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MASTER'S THESIS

Connectedness and spillover effects between forex and stock markets: Evidence from Scandinavia

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Declaration of Authorship

The author hereby declares that he compiled this thesis independently, using only the listed resources and literature, and the thesis has not been used to obtain a different or the same degree.

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Prague, April 19, 2019

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Abstract

In this thesis, we study the return and volatility spillovers between forex and stock markets in Scandinavian countries employing recently developed methodology of spillover indices. Those measures are based on forecast error variance decomposition of generalized vector autoregressive (GVAR) model. This allows us to estimate both total and directional spillovers. Moreover, frequency connectedness analysis is conducted by decomposing the spillover indices into frequency bands, corresponding to short-, medium- and long-run connectedness. We used daily data for major stock market indices and exchange rates of domestic currency towards US dollar for Norway, Sweden, Denmark and Finland. Our data spans from February 2002 till July 2018 that covers turmoil periods of global financial crisis in 2007-2009, European sovereign debt crisis 2010-2013 and Brexit referendum in mid 2016. Our empirical analysis reveals that Norwegian financial markets do not contribute much to both return and volatility spillovers. On the other hand, euro and Danish FX market perform very similarly, by exhibiting the highest spillover contributions for both returns and volatility. Furthermore, distinct increasing trends in spillovers are revealed during the turmoil periods for most of the markets. From frequency connectedness analysis, we inspect high short-run return connectedness for the whole period of time. For volatility, short-run connectedness is prevailing over long-run in normal times, while the pattern inverses during turmoil periods.

JEL Classification	C18, C58, F31, G01, G15
Keywords	Volatility, Spillover, Connectedness, Frequency, Forex market, Stock market
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Contents

List of Figures

List of Tables

Acronyms

ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criteria
BIC	Bayesian Information Criterion
FX	Foreign Exchange
(G)FEVD	(Generalized) Forecast Error Variance Decomposition
KPSS	Kwiatkowski-Phillips-Schmidt-Schin
PP	Phillips-Perron
RV	Realized Volatility
VAR	Vector Autoregression

Master’s Thesis Proposal

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Proposed topic	Connectedness and spillover effects between forex and stock markets: Evidence from Scandinavia

Motivation In the last two decades, financial markets all over the world became more interconnected in an unprecedented manner. This led to increase of interest in studying interconnectedness both across countries and across financial markets. The literature of analyzing those interconnections are focused on returns and their volatility. Stock return volatility and its features, such as leverage effect or volatility clustering, form a significant part of current econometric research. It is due to extensive usage of volatility as a risk measure, entering various pricing models, risk-assessment models or optimal portfolio construction frameworks. In other words, estimation of volatility and its accuracy is very important because this measure is relevant for all market participants and for their decision-making. The intense interest in volatility modeling began only after the seminal works of Engle (1982) and Bollerslev (1986) and has since become an extensively researched area in the field of financial econometrics.

It is very important to understand main drivers that allow us to estimate the actual volatility or forecast the future volatility. Njegic, Zivkov & Jankovic (2018) found that shock and volatility spillover effect is predominantly directed from exchange rate market to stock market. Granger, Huang, & Yang (2000) and Kyung-Chun (2008) found strong correlation between exchange rate and stock returns in many Asian countries. Thus, we can assume that exchange rate is one of many drivers of stock market volatility.

The main purpose of this thesis is to analyze return and volatility spillover effects between stock and forex markets and cross-country spillovers for Scandinavian countries. Thus, we can analyze the differences between exchange rate regimes of Nordic countries. The idea is that in case of constraining exchange rate regimes it is assumed that the exchange rates will not be as much volatile as for freely floating exchange rates, as suggested by Sidek, Abidin & Umar (2011) for some sector indices. That is the case with Denmark and Sweden that peg their currencies to Euro, while in Norway the monetary authorities follow inflation targeting policy and left exchange rate for free float. The case of Finland is also interesting for further investigation as it does not have its own monetary policy and has adopted Euro since 1999.

Hypotheses

> Hypothesis #1: The return and volatility spillovers from forex to stock market in countries with constraining exchange rate regimes is less than in countries with floating exchange rates.
>
> Hypothesis #2: Spillovers during financial crisis are not more than during normal times.
>
> Hypothesis #3: Connectedness of forex market with stock market is not higher for high frequencies than in lower frequencies.

Methodology For the analysis we will use daily data of stock market indices and exchange rates for 4 Scandinavian countries, namely Denmark, Sweden, Finland and Norway, for the period from February 2002 until the end of July 2018. The data is collected from Thomson Reuters Eikon platform.
The methodoligy that will be used in this thesis is based on simple measure of connectedness of asset returns and vlatilities introduced by Diebold & Yilmaz (2009). That measure is based on forecast error variance decomposition from vector autoregressive (VAR) model. This approach enables us to determine the proportion of forecast error variance of one asset which could be attributed to the shocks of the other asset, thus capturing cross-asset spillovers and also aggregate spillover effects between asset classes. However, that methodology relies on the Cholesky-factor identification of VAR and, thus, results depend on ordering of variables. As a result, Diebold & Yilmaz (2012) proposed new approach for measuring directional spillovers that relies on generalized VAR (GVAR) framework in which results are independent from ordering of variables.
Implementing the approach of Diebold & Yilmaz (2012) will allow us to measure both directional and total return and volatility spillovers and will reveal the cross-country and cross-market spillovers. Furthermore, to measure dynamics of connectedness in short-, medium- and long-term frequencies we will implement the approach of Baruník & Křehlík (2018). We will measure frequency dynamics of both cross-country and cross-market connectedness.

Expected Contribution While most of the researches on this topic focus mostly on many developed and developing countries, we analyze Scandinavian countries. The expected contribution of this thesis is fourfold. First, we will show the inter-market connectedness and spillover effects between forex and stock markets. Furthermore, we will reveal the differences of those effects between different exchange rate regimes, namely constraining exchange rate regimes (pegging to Euro), free floating exchange rate and adoption of regional currency (Euro). Secondly, we will analyze the cross-country spillovers for selected Nordic countries. This will reveal the level of integration among Nordic stock and foreign exchange markets. And, finally, the high, medium and low frequency shock effects will be investigated, giving deeper insight in the persistence of shocks in those markets. What's more, the results will help investors and other financial market participants to understand the spillover dynamics in Scandinavian countries for making accurate investment decisions. Additionally, we will point out the developments of diversification effects between those two markets for investors.

Outline

1. Introduction
2. Literature Review
3. Data Overview
4. Methodology
5. Results
6. Conclusions
7. Bibliography

Core bibliography

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Chapter 1

Introduction

Globalization and integration over the recent decades induced to increasing interconnectedness between countries. Although there are various advantages in integration, nothing comes without costs. Such a process makes countries more prone to shocks emerging in other countries. Similarly, financial liberalization led to increasing interconnectedness between financial markets. Those interconnections became even more tight after the global financial crisis in 2007-2009, when economies and financial markets worldwide were hit tremendously. Moreover, this kind of distress periods increase the uncertainty in the markets, thus leading to increased volatility. As volatility is used as a measure of risk, entering various pricing models and portfolio construction frameworks, it is interesting to examine the sources and volatility transmission mechanisms between various markets.

The huge amount of academic researches is devoted to volatility and connectedness modeling and studying volatility spillover effects both across countries and across financial markets. Major part of existing literature is focusing on analysis of developed markets, while in this thesis we will analyze the interconnectedness between stock and forex markets in Scandinavian countries, specifically, Sweden, Finland, Norway and Denmark. As a representative of stock markets in each country we chose the stock market indices, while for FX markets each country's domestic currency against US dollar is chosen. The aim of this thesis is to model and analyze not only volatility, but also return connectedness and spillovers effects among those markets. Our sample covers the period from February 2002 till July 2018, which enables us to examine such distress periods as the global financial crisis, European debt crisis and Brexit referendum. Moreover, there is sufficient data to cover also the calm periods and compare those with the abovementioned extreme events.

To conduct further analysis of connectedness effects we employed the methodology of spillover indices initially proposed by Diebold & Yilmaz (2009) and further updated by Diebold & Yilmaz (2012). This concept allows us to understand not only the total spillovers among the markets under analysis, but also to construct the directional spillover measures. The latest measures enable us to decompose forecast error variance of vector autoregressive (VAR) model and to estimate how shocks in one market affect the shocks in other markets, hence estimating the spillovers. Furthermore, we employ the extension to this methodology proposed by Baruník & Křehlík (2018) which allows to decompose the spillover indices into various frequency bands, specifically, short-term, medium-term and long-term. Those frequency bands correspond to daily, weekly and monthly frequencies, respectively. This new framework will give more insight about the transmission of return and volatility spillovers among markets at different frequencies, thus at different velocities.

The remainder of the thesis is organized as follows. Chapter 2 provides briefly the review of the existing literature on the topics of connectedness between financial markets, especially between stock and forex markets. Chapter 3 covers the data analysis providing with preliminary analysis of the dataset and construction of realized volatility (RV) measures. Chapter 4 provides the theoretical background of the methodologies used for spillover and connectedness estimations. Empirical results are discussed in Chapter 5. Finally, in Chapter 6 we provide the summary of our findings, discuss them and suggest possible extensions of our analysis.

Chapter 2

Literature Review

To better understand the research field and the topic in particular in this section we will go through the past researches on similar topics of return and volatility modeling, spillovers, etc. First, we will start with the history of development of volatility models. In the next two parts, we will review some of the literature connected to volatility spillovers and transmission mechanisms between stock and forex markets.

2.1 History of Volatility Models

It is worth mentioning that volatility models, such as Autoregressive Conditional Heteroskedasticity (ARCH) were first introduced by Engle (1982) and started to increase their popularity afterwards. Various extensions of ARCH model were introduced afterwards, depending on case-by-case application. The most popular volatility model is Generalized ARCH (GARCH) model introduced by Bollerslev (1986). Meanwhile Engle proposed another extension of ARCH model called ARCH-in-mean (ARCH-M) (Engle, Lilien & Robins, 1987). That model allowed the mean of time-series to depend on conditional variance. This can be used for modeling the risk premium depending on conditional variance of returns. Nelson (1991) proposed new model called exponential GARCH (EGARCH) that models the asymmetric effects of shocks on volatility (leverage effect). The three features of EGARCH model that makes it very useful are:

- Because of log-form of conditional variance, the implied value cannot be negative, regardless of the coefficients
- Instead of using ϵ_{t-1} EGARCH uses standardized value of $(\epsilon_{t-1}/\sqrt{h_{t-1}})$, which is unit free measure

- EGARCH allows for leverage effects

Two years later Glosten, Jagannathan & Runkle (1993) introduced new model called GJR-GARCH. It again captures the leverage effect for volatility, while just using dummy variable (it equals 1 if residuals, thus shock, is negative and zero otherwise). It is very similar to the model proposed by Zakoian (1994) called threshold GARCH (TGARCH or TARCH). The difference is that TARCH model uses standard deviation instead of variance as a dependent variable. Although the family of extensions of univariate GARCH models is huge, including SAARCH (Engle, 1990), PARCH (Higgins & Bera, 1992), etc., the multivariate framework was also introduced and currently is at least as much popular as univariate models.

Multivariate GARCH model was introduced by Bollerslev *et al.* (1988). Introducing VECH-MGARCH model it allows for analyzing comovements of two time-series. As VECH model uses too many variables in estimation and sometimes it makes the calculations too complex, diagonal VECH model was introduced. However, both models have a drawback of no guarantee that covariance matrix is positive semi-definite. To address that issue Engle & Kroner (1995) proposed new model called BEKK-GARCH that ensures the positive semi-definiteness of covariance matrix. Following that newer papers of Engle & Sheppard (2001) and Engle (2002) proposed new extension of MGARCH models which is dynamic conditional correlation (DCC) MGARCH that allows to analyze the dynamic (non-linear) conditional correlation between two series following univariate GARCH models. Compared to previous MGARCH models DCC-MGARCH number of parameters does not depend on number of variables used in the model. This feature makes it easier to estimate the model for the most cases. Cappiello *et al.* (2006) also had their investment in multivariate GARCH models, introducing asymmetric DCC-GARCH model to capture asymmetries in conditional variances and correlations (Kočenda, 2017).

In addition to ARCH-family models, developed earlier, Diebold & Yilmaz (2009) introduced new methodology for connectedness and spillover measuring. The methodology is based on forecast error variance decomposition from vector autoregressive (VAR) model. This approach enables to determine the proportion of forecast error variance of one asset class, which could be attributed to the shocks from the other asset class. Thus, this method captures cross-asset spillovers and aggregate spillover effects between asset classes. Nonetheless, this approach is based on Cholsesky-factor identification of VAR and therefore depends on ordering of variables. Consequently, Diebold & Yilmaz (2012) proposed new method for measuring directional spillovers that relies on generalized VAR framework, where results do not depend on variable ordering. This methodology was extended by Baruník *et al.* (2016) who proposed to use realized semivariance instead of realized variance for volatility spillover measuring. This approach enables to capture asymmetric behavior of volatility by decomposing volatility into bad and good, based on negative and positive returns respectively. Finally, recent extension of spillover index methodology is proposed by Baruník & Křehlík (2018). Based on their new method spillover dynamics are decomposed into various frequency bands, capturing high, medium and low frequency dynamics. Subsequently, we can measure connectedness dynamics of assets in short-, medium- and long-term periods.

2.2 Volatility Spillovers

The research literature of volatility spillovers across various markets is huge. In this subsection, we will discuss some of them.
Theodossiou & Lee (1993) examine mean and volatility spillovers across US, UK, German, Canadian and Japanese stock markets. They use multivariate GARCH-M model. The results suggest significant mean spillovers from US market to UK, Canada and Germany and from Japan to Germany. Also strong conditional volatility exists in returns of all markets. Own-volatility spillovers of Canada and UK are insignificant, meaning that those countries import conditional volatility from abroad, mostly from USA. To capture asymmetric volatility spillovers Koutmos & Booth (1995) use multivariate EGARCH model to examine relationship between US, UK and Japan stock markets. Using daily data, they reveal asymmetric volatility spillovers among all 3 markets, which are more pronounced during October 1987 crisis period, suggesting more interdependent growth of those markets.

Huge amount of existing literature is concentrated on modeling volatility spillovers across CEE financial markets. For instance, Kasch-Haroutounian & Price (2001) investigate the interdependence among CEE stock markets, namely Poland, Slovakia, Czech Republic and Hungary. They use daily data from 1994 to 1998 and employ two MGARCH approaches, constant conditional correlation (CCC) and BEKK models. CCC model results in positive and significant conditional correlation coefficients between Czech and Hungarian and Hungarian and Polish stock markets. For other pairs of stock markets the coefficients are very small and insignificant. However, when applying BEKK model only one unidirectional volatility spillover from Hungarian stock market to Polish stock market has been found. These results are in line with the findings of Scheicher (2001) when analyzing connectedness Czech, Polish and Hungarian stock markets over the period of 1995-1997. Using vector autoregression (VAR) constant conditional correlation (CCC) model they find that the highest correlation is between Budapest and Warsaw stock markets, with shocks coming from Budapest stock market affecting both return and volatilities in Warsaw stock market. Moreover, their results suggest that international shocks are transmitted to CEE equity markets through return shocks rather than volatility shocks.

