
|---|---|---|---|---|---|---|
| | Estimate | t-value | Pr(>\|t\|) | Estimate | t-value | Pr(>\|t\|) |
| Constant | 0.036 | 0.80 | 0.4249 | 0.065 | 1.48 | 0.14 |
| $\Delta CDS_{t-1}$ | **-0.066** | **-2.73** | **0.006 **** | -0.008 | -0.35 | 0.73 |
| $\Delta Stock_{t-1}$ | **-0.106** | **-4.01** | **<0.001 ***** | -0.040 | -1.55 | 0.12 |
| $\Delta IN_{t-1}$ | -0.038 | -1.78 | 0.0749 | 0.021 | 1.01 | 0.31 |
| $\Delta EX_{t-1}$ | -0.023 | -0.25 | 0.8023 | -0.062 | -0.69 | 0.49 |
| Adjusted R-squared | 0.0142 | | | -0.000478 | | |
| F-statistic | 7.19 on 4 and 1721 DF | | | 0.794 on 4 and 1721 DF | | |
| P-value | <0.001 | | | 0.529 | | |

*Table 11: VARX of Telenor 5-year CDS spread change and Telenor stock return*

| Dependent Variables / Independent Variables | $\Delta CDS_t$ | | | $\Delta Stock_t$ | | |
|---|---|---|---|---|---|---|
| | Estimate | t-value | Pr(>\|t\|) | Estimate | t-value | Pr(>\|t\|) |
| Constant | -0.009 | -0.23 | 0.8184 | 0.044 | 1.33 | 0.1846 |
| $\Delta CDS_{t-1}$ | **0.080** | **3.16** | **0.0016 **** | 0.004 | 0.23 | 0.8157 |
| $\Delta Stock_{t-1}$ | **-0.128** | **-4.20** | **<0.001 ***** | -0.028 | -1.14 | 0.2537 |
| $\Delta CDS_{t-2}$ | -0.005 | -0.23 | 0.8214 | 0.008 | 0.42 | 0.6711 |
| $\Delta Stock_{t-2}$ | -0.047 | -1.54 | 0.1226 | -0.014 | -0.57 | 0.5654 |
| $\Delta CDS_{t-3}$ | **0.051** | **2.09** | **0.0367 *** | 0.010 | 0.53 | 0.5980 |
| $\Delta Stock_{t-3}$ | -0.044 | -1.46 | 0.1452 | 0.014 | 0.59 | 0.5526 |
| $\Delta CDS_{t-4}$ | -0.029 | -1.18 | 0.2370 | 0.031 | 1.56 | 0.1180 |
| $\Delta Stock_{t-4}$ | -0.004 | -0.16 | 0.8725 | -0.043 | -1.73 | 0.0836 |
| $\Delta CDS_{t-5}$ | 0.011 | 0.45 | 0.6506 | -0.000 | 0.00 | 0.9980 |

| Independent Variables \ Dependent Variables | $\Delta CDS_t$ | | | $\Delta Stock_t$ | | |
|---|---|---|---|---|---|---|
| | Estimate | t-value | Pr(>\|t\|) | Estimate | t-value | Pr(>\|t\|) |
| $\Delta Stock_{t-5}$ | 0.001 | 0.06 | 0.9558 | **-0.052** | **-2.12** | **0.0342 *** |
| $\Delta CDS_{t-6}$ | -0.021 | -0.88 | 0.3799 | -0.027 | -1.36 | 0.1732 |
| $\Delta Stock_{t-6}$ | 0.019 | 0.65 | 0.5177 | **0.065** | **2.65** | **0.008 **** |
| $\Delta IN_{t-1}$ | -0.020 | -1.05 | 0.2927 | 0.011 | 0.72 | 0.4704 |
| $\Delta EX_{t-1}$ | **0.175** | **2.07** | **0.0390 *** | -0.019 | -0.29 | 0.7739 |
| Adjusted R-squared | 0.0295 | | | 0.00794 | | |
| F-statistic | 4.73 on 14 and 1706 DF | | | 1.98 on 14 and 1706 DF | | |
| P-value | <0.001 | | | 0.0159 | | |

*Table 12: VARX of Telenor 30-year CDS spread change and Telenor stock return*

| Independent Variables \ Dependent Variables | $\Delta CDS_t$ | | | $\Delta Stock_t$ | | |
|---|---|---|---|---|---|---|
| | Estimate | t-value | Pr(>\|t\|) | Estimate | t-value | Pr(>\|t\|) |
| Constant | 0.110 | 1.74 | 0.081 | 0.040 | 1.20 | 0.23 |
| $\Delta CDS_{t-1}$ | **-0.294** | **-12.15** | **<0.001 ***** | 0.001 | 0.12 | 0.90 |
| $\Delta Stock_{t-1}$ | **-0.221** | **-4.76** | **<0.001 ***** | -0.034 | -1.38 | 0.17 |
| $\Delta CDS_{t-2}$ | **-0.081** | **-3.38** | **<0.001 ***** | 0.018 | 1.42 | 0.16 |
| $\Delta Stock_{t-2}$ | **-0.118** | **-2.58** | **0.00997 **** | -0.013 | -0.55 | 0.58 |
| $\Delta IN_{t-1}$ | -0.032 | -1.10 | 0.270 | 0.010 | 0.70 | 0.49 |
| $\Delta EX_{t-1}$ | 0.096 | 0.75 | 0.455 | -0.007 | -0.10 | 0.92 |
| Adjusted R-squared | 0.0831 | | | -0.000715 | | |
| F-statistic | 27 on 6 and 1718 D | | | 0.795 on 6 and 1718 DF | | |
| P-value | <0.001 | | | 0.574 | | |