Some other studies delve into the connectedness effects between CEE countries and other regional markets. Studying the interdependence between the same three major emerging markets (Hungary, Czech Republic and Poland) and euro area Wang & Moore (2008) suggest that financial crisis and EU expansion substantially increased the correlations between CEE countries and euro area market. Moreover, evidence of contributions of financial depth to increased correlation has been found, while suggesting no influence of macroeconomic and monetary developments on those correlations. Further, Gjika & Horvath (2013), using asymmetric DCC-MGARCH model on daily data from 2001 to 2011, find similar results that are in line with Wang & Moore (2008) findings. In addition to those, they show positive linkage between conditional variances and correlations, thus suggesting decreased diversification benefits during volatile periods. Furthermore, they suggest that conditional variances and correlations exhibit asymmetric behavior. Using DCC approach on bigger sample of countries Syllignakis & Kouretas (2011) also show that stock market correlations increase over time and the diversification effect in CEE markets decreases. They explain the higher correlations by increasing financial openness, increased presence of foreign investors and entry in the European Union. On the other hand, Égert & Kočenda (2011), using DCC model, conclude that correlations between emerging markets and between emerging and developed markets are very low. However, they show high correlations between developed markets, pointing the high level of integration. Moreover, an increasing correlation between CEE markets after first half of 2004 is found, which is described by joining of those countries the European Union.
Employing wavelet tools to examine contagion among CEE and German stock markets during financial crisis (January 2008 - November 2009) Baruník & Vácha

(2013) show that correlations are continuously changing over time and across frequencies. They find strong relationship between Czech and Polish stock markets. Another aspect of findings is that correlation between CEE markets is generally low with DAX on high frequencies. Thus, they concluded that CEE markets are not still tightly connected to leading markets in the region.

Booth, Tse & Martikainen (1997) examine price and volatility spillovers in Scandinavian stock markets, namely, Denmark, Sweden, Norway and Finland. They also use multivariate EGARCH model to capture asymmetric volatility transmission. They reveal price and volatility spillovers between markets; however they are few in number. Moreover, the results suggest asymmetric volatility spillovers that are more pronounced for bad news.

Some other studies focus on spillover effects between developed markets. For instance, Ehrmann, Fratzscher, & Rigobon (2011) aim to explain the financial transmission mechanism among money, bond, forex and equity markets both within and between US and Euro area countries. They reveal strong international spillovers that are the strongest across the same markets and mostly are positive.

All the studies discussed above used multivariate GARCH or other ARCH family models. However, inability to quantify the spillover effects in enough detail (Baruník *et al.*, 2015) is the drawback of such models. To capture volatility spillovers Diebold & Yilmaz (2009) proposed new methodology that is based on forecast error variance decomposition (FEVD) of vector autoregressive (VAR) model. Using this framework they examine volatility and return spillovers in 19 global equity markets for the period of 1990-2009. Their results suggest increasing trend of return spillovers, which is explained by increased integration of international financial markets during recent decade. While, volatility spillovers display clear bursts associated with crisis events. Resolving several drawbacks of this methodology Diebold & Yilmaz (2012) introduced new methodology, based on generalized VAR mode, in which the results are invariant to ordering of the variables in the system. Using this new methodology, they investigate spillover effects of US stock, bond, forex and commodity markets for period of January 1999 until January 2010. They reveal that spillovers were limited before crisis of 2008-2009, while during crisis volatility spillovers intensified. Particularly, they emphasize spillovers from stock market to other markets, while spillovers from bond market are characterized as lower than those from other markets. Moreover, volatility spillovers from forex market are generally to stock and commodity markets. Continuing with the same methodology, Baruník *et al.* (2015) examined asymmetries in volatility transmission between four petroleum commodities for the period of 1987-2014. Using realized semivariances they have found increasing volatility spillovers since 2000s that substantially increase after 2008. According to them increasing volatility is due to progressive financialization of petroleum commodities after 2002. Surprisingly, they showed that before crisis 2008-2009 volatility transmission was higher than after it. Although there is asymmetric patter in volatility transmission between commodities, it decreased after crisis 2008. As opposed to Gjika & Horvath (2013), Baruník *et al.* (2016) on a sample of 21 US companies from different sectors show that volatility transmission across companies differs from sector to sector and there is no pronounced asymmetric behavior of volatility transmission, although they reject symmetric connectedness hypothesis for all sectors. Further, analyzing forex markets for the period of 2000-2016 Baruník *et al.* (2017) found asymmetric connectedness primarily dominated by negative volatility. They showed that bad volatility is due to sovereign debt crisis in Europe, while positive spillovers due to subprime mortgage crisis. Hence, they documented that net positive spillovers are caused by combination of monetary and real-economy events, while net negative spillovers come from fiscal factors.

2.3 Forex and Stock Market Linkages

There are many researches about stock and foreign exchange market linkages and spillovers. One of those studies is done by Ma & Kao (1990). They suggest that stock markets react to FX rate changes based on whether the country is import or export dominant. For import dominant countries, they show that currency appreciation boosts the stock markets, while export dominant countries lose their competitive power in case of currency appreciation, thus leading to stock market fall. These findings are in line with those of Ajayi & Mougoué (1996). Employing Vector Error Correction (VEC) model they also support the notion that currency depreciation leads to stock market fall. However, they do not divide their sample between import and export oriented countries. Moreover, they reveal significant negative short-run effect of FX rate on stock market.

Bartov, Bodnar & Kaul (1996) examine the impact of exchange rate changes on stock return volatility in USA. They show positive relationship between FX rate variability and stock market volatility. The results suggest that increase in FX rate variability after 1973 was perceived by investors to be associated with increase in riskiness of cash flows of multinational companies that required compensations in terms of higher expected returns. Continuing with the analysis of similar time period De Santis & Gerard (1998) examine for existence of currency risk premium in stock market in USA, UK, Germany and Japan. Using MGARCH model on monthly data for the period of 1973-1993, authors show currency risk premium in the data, but they vary across time and countries. Furthermore, they reveal negative currency risk premium for the period of 1980-1985 and positive risk premium for the period of 1989-1994. Increasing the sample of countries Kanas (2000) examine interdependence of stock returns and exchange rate changes in six industrialized countries. Using bivariate EGARCH model they study volatility spillovers between two markets in all countries. The results suggest volatility spillovers from stock market to FX market for all examined countries (USA, UK, Canada, Japan and France), except Germany. Increased spillovers are found since October 1987. They explain that phenomenon as a high integration of international financial markets. There is no evidence of spillovers from FX market to stock market in all researched countries. Further, Nieh & Lee (2001) examine dynamic relationship between stock prices and FX rates in G-7 countries. Using daily data for the period of 1993-1996 they do not find significant long-run relationship. Meanwhile, they show significant short-run relationship for some of the G-7 countries for only one day. Furthermore, they show that the stock prices and value of USD cannot depend on when forecasting the future in USA in both long-run and short-run. Using the same sample of countries and employing multivariate EGARCH model Yang, & Doong (2004) show asymmetric volatility transmission from stock market to FX market. This finding is in line with the findings of Jiang & Chiang (2000) who employ GJR-GARCH model and suggest that bad (good) news increase (reduce) market volatility. Moreover, the authors employ GARCH-M model and reveal that positive and negative shocks play different roles in markets' expectations formation about future volatility.

Huge part of existing literature is focused on forex and stock market linkages in Asian countries. One of those researches is done by Granger *et al.* (1998) who test causality relationship between stock prices and exchange rates. Their results disclose positive one-way correlation from exchange rates to stock prices in Japan and Thailand and negative one-way correlation from stock prices to exchange rates in Taiwan. For Indonesia, Korea, Malaysia and the Philippines they show strong feedback relationship, while for Singapore there are no discernible patterns of relationship. Further, Kyung-Chun (2008) find that local stock market volatility was significantly increased by exchange rate fluctuations in 8 East Asian countries in period of July 1994 - August 2001. The relationship was especially high for Asian Financial Crisis period. The results also suggest strong relationship between FX rates and stock market in case of Asian variables compared to the case of USA. Continuing with the analysis of Asian financial crisis Baharom, Habibullah, & Royfaizal (2008) employing Johansen (1991) cointegration method, analyze causation between FX and stock market in Malaysia. By dividing the sample into two periods, pre-crisis and post-crisis, they cannot find long-run relationship between stock prices and FX rates in both sub-periods. These findings are in line with finding of Nieh & Lee (2001).

Using cointegration and DCC methods Gudmundsson (2014) examine linkages between stock and foreign exchange markets in Iceland, Norway, Sweden and Hungary. The results suggest cointegrated relationships between domestic stock markets and real exchange rates. Moreover, significant time-varying correlation is revealed, however source of relationships is not clearly established. This is in line with the findings of Živkov, Njegić & Mirović (2016). Employing DCC-FIAPARCH model on a sample of Eastern European emerging markets they also show significant time-varying behavior between stock and FX markets, especially during global financial crisis period.

Chapter 3

Data Overview

In this chapter, we will discuss the dataset that will be used in our analysis. Section 3.1 describes how dataset is constructed and adjusted. Section 3.2 presents basic analysis of time series. In particular, summary statistics, results of tests for stationarity, normality and autocorrelations are discussed. In Section 3.3, we show the same basic analysis for realized volatility. At the end of the section we also perform simple correlation analysis of returns and realized volatility.

3.1 Data Construction

The goal of this thesis is to describe rigorously the interactions among financial markets in Scandinavian countries. More specifically, we aim to describe the return and volatility transmission mechanisms among stock and forex markets. We will analyze four countries of Scandinavia, namely Sweden, Finland, Norway and Denmark. In this section, we will define the way of obtaining and adjusting the dataset for further analysis of this thesis.

The data comprises of intra-day closing, high and low prices spanning from February 2002 until the end of July 2018. The data for all indices and exchange rates are obtained from Thomson Reuters Eikon platform.

We assumed that stock markets for each country is represented by stock index for that particular country. We obtained data for the following indices: Helsinki Stock Exchange Index (OMXH25), Copenhagen Stock Exchange Index (OMXC20), Stockholm Stock Exchange Index (OMXS30) and Oslo Bors All Share Index (OSEAX). For representation of foreign exchange markets for each country, we obtained exchange rates of the currency of respective country against US dollar: EUR/USD, NOK/USD, SEK/USD and DKK/USD.[1]

Due to inconsistencies in working days in analyzed countries, there were many omitted observations. To avoid it, we deleted all the observations for the days when at least one stock exchange is not working. What's more, we should note that the stock exchanges work only on weekdays, thus, the dataset has irregular frequency. Hence, we need to adjust the dataset before starting the analysis part. After all the adjustments, the dataset comprises of 4449 observations.

Furthermore, due to existence of anomaly called day-of-the-week effect (Roca, 1999), the daily data may be affected, thus the whole analysis can be influenced. We believe that feature of daily data will not cause significant issues to our analysis and the results will be robust.

As the aim of this thesis is to analyze return and volatility spillovers across markets and countries, we therefore adjust the dataset to get returns and volatilities for all time series. We transformed data by taking log first difference, producing the return series as

$$r_t = \ln \frac{P_t}{P_{t-1}} \tag{3.1}$$

To compute the volatilities for series we followed the approach of Diebold & Yilmaz (2012), who computed daily volatility using estimator derived by Parkinson (1980). The daily volatility is derived using daily high and low prices as

$$\hat{\sigma}^2_{it} = 0.361 \times (\ln P^{high}_{it} - \ln P^{low}_{it})^2 \tag{3.2}$$

$\hat{\sigma}^2_{it}$ is the estimator of daily variance. To obtain annualized daily percentage standard deviation, we will follow the (3.3).

$$\sigma_{it} = 100 \times \sqrt{365 \times \hat{\sigma}^2_{it}} \tag{3.3}$$

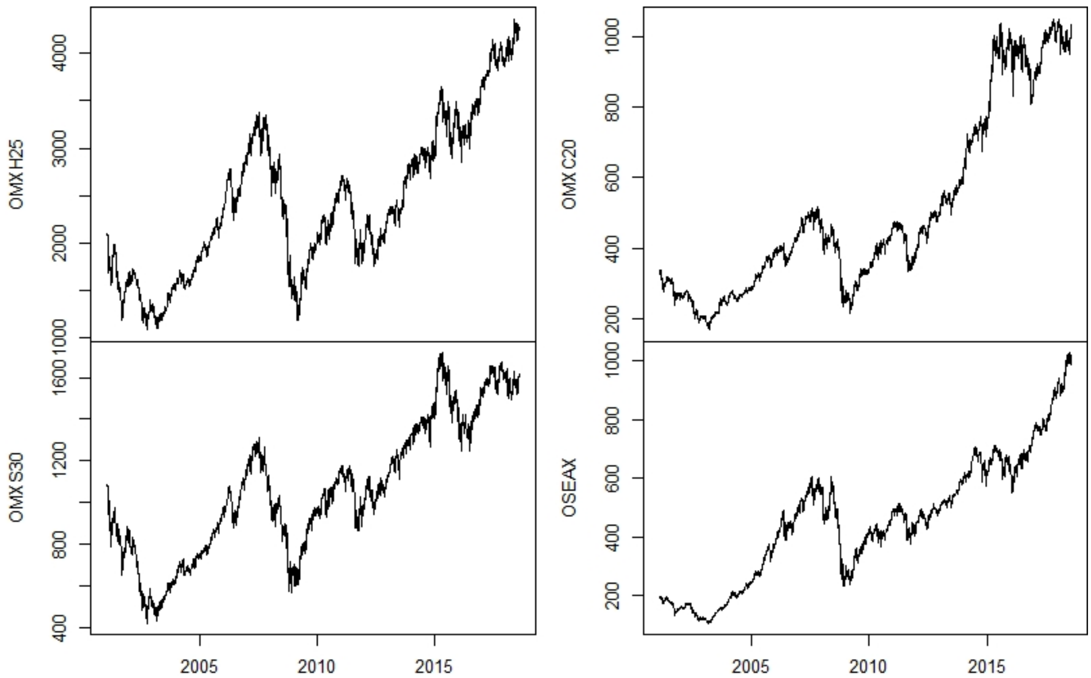
In (3.3), 365 represents the number of days in a year.

[1] The currency abbreviations represent the following national currencies: DKK – Danish Krone, NOK – Norwegian Krone, SEK – Swedish Krona, EUR – Euro, USD – US dollar

3.2 Level and Return Data

In this section, we will investigate basic properties of the series in our dataset. We present the graphs for level and returns, summary statistics, correlation analysis and basic tests for stationarity, normality and autocorrelation.

Figure 3.1: Evolution of Stock Markets

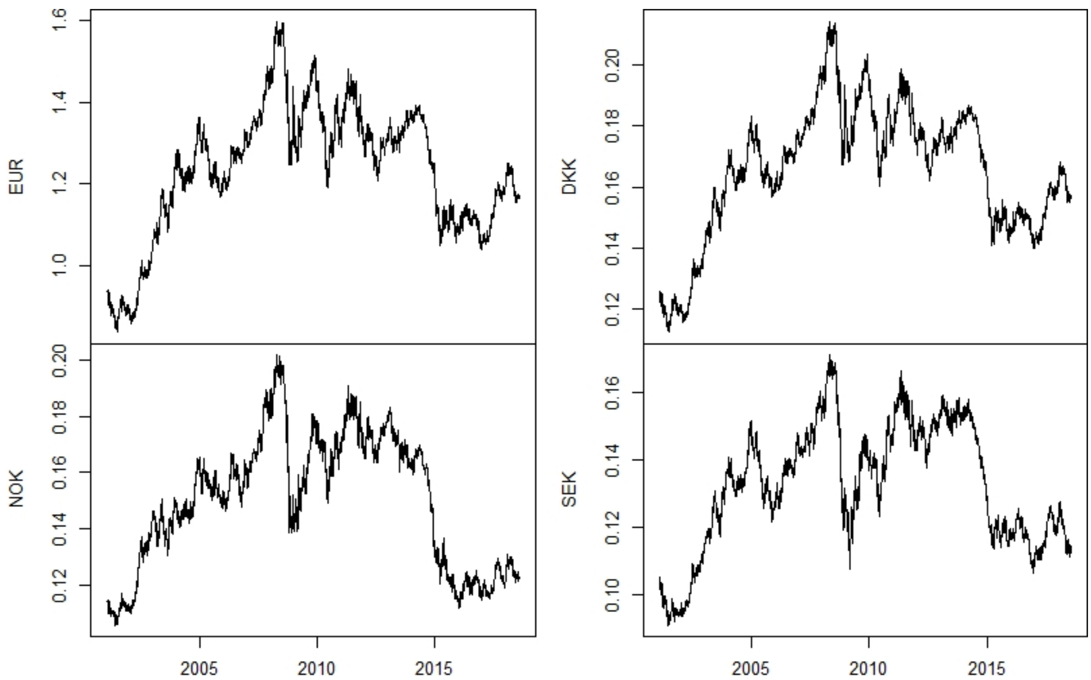


Source: Reuters Eikon

The level data for stock indices is presented in Figure 3.1. As can be seen from the graphs there are many ups and downs through the whole period of analysis in all countries. Those developments are mainly described by dot-com crisis in the beginning of 2000s, global financial crisis in 2008-2009, European sovereign debt crisis in 2011 and long-term uncertainty concerning Greece monetary shortfall, Russian sanction against EU and reverse sanctions against Russia at the end of 2015. All those events made stock markets in Scandinavian countries to shrink from period to period. As we can observe, Finish and Swedish stock markets perform very similar to each other, while Denmark and Norway stock markets are similar to each other in both development and volatility magnitudes. Moreover, we can notice that the level of changes in Finland and Denmark are of higher magnitude.

Figure 3.2 reports the development of forex market in Scandinavia for the same period as for stock indices. It is worth mentioning the EUR and DKK as their developments are very similar. That is due to the fact, that since 1982 Denmark adopted fixed-exchange-rate policy keeping krone stable against German mark and from 1999 against euro. Current fixed rate is 746.038 kroner per 100 EUR, with fluctuation band of ±2.25%. The aim of this exchange rate policy is to keep inflation low and stable. NOK and SEK also exhibit similar patterns. Otherwise, all exchange rate pairs behave as usual, displaying abrupt increase during global financial crisis of 2008-2009.

Figure 3.2: Evolution of FX Markets



Source: Reuters Eikon

After the performance of stationarity tests for level data, we can confirm that all the time-series are non-stationary. As we need to work with stationary data for our further analysis we transformed data by taking log first difference, producing the return series as described in the previous section. Table 3.1 documents stationarity tests for returns. Augmented Dickey-Fuller test statistic, KPSS test statistic and Phillips-Perron test statistic are presented.

From the table we can conclude that all the return series are stationary, as we reject the null hypothesis of non-stationarity for both ADF and Phillips-Perron

Table 3.1: Stationarity Tests for Returns

	ADF	KPSS	Phillips-Perron
OMXH25	-15.71***	0.14	-64.03***
OMXC20	-15.24***	0.19	-64.70***
OMXS30	-15.55***	0.19	-68.38***
OSEAX	-14.68***	0.10	-66.68***
EUR	-15.70***	0.25	-68.05***
NOK	-16.25***	0.34	-68.45***
DKK	-15.67***	0.26	-68.31***
SEK	-15.93***	0.23	-69.02***

Notes: ADF, KPSS and Phillips-Perron test lag orders are selected automatically and are 16, 15 and 10 for all series respectively. ***, **, * represent significance level of 1%, 5%, 10% respectively.

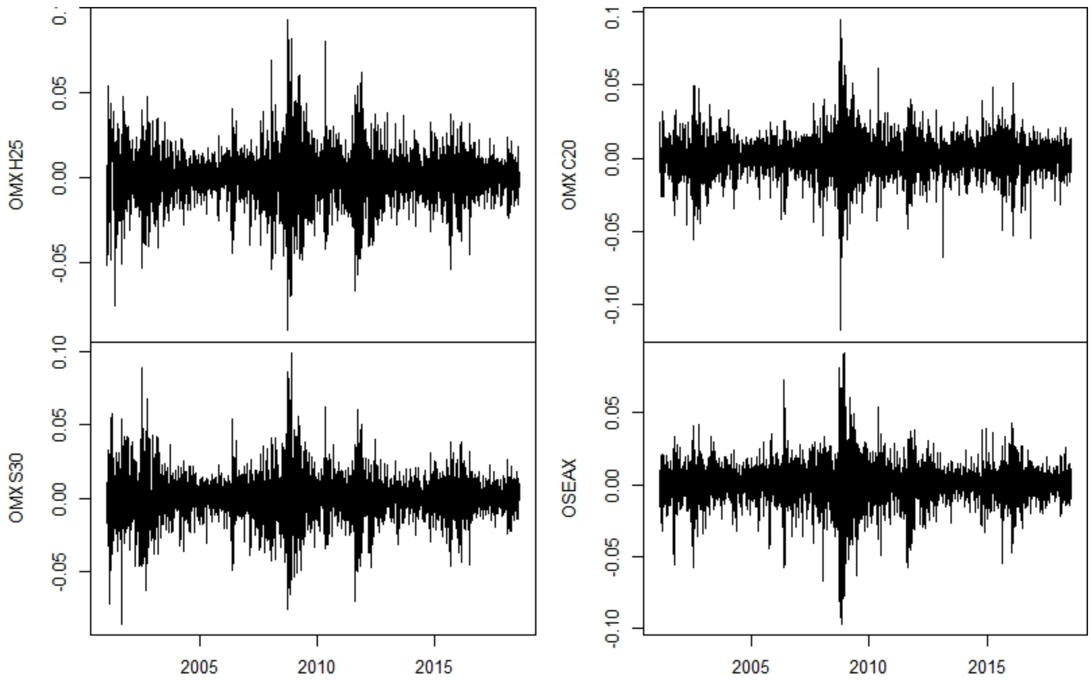
tests for all series at 1% significance level. What's more, we cannot reject at any acceptable level of significance the null hypothesis of stationarity for KPSS test for return series.

Figure 3.3 depicts the returns for stock indices. The volatilities vary substantially over the observed period. We can easily observe that the most unstable periods of all stock markets is global financial crisis of 2008-2009, starting with fall of Lehman Brothers in September 2008. From the plots, we also see that Danish stock market is the most affected during that period compared to other stock markets. Other period for most volatility is dot-com crisis in the beginning of this century. During that period, Swedish stock market is the most affected one.

Figure 3.4 documents the returns for forex markets. Once more we can confirm that global financial crisis is the most turbulent period. The most volatile exchange rate is NOK that reaches its minimum and maximum values during financial crisis. Furthermore, we can observe similar return patterns for EUR and DKK and for NOK and SEK.

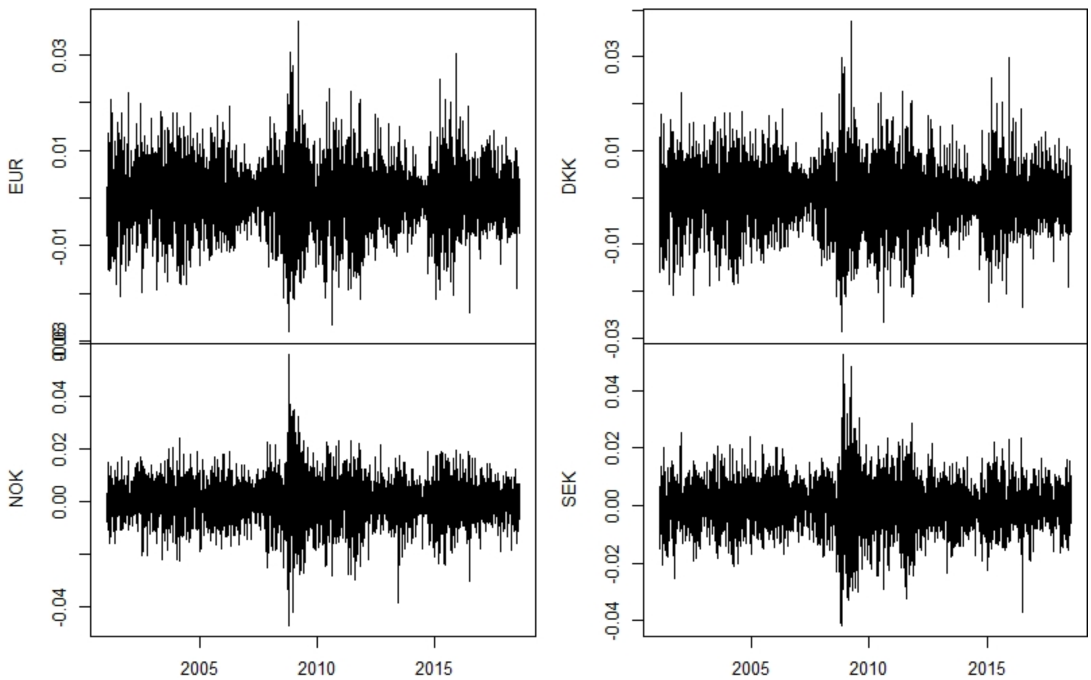
Table 3.2 provides descriptive statistic of returns of all time-series. The sample mean, standard deviation, minimum, maximum, kurtosis and skewness are presented for all series from period of February 2002 until August 2018. The same statistics for level data can be found in Appendix.

Figure 3.3: Stock Market Returns



Source: Reuters Eikon

Figure 3.4: FX Market Returns



Source: Reuters Eikon

Mean returns for all series are close to zero and positive. The greatest range of

Table 3.2: Descriptive Statistics for Returns

	Min	Mean	Max	S.D.	Kurtosis	Skewness	JB-stat	Ljung-Box Q-stat
OMXH25	-0.09	1.58E-04	0.09	1.39E-02	6.62	-0.10	2436.52***	30.97***
OMXC20	-0.12	2.50E-04	0.09	1.26E-02	8.88	-0.27	6469.95***	27.19***
OMXS30	-0.09	8.95E-05	0.10	1.44E-02	7.18	0.06	3240.07***	38.25***
OSEAX	-0.10	3.72E-04	0.09	1.37E-02	9.56	-0.60	8230.96***	24.45***
EUR	-0.03	5.00E-05	0.04	6.23E-03	4.71	0.06	545.40***	14.24*
NOK	-0.05	1.58E-05	0.06	7.72E-03	5.57	-0.14	1238.48***	13.68*
DKK	-0.03	5.06E-05	0.04	6.22E-03	4.72	0.03	549.88***	14.46*
SEK	-0.04	1.76E-05	0.05	7.74E-03	5.73	-0.04	1386.29***	22.59***

Notes: JB-stat stands for Jarque-Bera statistic. For Ljung-Box test we used 8 lags. ***, **, * represent significance level of 1%, 5%, 10%

values turns out to have Danish stock index. It also has the lowest return (-12%) and the second highest return (9%), after Swedish stock index (10%), among all series. The second lowest return has Norwegian stock index (-10%). Swedish stock index has the highest standard deviation, thus it has the most dispersed returns. Based on standard deviations, we can conclude that stock market are much more volatile compared to FX market. Besides, the return distributions for all series are non-normal. All return series have higher than three kurtosis and negative skewness, as typically the financial data are characterized. The exceptions are EUR, DKK and OMXS30. Those series are positively skewed. OSEAX has the highest both kurtosis and skewness (in absolute terms). The non-normality of series can be confirmed by Jarque-Bera statistics, as we reject the null hypothesis of normality at 1% significance level. Using Ljung-Box Q-statistic we test for the presence of autocorrelations in returns. Again, we reject the null hypothesis of no autocorrelation for all time series at 1% significance level. Exceptions are EUR, NOK and DKK exchange rates for which we reject at only 10% significance level.

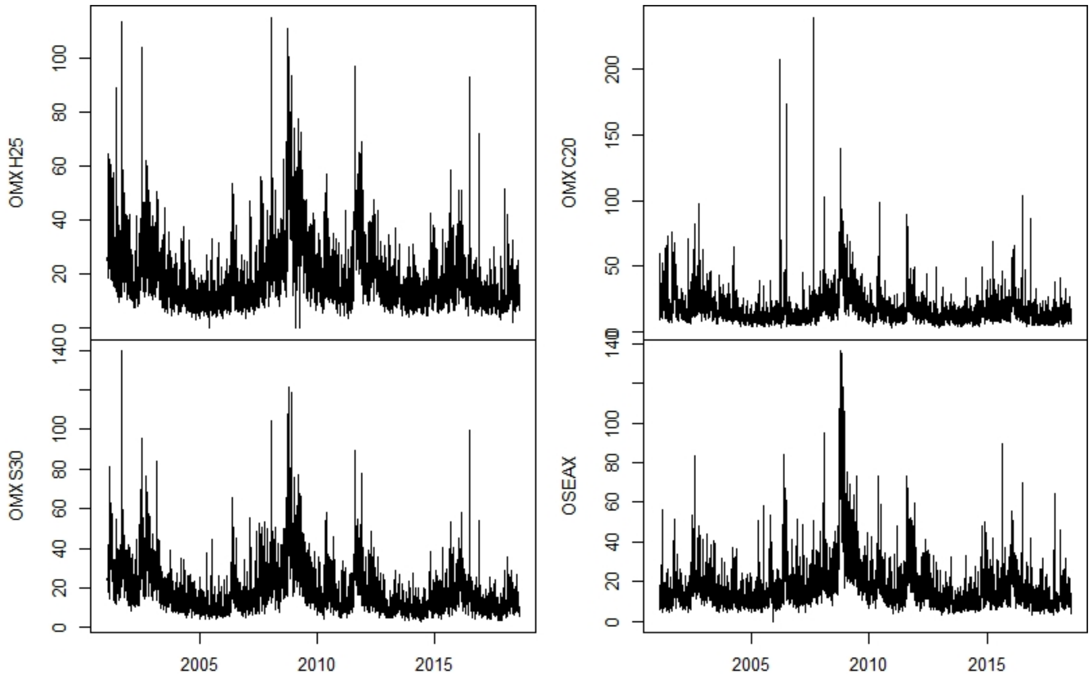
3.3 Realized Volatility

In this section, we will go through preliminary analysis of realized volatility measure. The construction of realized volatility (RV) is described in Section 3.1.