*Table 13: VARX of Statoil 5-year CDS spread change and Statoil stock return*

| Independent Variables \ Dependent Variables | $\Delta CDS_t$ | | | $\Delta Stock_t$ | | |
|---|---|---|---|---|---|---|
| | Estimate | t-value | Pr(>\|t\|) | Estimate | t-value | Pr(>\|t\|) |
| Constant | -0.019 | -0.35 | 0.72329 | 0.023 | 0.59 | 0.5565 |
| $\Delta CDS_{t-1}$ | **0.097** | **3.85** | **<0.001 ***** | -0.011 | -0.65 | 0.5187 |
| $\Delta Stock_{t-1}$ | **-0.244** | **-6.81** | **<0.001 ***** | 0.013 | 0.51 | 0.6091 |
| $\Delta CDS_{t-2}$ | **0.057** | **2.31** | **0.02122 *** | 0.003 | 0.19 | 0.8521 |
| $\Delta Stock_{t-2}$ | -0.025 | -0.71 | 0.48010 | **-0.077** | **-3.04** | **0.0024 **** |
| $\Delta CDS_{t-3}$ | 0.013 | 0.53 | 0.59413 | -0.013 | -0.78 | 0.4371 |
| $\Delta Stock_{t-3}$ | **-0.090** | **-2.56** | **0.01052 *** | -0.041 | -1.64 | 0.1009 |
| $\Delta CDS_{t-4}$ | **0.069** | **2.90** | **0.00383 **** | 0.009 | 0.55 | 0.5802 |

| Independent Variables \ Dependent Variables | $\Delta CDS_t$ | | | $\Delta Stock_t$ | | |
|---|---|---|---|---|---|---|
| | Estimate | t-value | Pr(>\|t\|) | Estimate | t-value | Pr(>\|t\|) |
| $\Delta Stock_{t-4}$ | -0.012 | -0.36 | 0.71896 | -0.010 | -0.41 | 0.6809 |
| $\Delta IN_{t-1}$ | -0.045 | -1.76 | 0.07859 | -0.025 | -1.40 | 0.1629 |
| $\Delta EX_{t-1}$ | 0.215 | 1.87 | 0.06118 | 0.003 | 0.04 | 0.9677 |
| Adjusted R-squared | 0.0745 | | | 0.0033 | | |
| F-statistic | 14.9 on 10 and 1712 DF | | | 1.57 on 10 and 1712 DF | | |
| P-value | <0.001 | | | 0.109 | | |

*Table 14: VARX of Statoil 30-year CDS spread change and Statoil stock return*

| Independent Variables \ Dependent Variables | $\Delta CDS_t$ | | | $\Delta Stock_t$ | | |
|---|---|---|---|---|---|---|
| | Estimate | t-value | Pr(>\|t\|) | Estimate | t-value | Pr(>\|t\|) |
| Constant | 0.039 | 0.66 | 0.50750 | 0.022 | 0.58 | 0.5612 |
| $\Delta CDS_{t-1}$ | **-0.192** | **-7.79** | **<0.001 *** ** | 0.002 | 0.13 | 0.8951 |
| $\Delta Stock_{t-1}$ | **-0.277** | **-7.24** | **<0.001 *** ** | 0.022 | 0.86 | 0.3890 |
| $\Delta CDS_{t-2}$ | 0.016 | 0.67 | 0.50019 | -0.0004 | -0.03 | 0.9774 |
| $\Delta Stock_{t-2}$ | -0.041 | -1.09 | 0.27718 | **-0.081** | **-3.23** | **0.0013 ** ** |
| $\Delta CDS_{t-3}$ | 0.027 | 1.09 | 0.27387 | -0.004 | -0.26 | 0.7918 |
| $\Delta Stock_{t-3}$ | **-0.090** | **-2.38** | **0.01736 * ** | -0.032 | -1.29 | 0.1978 |
| $\Delta CDS_{t-4}$ | 0.040 | 1.61 | 0.10681 | 0.004 | 0.25 | 0.8052 |
| $\Delta Stock_{t-4}$ | **-0.075** | **-1.99** | **0.04701 * ** | -0.014 | -0.55 | 0.5792 |
| $\Delta CDS_{t-5}$ | **0.057** | **2.31** | **0.02120 * ** | 0.001 | 0.09 | 0.9287 |
| $\Delta Stock_{t-5}$ | -0.022 | -0.59 | 0.55829 | -0.008 | -0.33 | 0.7413 |
| $\Delta CDS_{t-6}$ | 0.005 | 0.23 | 0.81529 | 0.004 | 0.26 | 0.7962 |
| $\Delta Stock_{t-6}$ | 0.034 | 0.92 | 0.36023 | -0.009 | -0.38 | 0.7027 |
| $\Delta CDS_{t-7}$ | **-0.079** | **-3.21** | **0.00136 ** ** | 0.0004 | 0.03 | 0.9790 |
| $\Delta Stock_{t-7}$ | -0.025 | -0.67 | 0.50141 | -0.029 | -1.15 | 0.2505 |
| $\Delta CDS_{t-8}$ | 0.017 | 0.72 | 0.47027 | 0.009 | 0.56 | 0.5753 |
| $\Delta Stock_{t-8}$ | -0.057 | -1.51 | 0.13234 | -0.001 | -0.07 | 0.9416 |
| $\Delta CDS_{t-9}$ | **0.059** | **2.42** | **0.01580 * ** | -0.018 | -1.16 | 0.2462 |
| $\Delta Stock_{t-9}$ | 0.035 | 0.95 | 0.33998 | 0.001 | 0.07 | 0.9457 |
| $\Delta CDS_{t-10}$ | **-0.090** | **-3.75** | **<0.001 *** ** | 0.017 | 1.09 | 0.2776 |
| $\Delta Stock_{t-10}$ | -0.039 | -1.04 | 0.29725 | 0.021 | 0.85 | 0.3952 |
| $\Delta IN_{t-1}$ | **-0.057** | **-2.10** | **0.03563 * ** | -0.024 | -1.33 | 0.1822 |
| $\Delta EX_{t-1}$ | **0.304** | **2.46** | **0.01413 * ** | 0.007 | 0.09 | 0.9306 |
| Adjusted R-squared | 0.0831 | | | 0.000336 | | |
| F-statistic | 8.07 on 22 and 1694 DF | | | 1.03 on 22 and 1694 DF | | |

<table>
<tr><td rowspan="2">Dependent Variables<br>Independent Variables</td><td colspan="3">$\Delta CDS_t$</td><td colspan="3">$\Delta Stock_t$</td></tr>
<tr><td>Estimate</td><td>t-value</td><td>Pr(>|t|)</td><td>Estimate</td><td>t-value</td><td>Pr(>|t|)</td></tr>
<tr><td>P-value</td><td colspan="3"><0.001</td><td colspan="3">0.427</td></tr>
</table>

### 4.3.3 Impulse Response Analysis

In order to better understand the dynamic relationship between the CDS and stock markets, I compute impulse response function for each VARX model. The figures 10-15 show how one dependent variable responds to shocks of the other dependent variable in the VARX models. The six figures present similar patterns that 1) the response of CDS spread changes to stock return shocks is negative and significant at lag one, 2) CDS spread change shocks does not affect stock returns since the confidence intervals are too wide. The results are consistent with the results of Granger causality tests.