The plot of RV for stock indices and FX rates are depicted in Figure 3.5 and 3.6 respectively. Those plots indicate that the most distressed period was global financial crisis. Amongst stock indices the most affected is OMXC20, which reaches its maximum values during those distressed times. The least volatile is OMXH25.

Once more we can confirm that forex markets are less volatile than stock markets. The most volatile currency is NOK. EUR and DKK have quite similar pattern of volatilities, too, as it was true for returns.

Figure 3.5: Stock Market RV

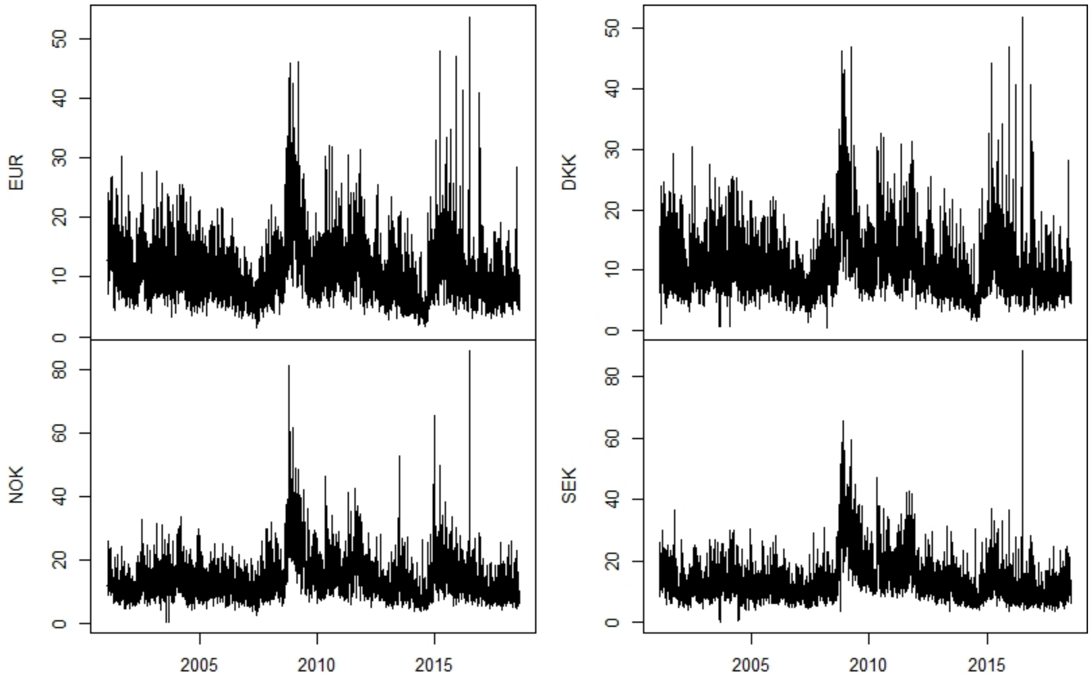


Source: Reuters Eikon

To avoid spurious results, before proceeding with further analysis of RV, we first need to check them for stationarity. Table 3.3 presents the stationarity tests for realized volatility for all series. Based on the results we reject the null hypotheses of non-stationarity for both ADF and Phillips-Perron tests for all series at 1% significance level. What's more, we reject at 1% level of significance the null hypothesis of stationarity for KPSS test for all series. Based on ADF and Phillips-Perron tests, we conclude that RV series are stationary and we can proceed with further analysis.

To further analyze the shape of distributions of realized volatility for the series we will inspect the descriptive statistics. Table 3.4 reports the results. We can easily observe that realized volatility values for OSEAX range from -16.12 to 4.92, which is the largest range of values among all series. However, the highest standard deviation of RV has OMXH25 (0.81), although they are quite low for all series. The mean volatility is almost the same for all series too, with the highest being for

Figure 3.6: FX Market RV



Source: Reuters Eikon

Table 3.3: Stationarity Tests for RV

	ADF	**KPSS**	**Phillips-Perron**
OMXH25	-8.61***	1.90***	-48.40***
OMXC20	-6.97***	1.99***	-43.28***
OMXS30	-6.11***	4.62***	-38.88***
OSEAX	-7.63***	2.29***	-39.45***
EUR	-5.67***	2.34***	-56.74***
NOK	-5.82***	1.42***	-51.90***
DKK	-5.78***	1.99***	-57.00***
SEK	-5.40***	2.40***	-51.66***

Notes: ADF, KPSS and Phillips-Perron test lag orders are selected automatically and are 16, 15 and 10 for all series respectively. ***, **, * represent significance level of 1%, 5%, 10% respectively.

OMXS30 (2.76). Based on skewness and kurtosis we observe that the distribution of realized volatility for EUR is close to normal, with a little bit higher than three kurtosis and almost zero skewness. Nonetheless, based on Jarque-Bera statistic we reject the null hypothesis of normality for all series at 1% level of significance. Thus, we can conclude that the distributions of realized volatility for all series are non-normal. Based on Ljung-Box Q-statistic we reject the null of no autocorrela-

Table 3.4: Descriptive Statistics for RV

	Min	**Mean**	**Max**	**S.D.**	**Kurtosis**	**Skewness**	**JB-stat**	**Ljung-Box Q-stat**
OMXH25	-16.12	2.74	4.75	0.81	269.72	-11.37	1.33E+07***	2854.07***
OMXC20	1.22	2.70	5.48	0.54	3.59	0.50	247.38***	8370.28***
OMXS30	1.17	2.76	4.94	0.57	2.90	0.30	66.62***	12846.35***
OSEAX	-16.12	2.67	4.92	0.69	250.28	-8.81	1.14E+07***	5416.46***
EUR	0.43	2.27	3.98	0.46	3.25	0.02	11.48***	5964.21***
NOK	-0.50	2.53	4.45	0.44	4.14	0.16	259.15***	6081.14***
DKK	-0.65	2.26	3.95	0.47	4.71	-0.24	582.71***	4851.75***
SEK	-1.05	2.51	4.48	0.45	5.31	0.02	985.39***	6365.78***

Notes: JB-stat stands for Jarque-Bera statistic. For Ljung-Box test we used 8 lags. ***, **, * represent significance level of 1%, 5%, 10% respectively.

tion at 1% significance level.

At the end of this section, we perform some simple connectedness analysis of time series. Table 3.5 and 3.6 report simple correlations between stock and FX market returns and realized volatility respectively. The results indicate that the highest correlation among stock market returns is between OMXS30 and OMXH25 (83.91%). Among the currencies the highest correlation is between EUR and DKK (99%). The later is described by already mentioned fixed-exchange-rate regime in Denmark. While inter-market return correlations are higher than 65%, cross-market ones are rather low, reaching 25.14% between NOK and OSEAX.

Volatility correlation patterns are the same for forex market, with the highest correlation between DKK and EUR (95.59%). The pattern changes for stock markets. The correlations range from 35.64% (between OSEAX and OMXH25) to 68.11% (between OMXS30 and OMXC20). Cross-market correlations are rather higher for volatilities, than for returns. The highest cross-market correlation is again between OSEAX and NOK (25.14%).

This was just a simplified analysis of time series. In order to elaborate more on the topic of interconnectedness and spillovers we will switch to forecast error variance decomposition (FEVD) of VAR model, discussed in further chapters.

Table 3.5: Return Correlations

	OMXH25	OMXC20	OMXS30	OSEAX	EUR	NOK	DKK	SEK
OMXH25	1							
OMXC20	0.71	1						
OMXS30	0.84	0.69	1					
OSEAX	0.71	0.66	0.67	1				
NOK	0.21	0.17	0.18	0.25	1			
SEK	0.23	0.17	0.20	0.24	0.80	1		
DKK	0.06	0.03	0.05	0.12	0.78	0.82	1	
EUR	0.06	0.03	0.05	0.12	0.78	0.82	0.99	1

Source: Author's Estimations

Table 3.6: Volatility Correlations

	OMXH25	OMXC20	OMXS30	OSEAX	EUR	NOK	DKK	SEK
OMXH25	1							
OMXC20	0.46	1						
OMXS30	0.55	0.68	1					
OSEAX	0.36	0.49	0.53	1				
NOK	0.25	0.37	0.38	0.34	1			
SEK	0.28	0.37	0.40	0.32	0.75	1		
DKK	0.24	0.35	0.38	0.28	0.74	0.74	1	
EUR	0.25	0.37	0.40	0.28	0.74	0.74	0.96	1

Source: Author's Estimations

Chapter 4

Methodology

In this chapter, we describe the theoretical background and the methodologies used in this thesis for estimation of return and volatility spillovers in stock and forex markets. In section 4.1, we discuss the construction of spillover indices with its decomposition into directional spillover measures, net spillover measures and net pairwise spillovers. For construction of spillover indices, we use the method initially developed by Diebold & Yilmaz (2009) and further amended by Diebold & Yilmaz (2012). Following that new approach, we use generalized vector autoregressive (VAR) model. Specifically, we use forecast error variance decomposition, which shows the shares of information each variable in the system contributes to the other ones. Moreover, with the amended method we can estimate also the directional spillovers, while initially only total spillover measure could be calculated.
In section 4.2, we will present the construction of frequency connectedness measures, proposed by Baruník & Křehlík (2018).

4.1 Spillover Indices

In this section, we discuss the measure of volatility spillovers, introduced by Diebold & Yilmaz (2009, 2012).
The uniform spillover index was initially proposed by Diebold & Yilmaz (2009), which was built on the variance decomposition of forecast errors of vector autoregressive (VAR) model. That measure records how much of H-step-ahead forecast error variance of variable i is due to exogenous shocks of another variable j. Thus, this concept provides intuitive way of measuring volatility spillovers. Nonetheless, this methodology has some limitations. The most important shortcoming of this

framework is that it relies on the Cholesky factor identification of covariance matrix of the VAR residuals. That may lead the resulting variance decompositions to be dependent on variable ordering of underlying VAR process. Furthermore, the initial spillover index, proposed by Diebold & Yilmaz (2009), enables to measure only total spillovers, while one may be interested in directional spillovers, i.e. how return or volatility from one specific asset i spilled over to another asset j and vice-versa. Consequently, those methodological drawbacks were eliminated by Diebold & Yilmaz (2012), who introduced generalized vector autoregressive framework. That new methodology allows us to measure volatility spillovers through forecast error variance decomposition that is invariant to the ordering of variables and enables to measure also the directional spillovers.

4.1.1 Total Spillover Index

In this part, we will go through the methodology of the construction of spillover index as proposed by Diebold & Yilmaz (2012), which follows from the forecast error variance decomposition in a generalized VAR model, instead of employing the Cholesky factor identification. So first, let us consider covariance stationary N-variable VAR(p) model that is defined as in (4.1):

$$Y_t = \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + ... + \Phi_p Y_{t-p} + \epsilon_t = \sum_{i=1}^{p} \Phi_i Y_{t-i} + \epsilon_t \tag{4.1}$$

where $Y_t = (Y_{1t}, ..., Y_{Nt})'$ denotes an N-dimensional vector of variables, Φ_i, with $i \in \{1, ..., p\}$, represents coefficient matrices and $\epsilon_t \sim N(0, \Sigma_\epsilon)$ is a vector of independently and identically distributed (*iid*) error terms. Under the assumption of weak stationarity, the VAR can be represented as an infinite moving average (MA) process that is given by

$$Y_t = \epsilon_t + \Psi_1 \epsilon_{t-1} + \Psi_2 \epsilon_{t-2} + ... = \sum_{i=1}^{\infty} \Psi_i \epsilon_{t-i} \tag{4.2}$$

where the $N \times N$ coefficient matrices Ψ_i can be computed recursively as in (4.3)

$$\Psi_t = \Phi_1 \Psi_{t-1} + \Phi_2 \Psi_{t-2} + ... = \sum_{j=1}^{\infty} \Phi_j \Psi_{t-j} \tag{4.3}$$

with Ψ_0 being an $N \times N$ identity matrix and $\Psi_i = 0, \forall \; i < 0$.

The MA representation is crucial in understanding the dynamics of the system as it allows us to compute the variance decompositions. These in turn enable to divide the forecast error variance decomposition of each variable in the VAR system into parts, corresponding to various shocks in the system. To obtain variance decompositions, that are invariant to ordering of variables in the VAR system, Diebold & Yilmaz (2012) utilized generalized VAR framework of Koop *et al.* (1996) and Pesaran & Shin (1998). This concept allows for correlated shocks and also takes them into account under assumption of normally distributed error terms. However, the shocks transmitted to each variable are not orthogonalized. Therefore, the sum of contributions to the forecast error variance may not be one.

The total spillover index proposed by Diebold & Yilmaz (2012) consists of two parts: own and cross variance shares. Own variance shares are determined as protions of H-step-ahead forecast error variance of Y_i due to shocks to Y_i, $\forall$ $i \in \{1, 2, ..., N\}$. Cross variance shares, spillovers, are determined as portions of H-step-ahead forecast error variance of Y_i due to shocks to Y_j, $\forall$ $i, j \in \{1, 2, ..., N\}$, such that $i \neq j$. Following the notation used by Baruník *et al.* (2016) and Palanska (2018), the H-step-ahead generalized FEVD matrix is as follows:

$$\omega_{ij}^H = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' \Psi_h \Sigma_\epsilon e_j)^2}{\sum_{h=0}^{H-1} e_i' \Psi_h \Sigma_\epsilon \Psi_h' e_j} \tag{4.4}$$

where σ_{jj} is the standard deviation of error term in the j^{th} equation, Σ_ϵ is the variance matrix of error vector ϵ_t, e_i is called selection vector that has 1 at i^{th} element and 0 elsewhere and Ψ_h are MA coefficients from forecast at time t. As mentioned above, the shocks of each variable are not orthogonalized, which can be formulized as

$$\sum_{j=1}^{N} \tilde{\omega}_{ij}^H \neq 1 \tag{4.5}$$

Hence, to make the information from total spillover table informative, normalization of each component of variance decomposition matrix by row sum is done, where row sum represents the directional spillovers from all assets in the system to some specific one:

$$\tilde{\omega}_{ij}^H = \frac{\omega_{ij}^H}{\sum_{j=1}^{N} \omega_{ij}^H} \tag{4.6}$$

This step ensures that $\Sigma_{j=1}^{N}\tilde{\omega}_{ij}^{H} = 1$ and $\Sigma_{i,j=1}^{N}\tilde{\omega}_{ij}^{H} = N$. Afterwards, Diebold & Yilmaz (2012) define the total spillover index as

$$S^H = 100 \times \frac{1}{N} \sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\omega}_{ij}^{H} \tag{4.7}$$

4.1.2 Directional Spillovers

The spillover index defined in (4.7) is useful for understanding the amount of shocks that spill over across the assets under analysis. The key advantage of generalized VAR framework, is that it enables the calculation of directional spillovers using normalized elements of generalized variance decomposition matrix. The directional spillovers enable us to further uncover the transmission mechanism, through the decomposition of total spillover index into those coming from and to a specific asset from the system.