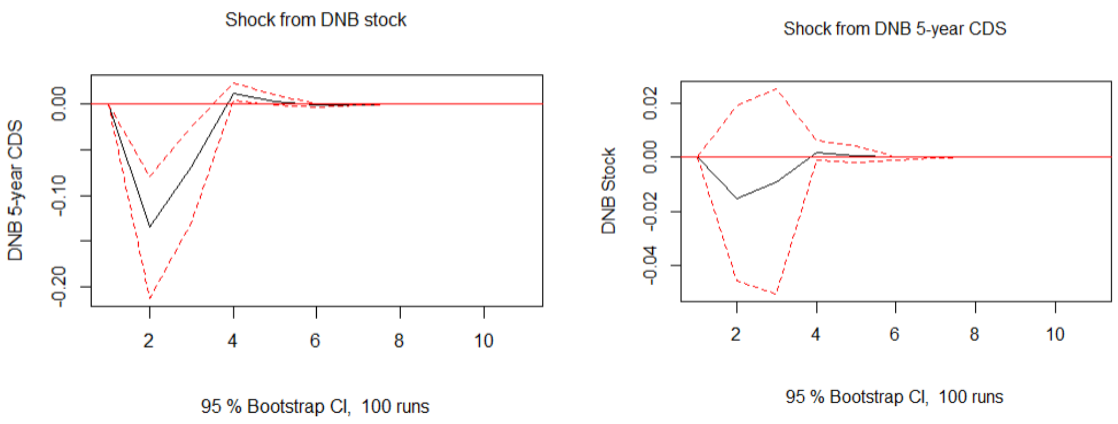


*Figure 10: Impulse Response Function of VARX Model 1*

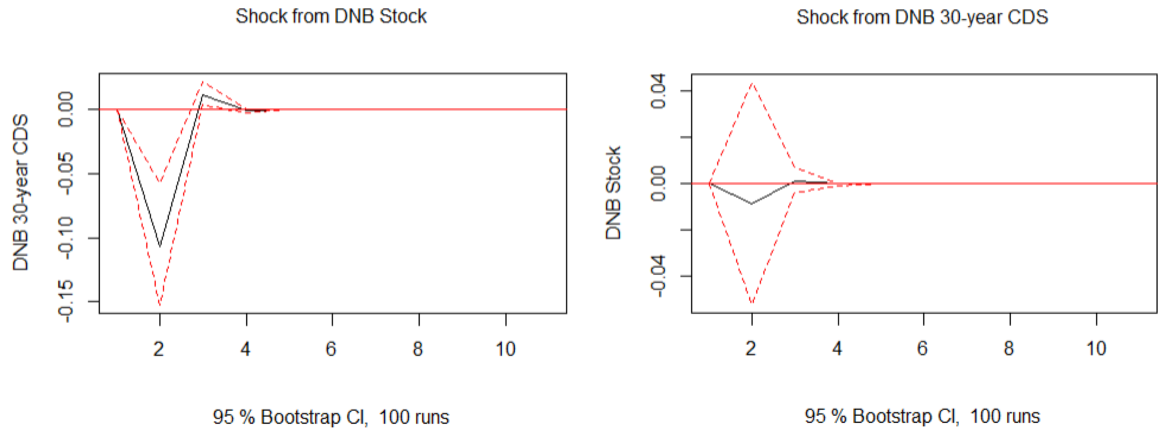


*Figure 11: Impulse Response Function of VARX Model 2*

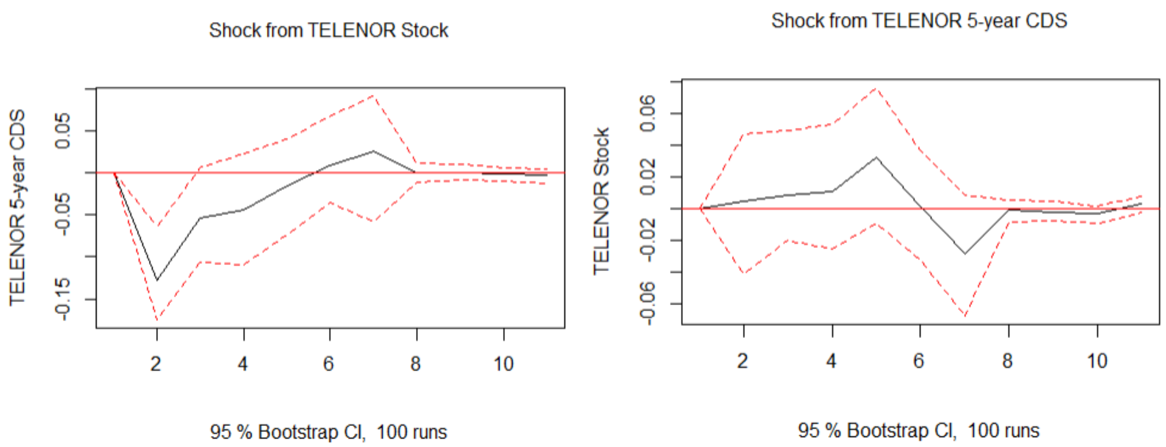


*Figure 12: Impulse Response Function of VARX Model 3*

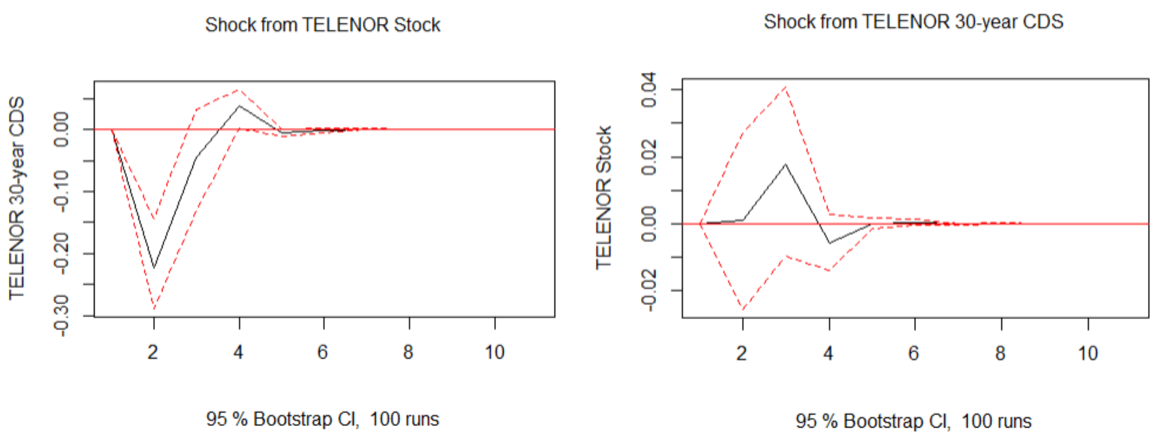


*Figure 13: Impulse Response Function of VARX Model 4*

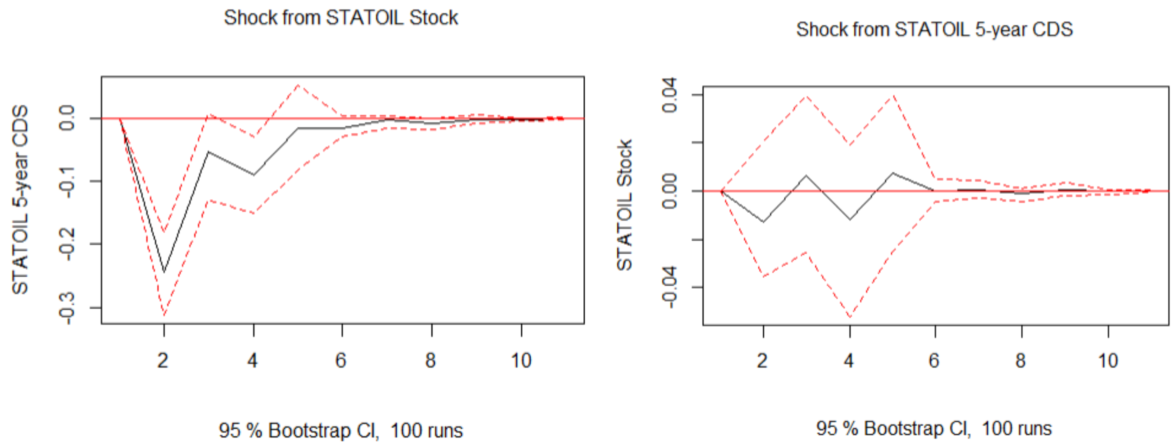


*Figure 14: Impulse Response Function of VARX Model 5*

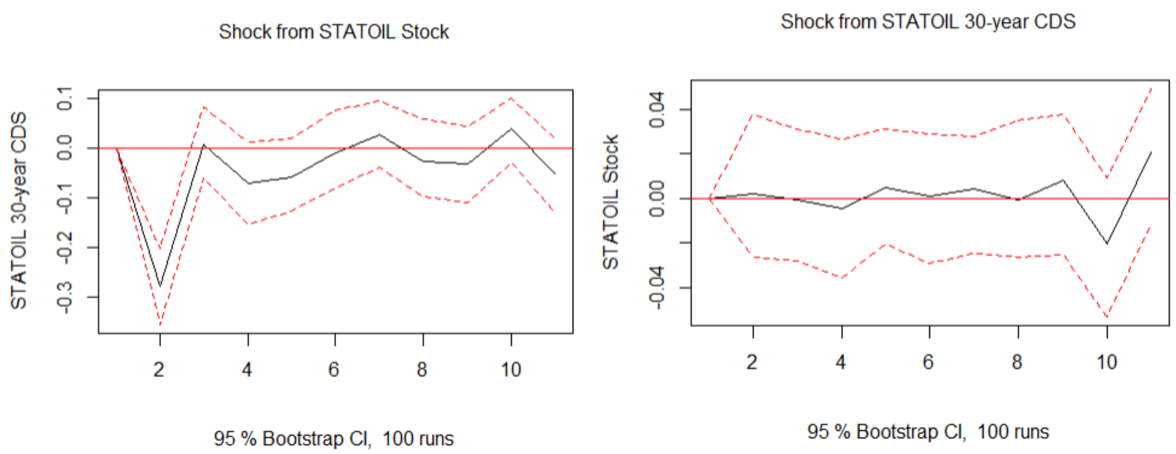


*Figure 15: Impulse Response Function of VARX Model 6*

## 4.4 VARX-L Models

The baseline results from section 4.3 suggest that the Norwegian stock market leads the CDS market. I now examine whether the finding is robust to allow for more flexible lag structures for both the endogenous and exogenous variables. To avoid the curse of dimensionality (estimating too many parameters), I use a recent machine learning penalization technique that shrinks the coefficients on irrelevant lags to 0. I outline the details of the methodology below.

### 4.4.1 Methodology

VARX-L framework, Structured Regularization for Large Vector Autoregressions with Exogenous Variables, was introduced by Nicholson et al. (2017). It is a structured family of VARX models, which provides efficient estimation and accurate forecasting in high-dimensional analysis. The specification of a VARX model with two endogenous variables and two exogenous variables $VARX_{2,2}(p,s)$ is as equation 2.1.

$$y_t = v + \sum_{i=1}^{p} \Phi^{(i)} y_{t-i} + \sum_{j=1}^{s} \Psi^{(j)} x_{t-j} + u_t \,, for\ t = 1, \dots, T \qquad (2.1)$$

with $y_t = \begin{pmatrix} \Delta CDS_t \\ \Delta Stock_t \end{pmatrix}$ : dependent variables CDS spread change and stock return;

$v = \begin{pmatrix} \alpha_0 \\ \beta_0 \end{pmatrix}$ : constant intercept vector;