The directional spillovers received by asset i from all other assets in the system, proposed by Diebold & Yilmaz (2012), has the following form:

$$S_{i \to Others}^{H} = 100 \times \frac{1}{N} \sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\omega}_{ij}^{H} \tag{4.8}$$

Similarly, the directional spillovers from asset i to all other assets in the system has the following form:

$$S_{i \leftarrow Others}^{H} = 100 \times \frac{1}{N} \sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\omega}_{ji}^{H} \tag{4.9}$$

4.1.3 Net Spillovers and Net Pairwise Spillovers

After defining directional spillovers, it is straightforward to obtain net spillovers from asset i to all other assets j. It can be calculated by simple difference between total volatility spillovers to and from all other assets as shown in (4.10).

$$S_i^H = S_{i \leftarrow Others}^{H} - S_{i \to Others}^{H} \tag{4.10}$$

Net spillover measure tells us how much each asset i contributes to other assets in the system in net terms (Baruník *et al.*, 2016). Furthermore, we can get net pairwise spillovers between two assets i and j. It can be computed simply as the difference between total spillovers from asset i to asset j and those from asset j to asset i.

$$S_{ij}^{H} = 100 \times \frac{1}{N}(\tilde{\omega}_{ji}^{H} - \tilde{\omega}_{ij}^{H}) \tag{4.11}$$

4.2 Frequency Connectedness

In this section, we will describe the theory behind the frequency dynamics measurement as proposed by Baruník & Křehlík (2018). This new methodology allows us to measure the connectedness between assets in long-, medium- and short-term time horizons.

First of all, let us consider a spectral representation of variance decompositions based on frequency responses, and not of impulse responses, to shocks. As a part of the aforementioned theory, we consider a frequency response function in the following form:

$$\Psi(e^{-i\omega}) = \Sigma_{H} e^{-i\omega h}\Psi_{h} \tag{4.12}$$

We can obtain (4.12) as a Fourier transform of the coefficients Ψ_h, with $i = \sqrt{-1}$. Consequently, the spectral density of realized variance at frequency ω can be estimated as Fourier transform of $MA(\infty)$ filtered sersies:

$$S_{RV}(\omega) = \sum_{h=-\infty}^{\infty} E(RV_t RV'_{t-h})e^{-i\omega h} = \Psi(e^{-i\omega})\Sigma\Psi'(e^{+i\omega}) \tag{4.13}$$

$S_{RV}(\omega)$ is the power spectrum, which describes the distribution of the variance of RV_t over the frequency components ω. The spectral representation of covariance matrix is estimated as

$$E(RV_t RV'_{t-h}) = \int_{-\pi}^{\pi} S_Y(\omega)e^{i\omega h} d\omega \tag{4.14}$$

Using standard discrete Fourier transforms, we can calculate the spectral quantities. The following is the cross-spectral density, on the interval of $d = (a; b); a, b \in (-\pi, \pi), a < b$:

$$\sum_{\omega} \hat{\Psi}(\omega)\hat{\sigma}\hat{\Psi}'(\omega) \tag{4.15}$$

for $\omega \in \{\frac{aH}{2\pi}, ..., \frac{bH}{2\pi}\}$, where $\hat{\Psi}(\omega) = \sum_{h=0}^{H-1} \hat{\Psi}_h e^{-2i\omega\pi/H}$ and $\hat{\Sigma} = \hat{\epsilon}'\hat{\epsilon}/(T-z)$, where z is correction for loss of degrees of freedom and depends on VAR specification.

Following the definitions of Baruník & Kočenda (2018) impulse response function decomposition at a desired frequency band is given as $\hat{\Psi}(d) = \Sigma_\omega \hat{\Psi}(\omega)$. Eventually, we can derive the generalized variance decompositions at given frequency bands as

$$(\hat{\theta}_d)_{j,k} = \sum_{\omega} \hat{\Gamma}_j(\omega)(\hat{f}(\omega))_{j,k} \tag{4.16}$$

where estimated generalized causation spectrum is given as

$$(\hat{f}(\omega))_{j,k} \equiv \frac{\hat{\sigma}_{kk}^{-1}[(\hat{\Psi}(\omega)\hat{\Sigma})_{j,k}]^2}{(\hat{\Psi}(\omega)\hat{\Sigma}\hat{\Psi}'(\omega))_{j,j}} \tag{4.17}$$

and weighting function is

$$\hat{\Gamma}_j(\omega) = \frac{(\hat{\Psi}(\omega)\hat{\Sigma}\hat{\Psi}'(\omega))_{j,j}}{\Omega_{j,j}} \tag{4.18}$$

where $\Omega = \Sigma_\omega \hat{\Psi}(\omega)\hat{\Sigma}\hat{\Psi}'(\omega)$. Finally, the connectedness measure at a desired frequency band can be obtained by substituting $(\hat{\theta}_d)_{j,k}$ into the aforementioned measures (Baruník & Kočenda, 2018).

Chapter 5

Empirical Results

In this chapter, we perform full analysis of return and volatility spillovers between stock and forex markets, as well inter-market spillover analysis. Moreover, we will perform frequency connectedness analysis for the same sample. This will allow us to understand the differences in connectedness in three different frequencies, namely short-, medium- and long-run, that are attributed to daily, weekly and monthly connectedness, respectively. The covered sample includes sufficient data to analyze the impact of financial distress periods on those connectedness measures, which is the main theme of our analysis. All the estimations are performed in free statistical software R.

This chapter is organized as follows. First, in Section 5.1, we perform the necessary analysis for the VAR model selection. In Section 5.2, we perform static spillover analysis for returns and then for realized volatility. This includes analysis of total spillover indices and its decomposition into directional TO, FROM NET and NET pairwise spillovers. Afterwards, in Section 5.3, we perform dynamic spillover analysis for returns and realized volatility using 200-day rolling window. This way we got the evolution of the spillover indices over time. Finally, in Section 5.4 we perform frequency connectedness analysis, where we decompose the total spillover indices for returns and realized volatility into three frequency bands, corresponding to daily, weekly and monthly connectedness.

5.1 Model Selection

In this section, we will discuss the vector autoregressive (VAR) model selection for our analysis. To do that, we first need to ensure that our data series are stationary. For that, we employ three commonly used stationarity tests:

- Augmented Dickey-Fuller (ADF) proposed by Dickey & Fuller (1979)
- Phillips-Perron (PP), proposed by Phillips & Perron (1988)
- Kwiatkowski, Phillips, Schmidt & Shin (KPSS) test, proposed by Kwiatkowski *et. al.* (1992)

ADF and PP tests are similar in a manner that both have null hypothesis of non-stationarity. On the other hand, KPSS test has stationarity as a null hypothesis. The results of those tests for both returns and realized measures are presented in Section 3.2 and 3.3, respectively. Based on those results, we confirm that all the series are stationary and can be used in further analysis. Consequently, we can proceed with the selection of VAR model.

In order to select the VAR model lag length, we use three widely used information criteria: Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), also called Schwarz Information Criterion, and Hannan-Quinn information criterion (HQ). The information criteria are given as:

$$AIC = T \log |\Sigma| + 2m \tag{5.1}$$

$$BIC = T \log |\Sigma| + m \log T \tag{5.2}$$

$$HQ = T \log |\Sigma| + 2m \log(\log T) \tag{5.3}$$

where T is the number of observations, $|\Sigma|$ is the determinant of variance-covariance matrix of residuals and m is number of parameters. The formulas reveal that AIC has the lowest penalty term for additional parameters, while BIC has the highest. Table 5.1 presents the results of suggested lag orders based on information criteria for returns and realized volatility respectively for maximum lag orders from 5 to 10.

For both returns and the realized volatility we can observe that all information criteria suggest different lag orders. For the returns SIC and HQ suggest the same lag order irrespective to maximum number of lags specified, one and four lags, respectively. Meanwhile, AIC suggests five lags, when maximum lag order

Table 5.1: Lag Length Selection for VAR based on Information Criteria

	Returns			RV		
Max. Lag Length	**AIC**	**SIC**	**HQ**	**AIC**	**SIC**	**HQ**
5	5	1	4	5	3	5
6	6	1	4	6	3	5
7	6	1	4	7	3	5
8	6	1	4	8	3	5
9	6	1	4	8	3	5
10	6	1	4	10	3	5

Source: Author's Estimations

is set to five, and six for all others. The patterns of SIC and HQ for realized volatility are rather similar. SIC suggests three lags, while HQ suggests five lags, regardless of the maximum number of lags. For volatilities, AIC suggestion is changing with the maximum number of lags applied. The results are evident, as AIC penalizes the least for additional parameters used in the model. Hence, based on the information criteria, we choose the VAR ordering to be one for returns and three for realized volatility. Moreover, using these number of lags will allow us to produce more parsimonious models. Although the selections are not consistent with the existing literature that employ the same spillover indices proposed by Diebold & Yilmaz (2009) (Baruník *et al.* (2015), Baruník *et al.* (2016), Baruník *et al.* (2017), Yilmaz (2010) used lag length of 2), all of them are showing, that the results are not dependent on the lag order of the model. For instance, Diebold & Yilmaz (2012) provide robustness analysis of the spillover index for the VAR lag of two to six, while Baruník *et al.* (2016) conducts the same analysis for lags two to four, both demonstrating the independence of the results on the lag length of the model. To ensure that our results are in line with the existing literature, we also perform robustness checks for both volatilities and returns. The results can be found in Appendix. Based on them we can conclude that the results are not significantly dependent on lag length for both returns and volatilities.

To perform the dynamic analysis, we need to define the length of rolling window, w, and forecasting horizon, H. To be consistent with the existing literature (Baruník *et al.* (2015), Baruník *et al.* (2016), Baruník *et al.* (2017), Diebold & Yilmaz (2012)) we have selected 200-day rolling window and 10-day forecasting horizon for the construction of spillover indices. Additionally, we performed a robustness check for both rolling window and forecasting horizon with alternative values of 150 and 250 days for w and for 5 and 15 days for H. The results can be found in Appendix. From them, we can observe that the spillover indices are not changing significantly due to changes in w and H for both returns and volatilities.

5.2 Unconditional Patterns

In this section we will perform static return and volatility spillover analysis between stock and forex markets of Scandinavian countries. The estimations of spillover indices are based on variance decomposition of 10-days-ahead forecast errors from VAR model. As mentioned in Section 5.1 lag order of VAR for returns is chosen to be one, while for realized volatility it is set to three. The spillover tables presented in further sub-sections are constructed in such a way, that diagonal elements show the own variance shares, while off-diagonal elements are cross-variance shares, thus the spillovers.

5.2.1 Static Analysis for Returns

Table 5.2 presents the return spillover indices for the full sample with stock indices and exchange rates. It provides with condensed information on how one specific asset transmits and receives spillovers. The highest values are reported on a diagonal as they represent own volatility shares. The off-diagonal values represent the directional spillover indices for returns.

Table 5.2: Return Spillover Table

	OMXH25	OMXC20	OMXS30	OSEAX	EUR	DKK	SEK	NOK	FROM Stocks	FROM FX	FROM Others
OMXH25	35.41	17.5	25.13	17.79	0.16	0.16	2.12	1.73	60.42	4.17	64.59
OMXC20	20.06	40.22	19.71	17.21	0.04	0.04	1.48	1.24	56.98	2.80	59.78
OMXS30	25.96	17.77	36.64	16.65	0.12	0.12	1.54	1.2	60.38	2.98	63.36
OSEAX	19.79	16.76	17.92	39.12	0.66	0.64	2.55	2.56	54.47	6.41	60.88
EUR	0.12	0.05	0.09	0.49	30.38	30.04	20.29	18.55	0.75	68.88	69.63
DKK	0.12	0.04	0.09	0.46	30.09	30.43	20.28	18.47	0.71	68.84	69.55
SEK	1.73	0.96	1.3	1.9	21.15	21.1	31.7	20.17	5.89	62.42	68.31
NOK	1.51	0.97	1.06	2.09	20.15	20.04	21.02	33.15	5.63	61.21	66.84
TO Stocks	65.81	52.03	62.76	51.65	0.98	0.96	7.69	6.73			
TO FX	3.48	2.02	2.54	4.94	71.39	71.18	61.59	57.19		**Total Spillover Index 65.37%**	
TO	69.29	54.05	65.30	56.59	72.37	72.14	69.28	63.92			

Source: Author's Estimations

From the results, we can conclude that the shares of return shocks spilled over the other markets vary significantly, from 0.04% to 2.56%. As can be observed from the spillovers from specific market TO all others (the last row from the table) the return shocks are spilled the least by OMXC20 (54.05%), while the most is transmitted by EUR (72.37%). Moreover, higher return transmission levels from forex markets TO all other markets are observed, compared to stock markets. Furthermore, we constructed inter-market and cross-market spillover indices. From those we can conclude that inter-market spillovers are rather higher than cross-market spillovers. This holds for both stock and forex markets. Among the stock markets OMXH25 exhibits the highest level of inter-market spillovers (65.81%), while OMXC20 exhibits the lowest ones (52.03%). On the other hand, between stock markets the highest cross-market spillovers are transmitted by OSEAX (4.94%), while the lowest again by OMXC20 (2.02%), followed by OMXS30 (2.54%). Among the forex markets the highest inter-market shock transmitter is EUR (71.39%), while the lowest one is NOK (57.19%), followed by SEK (61.59%). On the other hand, the highest cross-market shocks are spilled by SEK (7.69%), while the lowest by DKK (0.96%), followed by EUR (0.98%). What's more, we observe similar spillover magnitudes for EUR and DKK both FROM and TO other markets.

When exploring the directional spillovers FROM other markets to specific market (the most right three columns from the Table 5.2), we reveal a narrower range of values (from 0.71% to 68.88%) compared to directional spillovers TO other assets (from 0.96% to 71.39%). The last column indicates that the highest spillovers are received by EUR and DKK, 69.63% and 69.55%, respectively. The lowest spillovers are received by OMXC20 (59.78%), followed by OSEAX (60.88%). Furthermore, we decomposed the directional spillovers to observe the inter-market and cross-market spillovers to specific assets. Again, we can observe that inter-market shock transmission is higher compared to cross-market transmissions. Among the stock markets, the lowest inter-market shock receiver is OSEAX (54.47%), followed by OMXC20 (56.98%), whilst OMXH25 (60.42%) receives the most. On the other hand, from the cross-market spillovers, the most shocks are received by OSEAX, 6.41%, followed by OMXH25, 4.17%, whilst the lowest are received by OMXC20 (2.8%). Among the forex markets the highest inter-market spillovers are received by EUR and DKK, 68.88% and 68.84%, respectively, while NOK receives the lowest (61.21%). On the other hand, the pattern reverses for the spillovers received from stock markets. The highest shock receivers are SEK and NOK (5.89% and 5.3%, respectively), while EUR (0.75%) and DKK (0.71%)

receive the least.

Finally, total spillover index for returns shows the average shock transmission between the assets in the system. We may conclude that on average 65.37% of all shocks are transmitted to other markets. The rest of the shocks are associated with the ones that spill over from other markets that are not under the analysis in our research.

To get more insight from the static spillover analysis, we can proceed with the analysis of net and net pairwise spillovers. As already described, the net spillovers are estimated as the difference between the shocks transmitted TO other assets and those received FROM other assets. Using the same logic one can estimate the net pairwise spillovers. Table 5.3 documents the results of net spillovers.