$\Phi^{(i)} = \begin{pmatrix} \alpha_{1,i} & \alpha_{2,i} \\ \beta_{1,i} & \beta_{2,i} \end{pmatrix}$ : endogenous coefficient matrix at lag $i = 1, \dots, p$;

$y_{t-i} = \begin{pmatrix} \Delta CDS_{t-i} \\ \Delta Stock_{t-i} \end{pmatrix}$ : endogenous variables;

$\Psi^{(j)} = \begin{pmatrix} \alpha_{3,j} & \alpha_{4,j} \\ \beta_{3,j} & \beta_{4,j} \end{pmatrix}$ : exogenous coefficient matrix at lag $j = 1, \dots, s$;

$x_{t-j} = \begin{pmatrix} \Delta IN_{t-j} \\ \Delta EX_{t-j} \end{pmatrix}$ : exogenous variables bond yield change and exchange rate change;

$u_t = \begin{pmatrix} \varepsilon_t \\ \epsilon_t \end{pmatrix}$ : white noise vector.

In equation 2.1, the estimated coefficients number is $2 * (1 + 2\,p + 2s)$. Suppose p is 30 and s is 20, there are 202 estimated coefficients. The VARX-L framework can penalize the estimation to impose structured sparsity on the VARX model. The objective is (2.2):

$$\min_{v,\Phi,\Psi} \sum_{t=1}^{T} \left\| y_t - v - \sum_{i=1}^{p} \Phi^{(i)} y_{t-i} - \sum_{j=1}^{s} \Psi^{(j)} x_{t-j} \right\|_F^2 + \lambda\left(\rho_y(\Phi) + \rho_x(\Psi)\right) \qquad (2.2)$$

In which $\lambda \geq 0$ is a penalty parameter, $\rho_y(\Phi)$ and $\rho_x(\Psi)$ are penalty functions on endogenous coefficients and exogenous coefficients respectively. In this application, the penalty parameter is chosen by minimizing h-step (h=1) ahead mean-square forecast error (MSFE).

I fit five VARX-L structures for each VARX model since I have no prior knowledge about which one can achieve the best out of sample forecasting performance. The VARX-L structures and corresponding penalty functions are briefly explained below (Nicholson et al., 2017).

(1) Lag Group

The first VARX-L penalty structure is the Lag Group. The penalty functions are as below:

$$\rho_y(\Phi) = \sqrt{k^2}\sum_{i=1}^{p}\left\|\Phi^{(i)}\right\|_F, \;\; \rho_x(\Psi) = \sqrt{k}\sum_{j=1}^{s}\sum_{i=1}^{m}\left\|\Psi_{\cdot,i}^{(j)}\right\|_F \;,$$

in which k is the number of endogenous variables and m is the number of exogenous variables.

The endogenous coefficients are grouped by coefficient matrix $\Phi^{(i)}\ for\ i = 1, \dots, p$. The coefficients of all endogenous variables at the same lag are in the same group. Within a group, all endogenous coefficients are either all zero or all nonzero. For the exogenous variables, however, each exogenous variable is in its own group at every lag. Figure 16 shows a lag group penalty structure example of $VARX_{k,m}(p,s)$ where k=2, m=2, p=5, and s=3. The coefficients in grey colour are active coefficients and those in white colour are penalized to zero. In this example, all endogenous coefficients at lag 2, 3 and 5 are zero. The coefficients at lag 1 of the second exogenous variable are zero. All the exogenous coefficients at lag 2 are zero.

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\alpha_{1,1}$ | $\alpha_{2,1}$ | $\alpha_{1,2}$ | $\alpha_{2,2}$ | $\alpha_{1,3}$ | $\alpha_{2,3}$ | $\alpha_{1,4}$ | $\alpha_{2,4}$ | $\alpha_{1,5}$ | $\alpha_{2,5}$ | $\alpha_{3,1}$ | $\alpha_{4,1}$ | $\alpha_{3,2}$ | $\alpha_{4,2}$ | $\alpha_{3,3}$ | $\alpha_{4,3}$ |
| $\beta_{1,1}$ | $\beta_{2,1}$ | $\beta_{1,2}$ | $\beta_{2,2}$ | $\beta_{1,3}$ | $\beta_{2,3}$ | $\beta_{1,4}$ | $\beta_{2,4}$ | $\beta_{1,5}$ | $\beta_{2,5}$ | $\beta_{3,1}$ | $\beta_{4,1}$ | $\beta_{3,2}$ | $\beta_{4,2}$ | $\beta_{3,3}$ | $\beta_{4,3}$ |

*Figure 16: Lag group structure example of* $VARX_{2,2}(5,3)$*, gray coefficients are active*

(2) Own/Other Group VARX-L

In many macroeconomic applications, a series is more likely to be dependent on its own lags than the lags of other endogenous variables (Nicholson et al., 2017). Therefore, it is inappropriate to group all endogenous coefficients as in the lag group penalty structure. The own/other group structure treats a series' own lags and other endogenous variables' lags differently by assigning them to separate groups of endogenous coefficient matrix $\Phi^{(i)}\ for\ i = 1, \ldots, p$ at each lag. The penalty function $\rho_y(\Phi)$ is as below while $\rho_x(\Psi)$ is the same as in the lag group structure:

$$\rho_y(\Phi) = \sqrt{k}\sum_{i=1}^{p}\left\|\Phi_{own}^{(i)}\right\|_F + \sqrt{k(k-1)}\sum_{i=1}^{p}\left\|\Phi_{other}^{(i)}\right\|_F \ ,$$

in which $\Phi_{own}^{(i)}$ is a series' own lags locating on the diagonal of the coefficient matrix, and $\Phi_{other}^{(i)}$ is other endogenous variables' lags locating off the diagonal of the coefficient matrix.

Figure 17 shows an example of the own/other group structure $VARX_{2,2}(5,3)$. In this example, all endogenous coefficients at lag 2, 3 and 5 are zero. At lag 4, the coefficients of the own lags are active.

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\alpha_{1,1}$ | $\alpha_{2,1}$ | $\alpha_{1,2}$ | $\alpha_{2,2}$ | $\alpha_{1,3}$ | $\alpha_{2,3}$ | $\alpha_{1,4}$ | $\alpha_{2,4}$ | $\alpha_{1,5}$ | $\alpha_{2,5}$ | $\alpha_{3,1}$ | $\alpha_{4,1}$ | $\alpha_{3,2}$ | $\alpha_{4,2}$ | $\alpha_{3,3}$ | $\alpha_{4,3}$ |
| $\beta_{1,1}$ | $\beta_{2,1}$ | $\beta_{1,2}$ | $\beta_{2,2}$ | $\beta_{1,3}$ | $\beta_{2,3}$ | $\beta_{1,4}$ | $\beta_{2,4}$ | $\beta_{1,5}$ | $\beta_{2,5}$ | $\beta_{3,1}$ | $\beta_{4,1}$ | $\beta_{3,2}$ | $\beta_{4,2}$ | $\beta_{3,3}$ | $\beta_{4,3}$ |

*Figure 17: Own/other group penalty structure example of* $VARX_{2,2}(5,3)$

(3) Sparse Lag Group VARX-L

In the lag group penalty, all coefficients in the group are either all zero or all nonzero. It doesn't allow sparsity within group. Add an additional sparse lasso penalty to the penalty functions of lag group VARX-L, thus get the sparse lag group penalty functions as below:

$$\rho_y(\Phi) = (1-\delta)\left(\sqrt{k^2}\sum_{i=1}^{p}\left\|\Phi^{(i)}\right\|_F\right) + \delta\|\Phi\|_1,\ \ \rho_x(\Psi) = (1-\delta)(\sqrt{k}\sum_{j=1}^{s}\sum_{i=1}^{m}\left\|\Psi_{\cdot,i}^{(j)}\right\|_F) + \delta\|\Psi\|_1 \quad ,$$

in which $0 < \delta < 1$ is the sparse lasso penalty parameter.

Figure 18 shows an example of the sparse lag group structure $VARX_{2,2}(5,3)$. In this example, the lag 1 endogenous coefficients group is active, but there is an individual coefficient in this group is penalized to zero.

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\alpha_{1,1}$ | $\alpha_{2,1}$ | $\alpha_{1,2}$ | $\alpha_{2,2}$ | $\alpha_{1,3}$ | $\alpha_{2,3}$ | $\alpha_{1,4}$ | $\alpha_{2,4}$ | $\alpha_{1,5}$ | $\alpha_{2,5}$ | $\alpha_{3,1}$ | $\alpha_{4,1}$ | $\alpha_{3,2}$ | $\alpha_{4,2}$ | $\alpha_{3,3}$ | $\alpha_{4,3}$ |
| $\beta_{1,1}$ | $\beta_{2,1}$ | $\beta_{1,2}$ | $\beta_{2,2}$ | $\beta_{1,3}$ | $\beta_{2,3}$ | $\beta_{1,4}$ | $\beta_{2,4}$ | $\beta_{1,5}$ | $\beta_{2,5}$ | $\beta_{3,1}$ | $\beta_{4,1}$ | $\beta_{3,2}$ | $\beta_{4,2}$ | $\beta_{3,3}$ | $\beta_{4,3}$ |

*Figure 18: Sparse lag group penalty structure example of* $VARX_{2,2}(5,3)$

(4) Sparse Own/Other Group VARX-L

Similar to the lag group penalty, the own/other group penalty doesn't allow sparsity within group either. Add the sparse lasso penalty to the penalty functions of own/other group structure to get the sparse own/other group penalty functions. The penalty function $\rho_y(\Phi)$ is as below while $\rho_x(\Psi)$ is the same as in the sparse lag group structure:

$$\rho_y(\Phi) = (1-\delta)\left(\rho_y(\Phi) = \sqrt{k}\sum_{i=1}^{p}\left\|\Phi_{own}^{(i)}\right\|_F + \sqrt{k(k-1)}\sum_{i=1}^{p}\left\|\Phi_{other}^{(i)}\right\|_F\right) + \delta\|\Phi\|_1, \quad ,$$

in which $0 < \delta < 1$ is the sparse lasso penalty parameter.

(5) Basic VARX-L

The basic VARX-L doesn't group the coefficients. Every coefficient is a single group. The basic VARX-L is a special case of the sparse lag group VARX-L, where there is only sparse penalty and no group penalty. Let $\delta = 1$ in the sparse lag group penalty functions and get the basic VARX-L penalty functions as below:

$$\rho_y(\Phi) = \|\Phi\|_1, \ \rho_x(\Psi) = \|\Psi\|_1$$

### 4.4.2 Empirical Results

The fraction of active coefficients is the average proportion of coefficients that are not penalized to zero. Sparsity ratio is one minus the fraction of active coefficients. For the six VARX models in section 4.3, their sparsity ratio is zero and the fraction of active coefficients is one, meaning that none coefficients are set to zero. Five different VARX-L penalty structures are implemented to each of the six VARX models where lag order for endogenous variables is 30 and lag order for exogenous variables is 20. Therefore, 30 VARX-L models are fitted.

Table 15 shows the fractions of active coefficients. That basic VARX-L penalty structure has the highest sparsity ratio in average, because it is not restricted to any group structure. The sparse own/other VARX-L penalty structure is most flexible, since it can have within-group sparsity. Therefore, it has lowest sparsity ratio, almost half coefficients are active.

*Table 15: Fraction of active coefficients*

| VARX-L Penalty Structure | DNB 5y | DNB 30y | Telenor 5y | Telenor 30y | Statoil 5y | Statoil 30y | Average |
|---|---|---|---|---|---|---|---|
| Basic | 0.031 | 0.028 | 0.079 | 0.15 | 0.2 | 0.32 | 0.13 |
| Lag Group | 0.15 | 0.064 | 0.089 | 0.42 | 0.32 | 0.59 | 0.27 |
| Own/Other Group | 0.05 | 0.049 | 0.099 | 0.26 | 0.16 | 0.41 | 0.17 |
| Sparse Lag Group | 0.047 | 0.18 | 0.082 | 0.27 | 0.34 | 0.44 | 0.23 |
| Sparse Own/Other Group | 0.03 | 0.005 | 0.68 | 0.24 | 0.76 | 0.81 | 0.42 |

Table 16 shows the one-step ahead out of sample relative MSFE of the 30 VARX-L models. For each of the VARX models, there are four benchmarks to compare performance with the five VARX-L penalty structures. Over all the benchmarks, the least squares VARX with lags selected by BIC has the best performance in average, while the random walk has the worst performance in average. The VARX with lags selected by AIC outperforms the sample mean by 0.01 in average.