Table 5.3: Net Return Spillover Table

OMXH25	OMXC20	OMXS30	OSEAX	EUR	DKK	SEK	NOK
4.70	-5.73	1.94	-4.29	2.74	2.59	0.97	-2.92

Source: Author's Estimations

The results indicate that Norwegian both markets are net return spillover receivers. Moreover, the other net spillover receiver is OMXC20. All other markets are net volatility givers. The highest volatility giver is OMXH25 (4.7%). OMXC20 turns to be the highest spillover receiver (5.73%). Moreover, the results reveal the difference between pegged and floating currency regimes. DKK and SEK mimic EUR in terms of shock transmission and all three are net givers, although the volume for SEK is much less, while free floating NOK is net receiver.

Table 5.4 documents the net pairwise spillovers among markets. OMXC20 acts as a net shock receiver in all its pairs, with exceptions of EUR (receives only 0.01%) and DKK (net shock transmission is zero, thus suggesting no net transmission between domestic stock and forex markets in Denmark). On the other hand, EUR dominates over all other pairs. Similar pattern can be observed for OSEAX that is dominating in all pairs, except for OMXC20. We can easily observe that forex markets are dominating over stock markets in all pairs, although the volumes are rather low. Even OMXH25, that is highest shock transmitter, dominates only over stock markets.

Table 5.4: Net Pairwise Return Spillover Table

		FROM						
		OMXH25	OMXC20	OMXS30	OSEAX	EUR	DKK	SEK
	OMXC20	2.56						
	OMXS30	0.83	-1.94					
	OSEAX	2.00	-0.45	1.27				
TO	EUR	-0.04	0.01	-0.03	-0.17			
	DKK	-0.04	0.00	-0.03	-0.18	0.05		
	SEK	-0.39	-0.52	-0.24	-0.65	0.86	0.82	
	NOK	-0.22	-0.27	-0.14	-0.47	1.6	1.57	0.85

Source: Author's Estimations

5.2.2 Static Analysis for Realized Volatility

In this section, we will perform similar analysis for realized volatilities. Table 5.5 reports the total volatility spillover table. Total spillover index reveals that on average 55.66% of volatility are transmitted to other markets, while the rest is transmitted from other markets not included in our sample. Compared to return spillovers, on average less volatility shocks are transmitted between the markets under analysis.

Table 5.5: Volatility Spillover Table

	OMXH25	OMXC20	OMXS30	OSEAX	EUR	DKK	SEK	NOK	FROM Stocks	FROM FX	FROM Others
OMXH25	60.56	9.55	16.95	4.01	2.33	1.97	2.66	1.98	30.51	8.94	39.45
OMXC20	5.81	49.61	21.26	6.7	4.63	4.07	4.13	3.78	33.77	16.61	50.38
OMXS30	8.45	16.81	51.29	7.26	4.74	4.06	4.17	3.22	32.52	16.19	48.71
OSEAX	3.77	9.96	13.8	57.45	2.89	2.96	4.13	5.04	27.53	15.02	42.55
EUR	0.74	2.6	3.34	1.07	32.23	28.39	16.05	15.57	7.75	60.01	67.76
DKK	0.67	2.32	2.94	1.2	29.35	31.36	16.25	15.92	7.13	61.52	68.65
SEK	1.09	2.96	3.83	2.15	18.29	17.54	36.05	18.09	10.03	53.92	63.95
NOK	0.81	3.13	3.3	2.58	18.1	17.39	18.54	36.14	9.82	54.03	63.85
TO Stocks	18.03	36.32	52.01	17.97	14.59	13.06	15.09	14.02			
TO FX	3.31	11.01	13.41	7.00	65.74	63.32	50.84	49.58	**Total Spillover Index 55.66%**		
TO	21.34	47.33	65.42	24.97	80.33	76.38	65.93	63.60			

Source: Author's Estimations

The directional spillovers TO other markets from each specific market range from 21.34% to 80.33% for OMXH25 and EUR, respectively. As for the return spillovers, the forex markets transmit more volatility to other markets compared to stock markets. From the decomposed directional spillovers to other assets we observe higher inter-market transmission than cross-market ones. This holds for both stock and forex markets. In the stock market the highest inter-market volatility transmission comes from OMXS30 (52.01%), while the lowest is from OSEAX (17.97%), followed by OMXH25 (18.03%). The volatility spillovers from stock market to forex market is also dominated by OMXS30 (13.41%), while OMXH25 contributes to the cross-market spillovers the least (3.31%). In the forex market the highest contributor of inter-market volatility spillovers is EUR (65.74%), while NOK contributes the least. On the other hand, the pattern changes for cross-market spillovers, where SEK transmits 15% of the volatility to stock markets, while DKK contributes the least.

The directional spillovers FROM other markets to each specific market range from 39.45% to 68.65%, a narrower range compared with directional spillovers TO other assets. Again, we observe higher spillover values for forex markets, compared to stock markets under analysis. The least volatility receiver is OMXH25 (similarly, as mentioned, it is transmitting the least TO other markets), while the most receiver is DKK (68.65%). Decomposed directional spillovers reveal higher inter-market volumes compared to those of cross-market spillovers. Moreover, inter-market spillover volumes are twice higher in forex markets. The highest volatility spillover transmitter among forex markets is DKK that transmits almost 62% of uncertainty to other markets. SEK and NOK report the lowest inter-market volatility volumes received, although they still receive more than 50% of uncertainty from other forex markets under analysis. On the other hand, SEK receives the most volatility from stock markets among forex markets, while DKK receives the least (10.03% and 7.13%, respectively). Among stock markets, as in case of forex markets, Danish stock market dominates in receiving inter-market volatility spillovers. The pattern does not change in cross-market spillovers. On the other hand, the least inter-market spillovers are received by OSAEX (27.53%), while OMXH25 receives the least from forex markets (8.94%).

Table 5.6: Net Volatility Spillover Table

OMXH25	OMXC20	OMXS30	OSEAX	EUR	DKK	SEK	NOK
-18.11	-3.05	16.71	-17.58	12.57	7.73	1.98	-0.25

Source: Author's Estimations

To get more insight about the spillovers, let's proceed with net and net pairwise volatility spillover analysis. Table 5.6 reports the net volatility spillovers. As it was for return spillovers, forex markets, except Norwegian one, are net spillover transmitters. Moreover, stock markets are net volatility receivers, except Swedish stock market that transmits the highest volume of volatility to other markets. The most volatility is received by OMXH25 and OSAEX, 18.11% and 16.71%, respectively.

Table 5.7: Net Pairwise Volatility Spillover Table

		FROM						
		OMXH25	OMXC20	OMXS30	OSEAX	EUR	DKK	SEK
	OMXC20	-3.74						
	OMXS30	-8.5	-4.45					
	OSEAX	-0.24	3.26	6.54				
TO	EUR	-1.59	-2.03	-1.4	-1.82			
	DKK	-1.3	-1.75	-1.12	-1.76	0.96		
	SEK	-1.57	-1.17	-0.34	-1.98	2.24	1.29	
	NOK	-1.17	-0.65	0.08	-2.46	2.53	1.47	0.45

Source: Author's Estimations

Table 5.7 presents the net pairwise volatility spillover table that provides more insight about the volatility spillovers between the markets. As for the returns, forex markets are dominating over the stock markets. OMXH25 turns to be net receiver in all pairs, while EUR is net giver for its all pairs. OSEAX is also dominated in all its pairs, with exception of OMXH25, while NOK is dominating in stock pairs, except for OMXS30, and is dominated in its FX pairs.

Now we can proceed with dynamic analysis and shed light on the evolution of connectedness and the spillovers during pre- and post-crisis periods.

5.3 Conditional Patterns

In previous section, we performed static spillover analysis for returns and realized volatilities, which provides with overview of average spillover effects over the period of our research. To get more insight in the spillover effects, we will proceed with dynamic spillovers analysis. In this section, we will construct dynamic spillover measures using the methodology, proposed by Diebold & Yilmaz (2012). As described in Section 4.1, their methodology is based on H-step-ahead forecast error variance decomposition of vector autoregressive (VAR) model. To capture dynamics of spillover effects we employ 200-day rolling window and forecast horizon of 10 days. VAR model order will be one for returns and three for volatilities, the same as for static analysis.

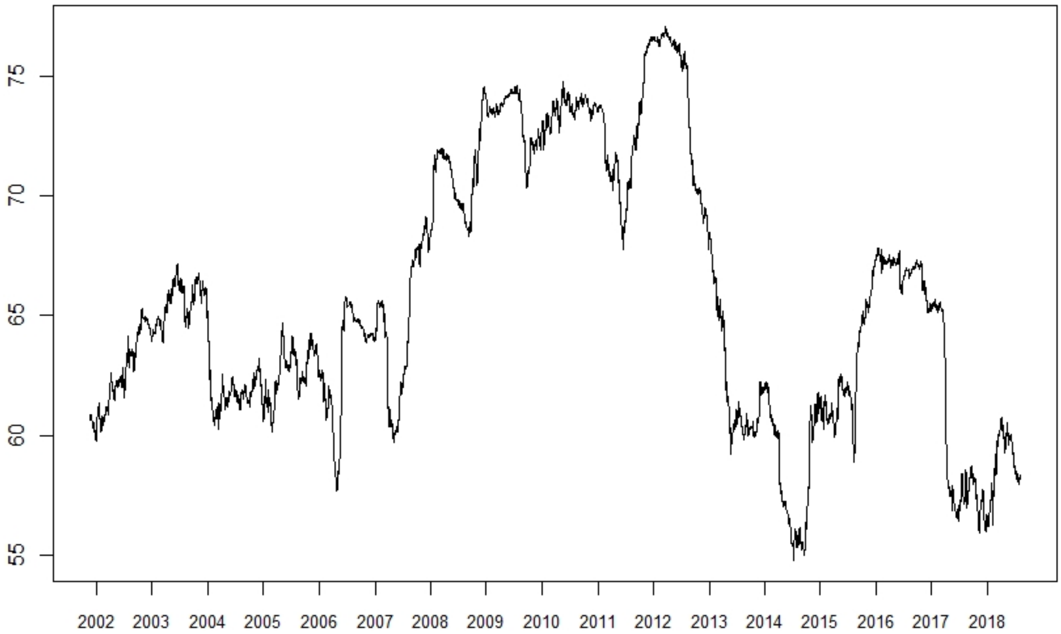
First, we will analyze the dynamics of total spillovers for the analyzed period of time. Afterwards, we will go through the directional spillover contributions FROM and TO other markets. Finally, we will discuss the net total spillovers. All these dynamics will be discussed for both returns and realized volatilities.

5.3.1 Dynamic Analysis for Returns

Figure 5.1 reports the evolution of the total spillovers index for returns. We can observe rather volatile dynamics of the spillovers. No long-run trends are observed, however, some short ones can be noticed. High levels of spillovers are observed during the whole period under the analysis. They are fluctuating between 55% to 77%. In the beginning of the analyzed period we observe increase in the return spillovers, attributed to October 2002 stock market downturn, when stock markets worldwide reached their lows since 1997. Moreover, we can inspect high spikes during the global financial crisis starting from April of 2007, when Bear and Stearns was bailed out, followed by suspension of the withdrawals from two of BNP Paribas hedge funds, bankruptcy of Lehman Brother's in September 14, 2008 and US subprime mortgage crisis that led to global financial crisis. The turmoil in the markets persisted for quite a long period of time, until the end of 2009. However, immediately after that European sovereign debt crisis tensions started in 2010 and we again observe spike in the total spillover index. It reaches its peak in 2012, when Greece was downgraded to default rates by Fitch and S&P rating companies. As those tensions wiped out, we examine downward evolution of spillover index. The surge of the spillover index is also noticed in mid-October of 2014, when US stock market started to decline. Those levels were persisted until the end of 2015. Furthermore, in the end of 2014 global stock markets declined with tumbling oil prices and political uncertainty in Greece with negative outlook of possible new Eurozone crisis. In the end of 2015 we easily observe another jump of spillover index. This may be caused by the Black Monday in China, when stock markets worldwide were hit. Moreover, in 2016 Brexit referendum forced the spillover index hit its second peak since 2013. Those high volumes of spillovers persist until 2017 and afterwards it returns to its pre-crisis periods.

To shed more light on the spillovers between the markets under analysis, we will proceed with the directional spillovers. As already mentioned in Section 4.1, direc-

Figure 5.1: Total Return Spillover Index

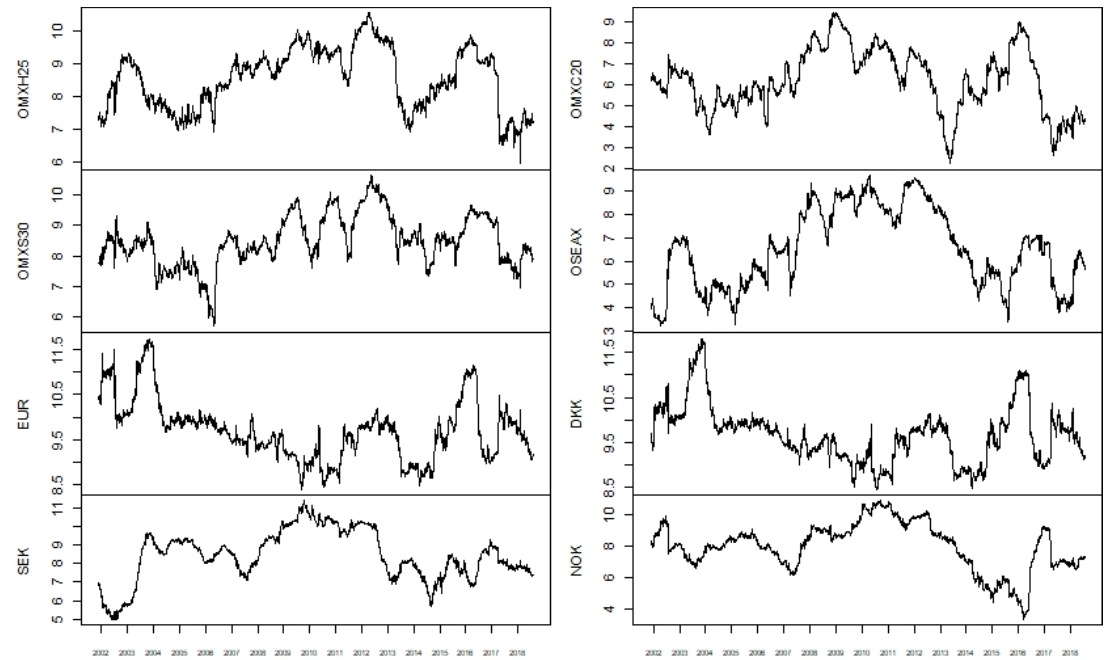


Source: Author's Estimations

tional spillovers are useful for understanding how each of the markets affects the other markets and vice versa. Figure 5.2 presents the directional return spillovers from one specific market TO all other markets during the whole period of analysis. The results indicate that OMXH25, OMXS30, EUR and DKK have rather smooth spillovers during global financial crisis period of 2007-2009, while in other markets we notice spikes. This suggests that Finnish both financial markets are not much affected by GFC. Moreover, EUR and DKK exhibit even decreasing trend during those periods. Further, we observe three main cycles in stock markets since 2010, attributed to European debt crisis tensions. On the other hand, cannot examine such big cycles in forex market, only for EUR and DKK increased spillovers are noticed for the period of 2011-2013. Another sharp increase in spillovers TO other markets can be examined in the end of 2015, due to Black Monday in China and in mid 2016 after Brexit referendum.