In average, the sparse lag group and own/other group penalty structures have the best performance among the five penalty structures and are as good as the best benchmark. The other three penalty structures' performances are not far behind, they are between the best and second-best benchmarks. Overall, the VARX-L frameworks have good forecasting performance measured by one-step ahead out of sample relative MSFE.

*Table 16: One-step ahead out of sample relative MSFE and benchmarks*

| Model | DNB 5y | DNB 30y | Telenor 5y | Telenor 30y | Statoil 5y | Statoil 30y | Average |
|---|---|---|---|---|---|---|---|
| One-step ahead Out of Sample Relative MSFE | | | | | | | |
| Basic | 2.2 | 1.8 | 2.3 | 2.3 | 2.9 | 2.6 | 2.35 |
| Lag Group | 2.2 | 1.8 | 2.3 | 2.3 | 2.9 | 2.6 | 2.35 |
| Own/Other Group | 2.2 | 1.8 | 2.3 | 2.3 | 2.9 | 2.5 | 2.33 |
| Sparse Lag Group | 2.2 | 1.8 | 2.3 | 2.3 | 2.9 | 2.5 | 2.33 |
| Sparse Own/Other Group | 2.2 | 1.8 | 2.4 | 2.3 | 3 | 2.5 | 2.37 |
| Benchmark Results | | | | | | | |
| Conditional Mean | 2.2 | 1.8 | 2.4 | 2.4 | 3 | 2.5 | 2.38 |
| VARX with lags selected by AIC | 2.3 | 1.8 | 2.3 | 2.2 | 3 | 2.6 | 2.37 |
| VARX with lags selected by BIC | 2.2 | 1.8 | 2.3 | 2.3 | 2.9 | 2.5 | 2.33 |
| Random Walk | 4.6 | 3.6 | 4.3 | 5.6 | 4.9 | 4.8 | 4.63 |

Table 17 shows the results of VARX-L models with endogenous variables DNB 5-year CDS spread change and DNB stock return. Even though more than half of the 202 estimated coefficients are penalised to 0, there are still too many coefficients. Since the purpose of the study is the lead-lag relation between the CDS and stock markets, the tables only show the most active coefficients of $\Delta CDS_{t-i}$ predicting $\Delta Stock_t$ and the active coefficients of $\Delta STOCK_{t-i}$ predicting $\Delta CDS_t$. The estimated coefficients are in the parentheses. The tables do not show the coefficients of constant term or exogenous variables.

In section 4.3, the results of VARX models conclude that the lagged CDS spread changes do not predict the stock returns while the lagged equity returns significantly predict the CDS returns. To be specific, lag 1&2 of DNB stock return predict DNB 5-year maturity CDS spread change (table 9); lag 1 of DNB stock return predicts DNB 30-year maturity CDS spread change (table 10); lag 1&3 of Telenor stock return predict Telenor 5-year maturity CDS spread change (table 11); lag 1&2 of Telenor stock return predict Telenor 30-year maturity CDS spread change (table 12); lag 1&3 of Statoil stock return predict Statoil 5-year maturity CDS spread change (table 13); lag 1, 3&4 of Statoil stock return predict Statoil 30-year maturity CDS spread change (table 14).

The VARX-L framework allows for larger lag order; therefore, it shows more lags than the conventional VARX models. In the results of VARX-L models, similar conclusion can be drawn with regards to the coefficients of lagged stock returns predicting CDS spread changes. However, lagged CDS spread changes can predict stock returns according to table 17-22. Specifically, lag 7&14 of DNB CDS spread change predict DNB stock return (table 17 and 18); lag 6&26 of Telenor 5-year maturity CDS spread change predict Telenor stock return (table 19); lag 9 of Telenor 30-year maturity CDS spread change predicts Telenor stock return (table 20); lag 9 of Statoil CDS spread change predicts Statoil stock return (table 21 and 22).

*Table 17:VARX-L of DNB 5-year CDS spread change and DNB stock return*

| DNB 5-year | Active coefficients of $\Delta CDS_{t-i}$ predict $\Delta Stock_t$ | Active coefficients of $\Delta STOCK_{t-i}$ predict $\Delta CDS_t$ |
|---|---|---|
| Basic | Lag7 (-0.023) | Lag1 (-0.057), lag2(-0.006) |
| Lag | Lag7(-0.008), Lag14(-0.007) | Lag1(-0.047), lag6(-0.019) |
| Own Other | Lag7(-0.013) | Lag1(-0.048), |
| Sparse Lag | Lag7(-0.013), lag 14(-0.004) | Lag1(-0.049), lag6(-0.014) |
| Sparse Own/Other | Na | Lag1(-0.004) |

*Table 18:VARX-L of DNB 30-year CDS spread change and DNB stock return*

| DNB 30-year | Active coefficients of $\Delta CDS_{t-i}$ predict $\Delta Stock_t$ | Active coefficients of $\Delta STOCK_{t-i}$ predict $\Delta CDS_t$ |
|---|---|---|
| Basic | Lag7(-0.023) | Lag1(-0.049) |
| Lag | Lag14(-0.004) | Lag1(-0.04) |
| Own Other | Lag7(-0.016) | Lag1(-0.042) |
| Sparse Lag | Lag7(-0.03), lag14(-0.014) | Lag1(-0.064), lag6(-0.012) |
| Sparse Own/Other | Na | Lag1 |

*Table 19:VARX-L of Telenor 5-year CDS spread change and Telenor stock return*

| Telenor 5-year | Active coefficients of $\Delta CDS_{t-i}$ predict $\Delta Stock_t$ | Active coefficients of $\Delta STOCK_{t-i}$ predict $\Delta CDS_t$ |
|---|---|---|
| Basic | Lag26(-0.017) | Lag1(-0.078) |
| Lag | Lag6(-0.006) | Lag1(-0.069) |
| Own Other | Lag26(-0.015) | Lag1(-0.07), lag26(-0.009) |
| Sparse Lag | Lag6(-0.006), lag26(-0.008) | Lag1(-0.074) |
| Sparse Own/Other | Na | Lag1(-0.0013) |

*Table 20:VARX-L of Telenor 30-year CDS spread change and Telenor stock return*

| Telenor 30-year | Active coefficients of $\Delta CDS_{t-i}$ predict $\Delta Stock_t$ | Active coefficients of $\Delta STOCK_{t-i}$ predict $\Delta CDS_t$ |
|---|---|---|
| Basic | Lag9(-0.005) | Lag1(-0.085), lag2(-0.021) |
| Lag | Lag9(-0.008) | Lag1(-0.098), lag2(-0.03) |
| Own Other | Lag9(-0.01) | Lag1(-0.079), lag2(-0.023) |
| Sparse Lag | Lag9(-0.007) | Lag1(-0.094), lag2(-0.028) |
| Sparse Own/Other | Na | Lag1(-0.004) |

*Table 21:VARX-L of Statoil 5-year CDS spread change and Statoil stock return*

| Statoil 5-year | Active coefficients of $\Delta CDS_{t-i}$ predict $\Delta Stock_t$ | Active coefficients of $\Delta STOCK_{t-i}$ predict $\Delta CDS_t$ |
|---|---|---|
| Basic | Lag9(-0.042) | Lag1(-0.16), lag3(-0.042) |
| Lag | Lag9(-0.028) | Lag1(-0.15), lag3(-0.027) |
| Own Other | Lag9(-0.023) | Lag1(-0.14), lag3(-0.027) |
| Sparse Lag | Lag9(-0.03) | Lag1(-0.15), lag3(-0.028) |
| Sparse Own/Other | Lag9(-0.003) | Lag1(-0.015), lag3(-0.004) |

*Table 22:VARX-L of Statoil 30-year CDS spread change and Statoil stock return*

| Statoil 30-year | Active coefficients of $\Delta CDS_{t-i}$ predict $\Delta Stock_t$ | Active coefficients of $\Delta STOCK_{t-i}$ predict $\Delta CDS_t$ |
|---|---|---|
| Basic | Lag9(-0.016), lag25(-0.021) | Lag1(-0.17), lag3(-0.039), lag4(-0.035), lag19(-0.036) |
| Lag | Lag9(-0.017) | Lag1(-0.17), lag2(-0.017), lag3(-0.027), lag4(-0.025) |
| Own Other | Lag9(-0.01) | Lag1(-0.16), lag3(-0.03), lag4(-0.02) |
| Sparse Lag | Lag9(-0.017) | Lag1(-0.17), lag2(-0.015), lag3(-0.031), lag4(-0.028) |
| Sparse Own/Other | Lag9(-0.002) | Lag1(-0.01) |

# 5. Concluding Remarks

The master thesis empirically analysis the lead-lag relation between the Norwegian CDS and stock markets. The data contains daily observations from June 24$^{th}$, 2010 to May 5$^{th}$, 2017 of stock price, credit default swap spread, exchange rate (NOK/Euro), and 10-year Norwegian government bond yield. The final sample includes three Norwegian firms, DNB Bank ASA, Telenor ASA, and Statoil ASA. The thesis uses the CDS contracts that are drawn on senior unsecured debt with modified-modified restructuring type, and Euro settlement currency, because it is most popular in the Norwegian CDS market. Both the 30-year maturity CDS and 5-year maturity CDS are chosen as samples because 30-year maturity CDS is most liquid in the Norwegian CDS market and the 5-year maturity CDS is widely used in the empirical analysis. By calculating the percentage of non-zero daily changes in both CDS spread series and stock price series, it is obvious that the Norwegian stock market is more liquid than the CDS market.

All the level time-series (stock prices, CDS spreads, bond yield, and exchange rate) are non-stationary, while all daily stock returns, CDS spread changes, bond yield change, and exchange rate change are stationary. I show that the Norwegian stock market and CDS market do not have a long-run equilibrium relationship, thus the thesis uses vector autoregression with exogenous variables models (VARX) instead of a VECM framework.

The results of VARX models draw the conclusions that the lagged equity returns predict the CDS returns while the lagged CDS spread changes don't predict the stock returns. Combined with the fact that the Norwegian stock market is more liquid than the Norwegian CDS market, one hypothesis is that CDS market is slow to reflect information due to the liquidity problem.

The possible explanations of the liquidity problem are as below. Firstly, the CDS buyers and sellers are both financial institutions. The CDS market may not be as active as the stock market, which has both institutional investors and retail investors. Secondly, CDSs are traded over-the-counter. The OTC trading venue is relatively more difficult to find counterparties than the exchange trading venue. Finally, the market makers play an important role in the CDS market, however, they provide rather wide CDS bid-ask spread. For the same company, the CDS percentage bid-ask spread is much higher than the stock percentage bid-ask spread. Hence, the CDS transaction costs are higher than the equity transaction costs. According to the market selection theory, some informed traders are deterred by the high transaction costs of the CDS market and would choose only the equity market.

To deepen the understanding of the results, I use the VARX-L framework, Structured Regularization for Large Vector Autoregressions with Exogenous Variables, introduced by Nicholson et al. (2017). It implements penalty structures to the conventional VARX models, around 60-80% of the coefficients are penalised to zero in different penalty structures. In the VARX-L framework, the maximum lag order of endogenous variables is 30. It allows for larger lag order that is not feasible in the conventional VARX models. In the results of VARX-L models, lagged CDS spread changes at lag 6, 7, 9, 14 or 26 are found to predict stock returns. It seems to be consistent with the insider trading theory supported by Acharya and Johnson (2007) and Berndt and Ostrovnaya (2007). One hypothesis is that although the market makers raise bid-ask spread to deter informed traders, there are still signs of insider trading in the CDS market. The CDS spread changes may lead the stock returns by a week, even a month.

The thesis contributes to the literature in two ways. First, the thesis uses the sample of Norwegian companies. The current literature claims that the 5-year maturity CDS is most popular and liquid. However, in the Norwegian CDS market, the longer the maturity, the more liquid the CDS, while holding the others the same. Second, the thesis uses the VARX-L framework. It shows that large lags of CDS spread changes can predict stock returns.

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