Figure 5.3 presents the directional spillovers FROM other markets to each specific market, thus, showing how much shocks are received by each market. We observe in general rather lower volumes of transmission, compared to spillovers TO others. As opposed to directional spillovers TO other markets, all markets exhibit higher volumes of spillovers FROM other markets during global financial

Figure 5.2: Directional Return Spillovers TO others



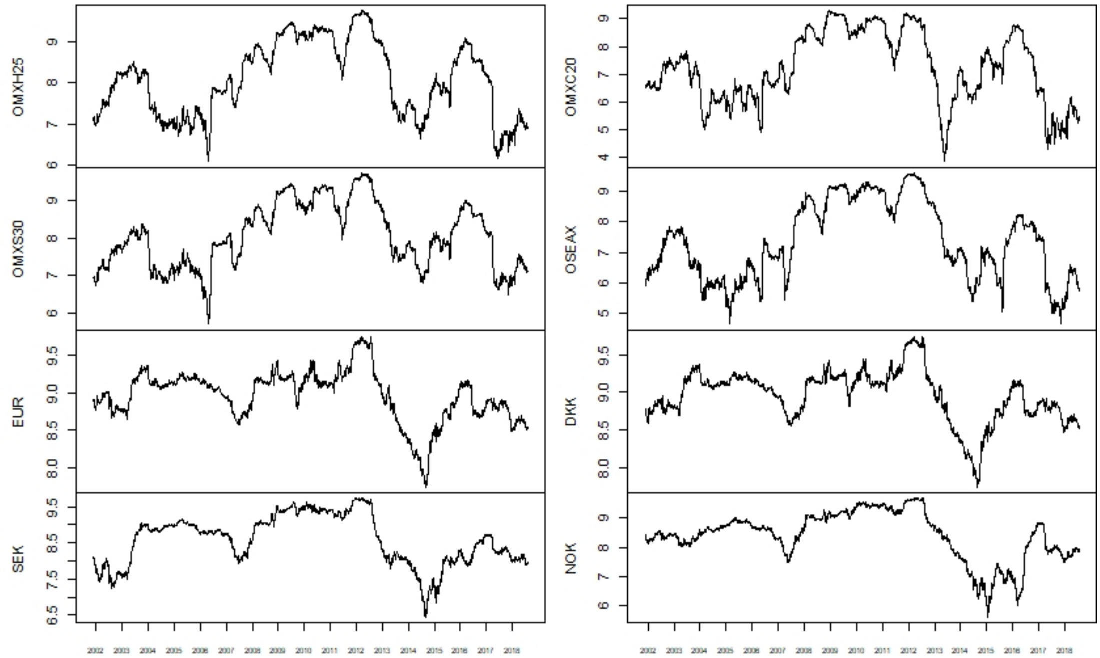
Source: Author's Estimations

crisis of 2007-2009. Those kind of high levels of spillovers remain until 2013, due to sovereign debt crisis immediately following global financial crisis.

Moreover, it can be easily examined that the markets under analysis, but OMXC20, reach their peaks in 2012. The latest reaches its peak in 2010, when the tensions of sovereign debt crisis just started. Thus, this suggests that the markets under analysis are more affected by sovereign debt crisis, rather than global financial crisis. Furthermore, we can distinctly observe two more spikes in all markets since 2014. Those periods correspond to oil market turmoil in the end of 2014 and mid 2015 Chinese Black Monday. What's also interesting, after Brexit referendum in June 2016 we observe declining trends in all markets, except SEK and NOK. The latest two are reaching their second peak since sovereign debt crisis. This suggests the notion that floating exchange rates are more prone to shocks from Brexit turmoil, while others exhibit downward trend. Similar trend is noticed in stock markets.

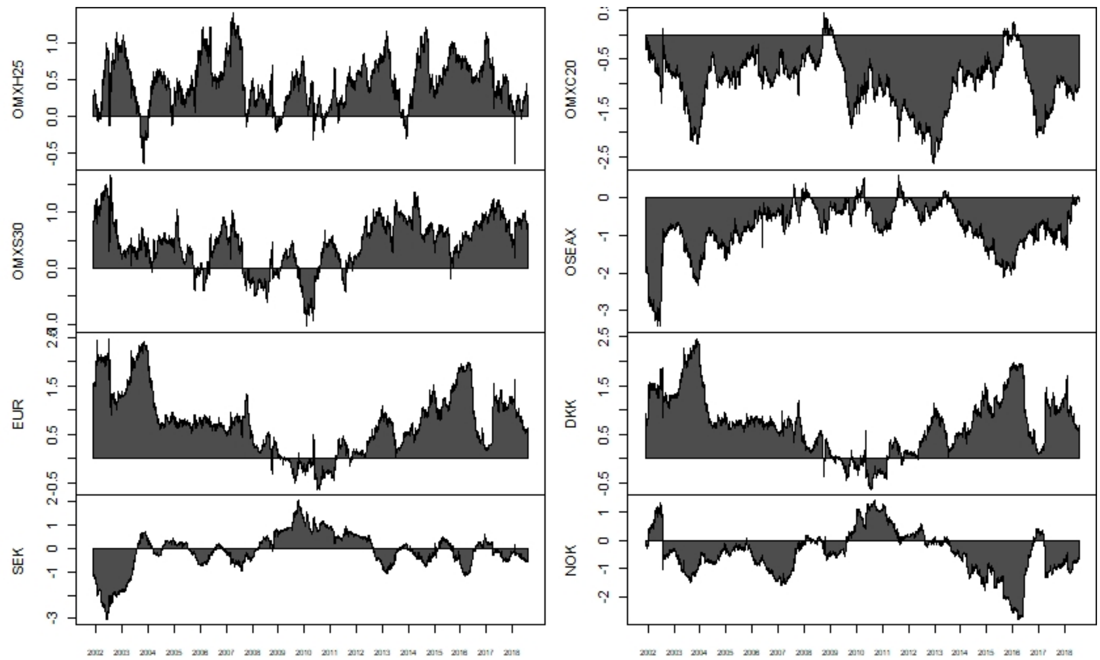
Figure 5.4 documents the NET return spillovers for the 18-year period. Those are determined as the difference between the shock transmissions TO others and transmissions FROM others. Thus, the positive values mean that the particular

Figure 5.3: Directional Return Spillovers FROM others



Source: Author's Estimations

Figure 5.4: NET Return Spillovers



Source: Author's Estimations

market transmits more shocks to others than it receives from others and vice versa. In case of positive values the market will be called net spillover giver (transmitter) and in case of negative values market is called net spillover receiver. The results indicate that EUR and DKK exhibit similar patterns for the whole period of time and they are predominantly net spillover transmitters along with OMXH25 and OMXS30. The other four markets exhibit inverse pattern, thus being net spillover receivers for the whole span. These findings suggest that Norwegian financial markets, SEK and OMXC20 do not contribute much to return spillovers. The only distinct period is the sovereign debt crisis, when all the forex markets along with OMXS30 invert their signs.

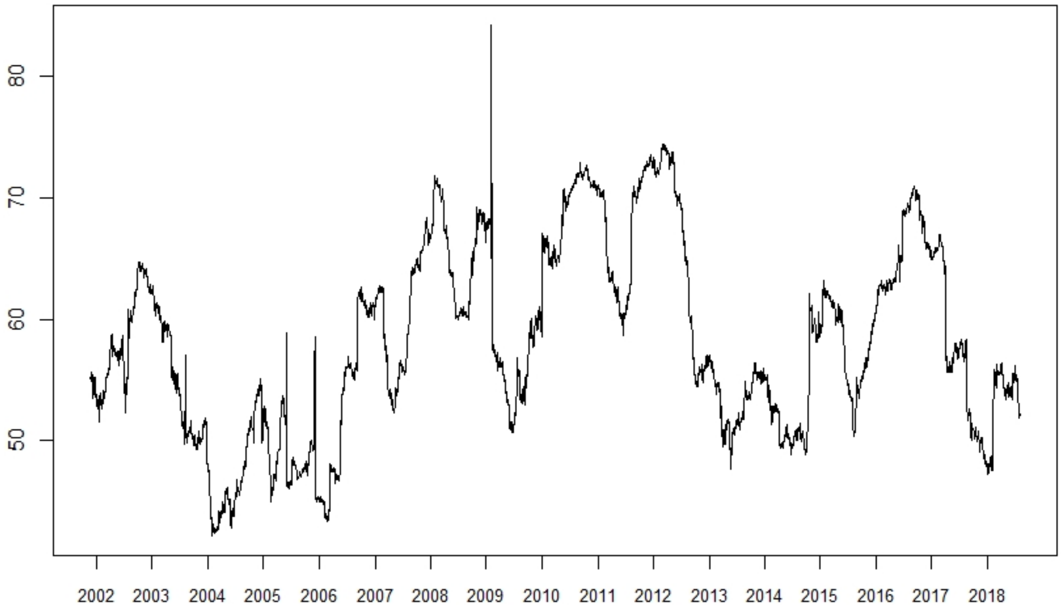
5.3.2 Dynamic Analysis for Realized Volatility

In the previous section, we discussed the dynamic return spillovers. Now we will proceed with a similar analysis of volatility spillovers. Figure 5.5 documents the total volatility spillover index evolution through the 18-year time period. As for the returns, the volatility spillovers used to be rather low in the beginning of the century, while there is persistent jump for almost two years. This may be caused by the turmoil in October 2002, that led to huge losses in stock markets globally. Moreover, we observe persistent increase in volatility spillovers in during the period of global financial crisis, when the uncertainty hits the financial market globally. During that period the spillover index reaches 72% in 2008, attributable to Lehman Brothers' collapse. Since 2009 we observe rather calmer times that last only one year. Those times are interrupted by sovereign debt crisis in 2010.

The volatility spillover index reaches its peak during those times, more precisely in mid 2012. This again supports the notion that market under analysis are more affected by sovereign debt crisis, rather than by global financial crisis. Further, turmoil periods are noticed since the end of 2014, when financial market worldwide incurred losses due to oil price tumbling. In 2015 and 2016 we observe uncertainty hitting the markets again. We can easily examine the that Brexit referendum led to as much turmoil in the markets as the global financial crisis. Since mid 2017 the total volatility spillover levels returned to their pre-crisis levels. To shed more light on dynamics of volatility spillovers between the markets, we will proceed with the directional spillover analysis.

Figure 5.6 documents the development of directional volatility spillovers from each specific market under analysis TO all other markets in the system. Due to high non-persistent jumps in directional spillovers in some markets, directional volatility spillover figures present the developments in a limited band. The full

Figure 5.5: Total Volatility Spillover Index

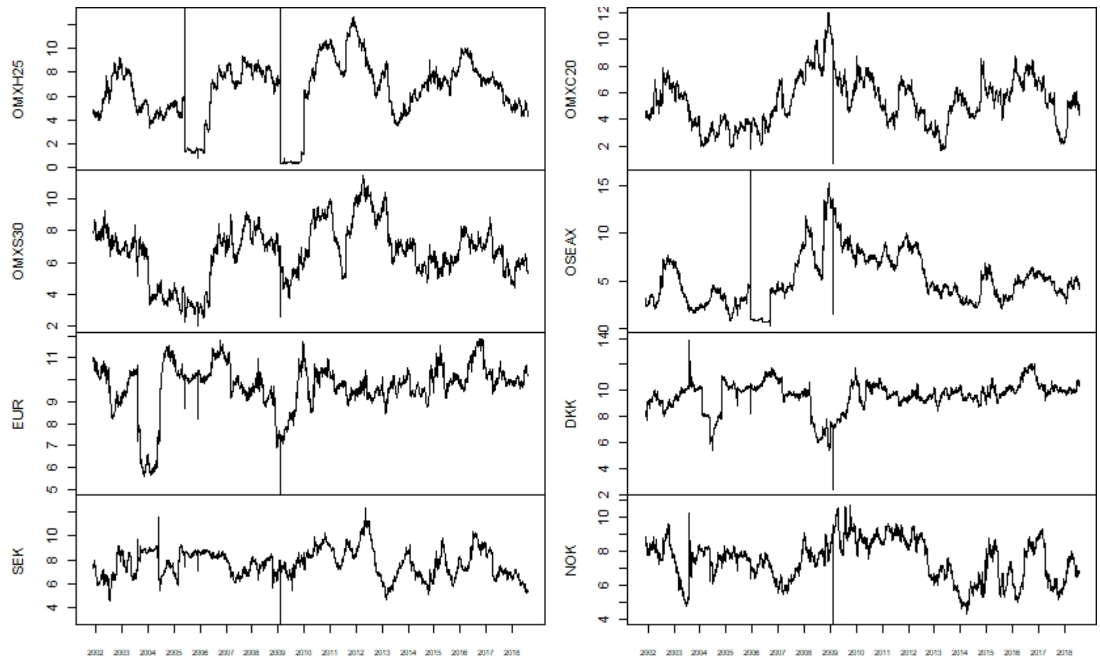


Source: Author's Estimations

figures can be found in Appendix. From the results we can conclude that the cycles, corresponding to the turmoil periods, are not that distinct in forex market, while we can observe rather distinctive patterns in stock markets. In stock markets persistent jump in directional spillovers TO others during global financial crisis since mid 2007 till end of 2008.

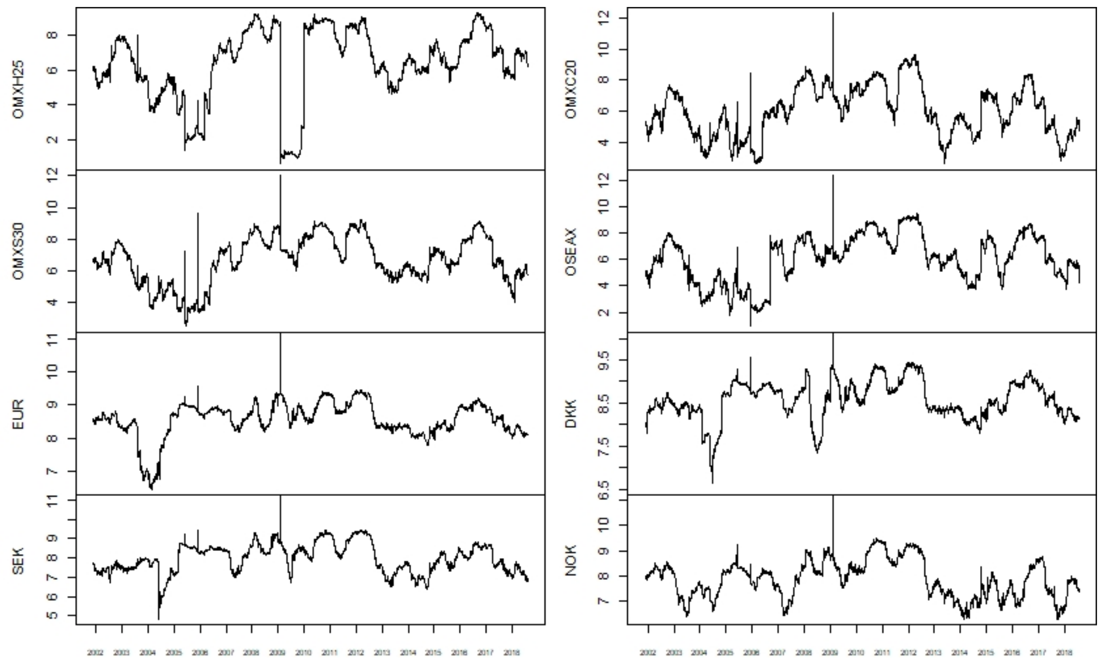
On the other hand, the forex markets exhibit rather decreasing trends during those times. The next high volatility transmission period from stock markets is noticed since 2010, the beginning of sovereign debt crisis tensions. We can easily examine that OMXH25 and OMXS30 reach their highs during that period, while OSEAX and OMXC20 during 2007-2009 period. This suggests that the Norwegian and Danish stock markets do not contribute much to volatility spillovers during sovereign debt crisis. On the other hand, the forex markets evolve similar to OMXH25 adn OMXS30, exhibiting increase in spillovers during 2010-2013 period. Moreover, we observe distinct cycle in the end of the span under analysis. This pattern is not that distinct in OSEAX. This again supports our previous finding that Norwegian stock market does not contribute much to spillover transmissions. On average we can observe that EUR and DKK transmit spillovers the most, while OSEAX has the least contribution.

Figure 5.6: Directional Volatility Spillovers TO others



Source: Author's Estimations

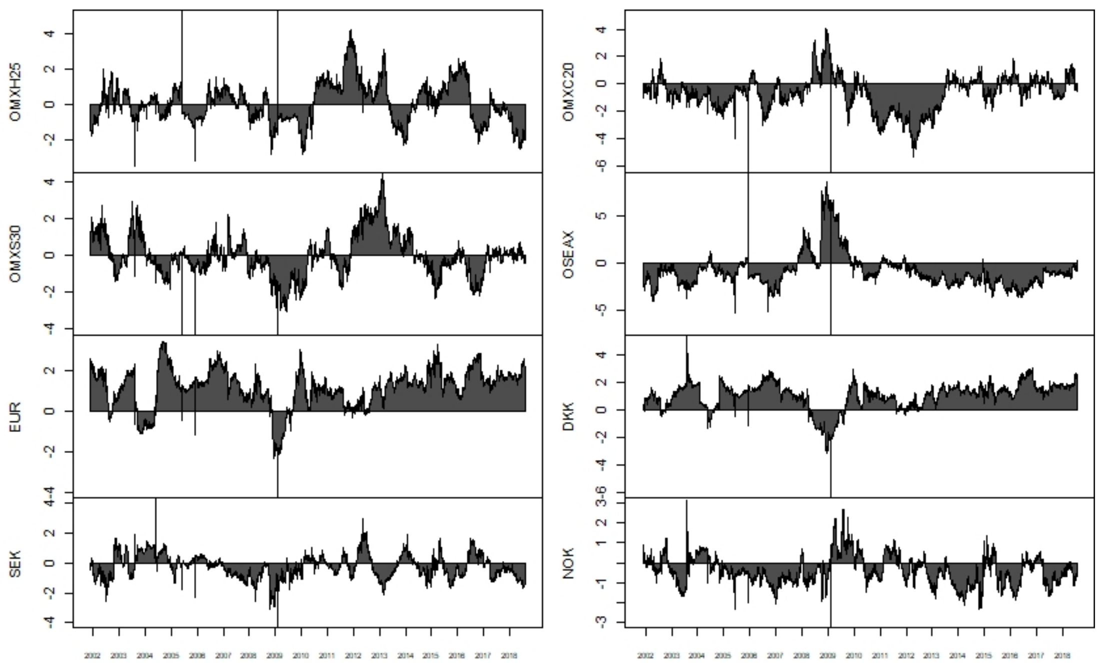
Figure 5.7: Directional Volatility Spillovers FROM others



Source: Author's Estimations

Figure 5.7 documents the directional volatility spillovers FROM other markets to each specific market. In general, we observe lower volumes of transmission FROM other markets, compared to those TO others, as it was the case for returns. An interesting observation from all markets is that all turmoil periods are represented with cycles of similar magnitudes in all markets under analysis. Slightly higher volumes of spillovers can be observed for OSEAX and OMXC20 during sovereign debt crisis, compared to other events leading to high spillover transmission. This suggests that the level of uncertainty in the markets was almost the same for all the events. Another interesting observation is that FX markets seem to receive volatility spillovers more on average, compared to stock markets. Moreover, only OSEAX, OMXC20 and NOK return to their pre-crisis volatility spillover levels after 2013, while other markets seem to have high spillover transmission levels up to the end of the period under analysis. This is in line with our previous findings.

Figure 5.8: NET Volatility Spillovers



Source: Author's Estimations

Figure 5.8 reports the net volatility spillovers in all markets. As already described in Section 4.1 those spillover measures are estimated as the difference between the spillovers transmitted TO other markets and spillovers received FROM other markets. From the results, we can inspect positive values of net volatility spillovers during the whole period for EUR and DKK. This suggests that those two markets are net volatility givers. OSEAX, NOK and OMXC20 are net volatility receiver for the whole period under analysis, with exception of rather short time period of 2008-2010. These results are in line with our previous findings.

Other markets exhibit rather balanced patterns of volatility transmissions, with dominance of negative net volatility transmission values during the global financial crisis period. The only net volatility transmitters during that period are OSEAX, OMXC20 and NOK. On the other hand, European debt crisis is characterized by positive net spillovers for EUR, DKK, OMXH25 and OMXS30, while OSEAX and OMXC20 exhibit negative values. The other markets have balanced patterns.

5.4 Frequency Connectedness

In this section, we will demonstrate the frequency connectedness between forex and stock markets in Scandinavian countries. Based on the approach of Baruník & Křehlík (2018) we will decompose the total spillover indices for returns and volatilities into frequency bands representing short-, medium- and long-term connectedness. [1]
This section is constructed as follows: first, we will perform a static analysis for frequency connectedness for both returns and realized volatilities and afterwards we will proceed with dynamic analysis.

5.4.1 Static Frequency Connectedness

Table 5.8 presents the static connectedness table for returns on different frequencies. From total spillover indices, we can observe that short-term return spillovers prevail over those both in medium- and long-term horizons. This is in contrary with our third hypothesis, that states that connectedness in higher frequencies is not higher than in lower frequencies. Furthermore, we may examine no spillover effects in medium- and long-run between some of the markets, such as in pairs like OMXC20–EUR, OMXC20–DKK in medium-run and EUR and DKK with OMXH25, OMXS30 and OMXC20 in long-run. From directional spillovers TO other markets, we can examine higher inter-market return connectedness in forex markets in short-run, compared to stock markets. On the other hand, stock markets on average contribute more to inter-market connectedness in medium- and

[1] The frequency connectedness at short-term horizon is defined at $d_1 \in [1;5]$ days (week), medium-term horizon is defined at $d_2 \in (5;20]$ days (month) and long-term horizon is defined at $d_3 \in (20;200]$ days (year).

long-run horizons. The difference between contribution of forex and stock markets in cross-market return spillovers is not that distinct, but again forex market prevalence can be observed. Directional spillovers FROM other markets reveals different pattern regarding inter-market and cross-market return connectedness. Forex markets prevail over stock markets in inter-market return connectedness in all frequencies. The pattern is the same for cross-market return spillovers.

Table 5.8: Frequency Decomposition of Static Return Connectedness

	OMXH25	OMXC20	OMXS30	OSEAX	EUR	DKK	SEK	NOK	FROM Stocks	FROM FX	FROM Others
Short-term Connectedness											
OMXH25	28.3	14.06	19.89	14.33	0.11	0.11	1.52	1.26	48.28	3.00	51.28
OMXC20	15.65	32.28	15.28	13.75	0.03	0.03	1.01	0.9	44.68	1.97	46.65
OMXS30	21.38	14.71	30.02	13.89	0.08	0.09	1.17	0.92	49.98	2.26	52.24
OSEAX	15.6	13.36	13.94	31.82	0.47	0.46	1.83	1.92	42.90	4.68	47.58
EUR	0.11	0.05	0.07	0.43	24.9	24.62	16.72	15.51	0.66	56.85	57.51
DKK	0.11	0.04	0.07	0.41	24.64	24.96	16.71	15.42	0.63	56.77	57.40
SEK	1.42	0.83	1.03	1.63	17.32	17.28	26.14	16.83	4.91	51.43	56.34
NOK	1.23	0.85	0.85	1.74	16.33	16.24	17.02	27.22	4.67	49.59	54.26
TO Stocks	52.63	42.13	49.11	41.97	0.69	0.69	5.53	5.00			
TO FX	2.87	1.77	2.02	4.21	58.29	58.14	50.45	47.76	**Total Spillover Index 52.91%**		
TO	55.50	43.90	51.13	46.18	58.98	58.83	55.98	52.76			
Medium-term Connectedness											
OMXH25	5.24	2.53	3.86	2.54	0.04	0.04	0.44	0.34	8.93	0.86	9.79
OMXC20	3.24	5.86	3.25	2.55	0.01	0.01	0.34	0.25	9.04	0.61	9.65
OMXS30	3.38	2.26	4.89	2.04	0.03	0.03	0.27	0.21	7.68	0.54	8.22
OSEAX	3.08	2.50	2.92	5.38	0.14	0.14	0.53	0.47	8.50	1.28	9.78
EUR	0.01	0.00	0.01	0.04	4.04	4.00	2.64	2.25	0.06	8.89	8.95
DKK	0.01	0.00	0.01	0.04	4.02	4.04	2.64	2.26	0.06	8.92	8.98
SEK	0.23	0.10	0.20	0.20	2.82	2.82	4.10	2.47	0.73	8.11	8.84
NOK	0.21	0.09	0.15	0.26	2.82	2.80	2.95	4.37	0.71	8.57	9.28
TO Stocks	9.70	7.29	10.03	7.13	0.22	0.22	1.58	1.27			
TO FX	0.46	0.19	0.37	0.54	9.66	9.62	8.23	6.98	**Total Spillover Index 9.19%**		
TO	10.16	7.48	10.40	7.67	9.88	9.84	9.81	8.25			
Long-term Connectedness											
OMXH25	1.88	0.9	1.38	0.91	0.01	0.01	0.16	0.12	3.19	0.30	3.49
OMXC20	1.17	2.09	1.17	0.91	0.00	0.00	0.13	0.09	3.25	0.22	3.47
OMXS30	1.20	0.80	1.74	0.72	0.01	0.01	0.1	0.07	2.72	0.19	2.91
OSEAX	1.11	0.89	1.05	1.92	0.05	0.05	0.19	0.17	3.05	0.46	3.51
EUR	0.00	0.00	0.00	0.01	1.44	1.42	0.93	0.79	0.01	3.14	3.15
DKK	0.00	0.00	0.00	0.01	1.43	1.44	0.94	0.80	0.01	3.17	3.18
SEK	0.08	0.03	0.07	0.07	1.00	1.00	1.45	0.87	0.25	2.87	3.12
NOK	0.07	0.03	0.05	0.09	1.01	1.00	1.05	1.55	0.24	3.06	3.30
TO Stocks	3.48	2.59	3.60	2.54	0.07	0.07	0.58	0.45			
TO FX	0.15	0.06	0.12	0.18	3.44	3.42	2.92	2.46	**Total Spillover Index 3.27%**		
TO	3.63	2.65	3.72	2.72	3.51	3.49	3.50	2.91			

Table 5.9 presents the net return spillovers in three frequencies. We can examine more net return spillover receivers in short-run, than in medium- and long-run

Table 5.9: Frequency Decomposition of NET Return Connectedness

OMXH25	OMXC20	OMXS30	OSEAX	EUR	DKK	SEK	NOK
Short-term Connectedness							
4.22	-2.75	-1.11	-1.40	1.47	1.43	-0.36	-1.50
Medium-term Connectedness							
0.37	-2.17	2.18	-2.11	0.93	0.86	0.97	-1.03
Long-term Connectedness							
0.14	-0.82	0.81	-0.79	0.36	0.31	0.38	-0.39

horizons. This is mainly due to SEK and OMXS30 that are net receivers in short-run, while net spillover givers in medium- and long-run. All other markets keep the same sign of net spillover contribution in all frequencies. Furthermore, we observe higher volumes of net spillovers in shorter terms than in longer-term periods. This is in line with our previous finding.

Now let us proceed with the static frequency connectedness analysis for realized volatilities. Table 5.10 reports total spillover table for volatilities. From total spillover indices in different frequencies, we can observe that on average long-term connectedness (29.13%) is much tighter than short-term one (16.53%), while medium-term connectedness is the lowest (12.09%). Furthermore, we examine prevalence of inter-market volatility connectedness, based on spillovers TO other markets, in forex markets over stock markets in short- and medium-term horizons, while the contributions TO others in long-run are almost similar from both markets. On the other hand, the cross-market volatility spillovers are prevailed by forex markets in all frequencies. Similar patterns can be noticed from directional spillovers FROM other markets. Again, we document high dominance of forex markets in inter-market volatility connectedness in short- and medium-run periods, while stock markets take over in long-run. The directional cross-market volatility connectedness FROM others reveals dominance of forex markets in all frequencies.

Table 5.11 documents the NET volatility connectedness decomposed into different frequencies. In NET spillovers the pattern reverses a little bit. We observe higher NET spillover volumes in lower frequencies. Thus, the short-run connectedness is the lowest, while long-run is the highest. As it was for returns, SEK is net volatility receiver in short-run, while it is net volatility transmitter in long-run. NOK performs similarly, being net receiver in short- and medium-run and net

Table 5.10: Frequency Decomposition of Static Volatility Connectedness

	OMXH25	OMXC20	OMXS30	OSEAX	EUR	DKK	SEK	NOK	FROM Stocks	FROM FX	FROM Others
Short-term Connectedness											
OMXH25	34.71	1.64	3.68	0.95 0	.35	0.34	0.38	0.31	6.27	1.38	7.65
OMXC20	1.08	19.89	2.96	1.04	0.50	0.48	0.42	0.46	5.08	1.86	6.94
OMXS30	1.86	2.3	14.53	1.17	0.59	0.60	0.60	0.60	5.33	2.39	7.72
OSEAX	0.71	1.22	1.75	26.24	0.18	0.20	0.21	0.35	3.68	0.94	4.62
EUR	0.20	0.39	0.59	0.11	15.66	14.08	7.06	6.67	1.29	27.81	29.10
DKK	0.20	0.39	0.62	0.13	14.66	16.56	7.09	6.75	1.34	28.50	29.84
SEK	0.21	0.35	0.63	0.14	7.65	7.60	16.88	6.99	1.33	22.24	23.57
NOK	0.18	0.37	0.63	0.24	7.23	7.22	6.95	17.11	1.42	21.40	22.82
TO Stocks	3.65	5.16	8.39	3.16	1.62	1.62	1.61	1.72			
TO FX	0.79	1.50	2.47	0.62	29.54	28.90	21.10	20.41	**Total Spillover Index 16.53%**		
TO	4.44	6.66	10.86	3.78	31.16	30.52	22.71	22.13			
Medium-term Connectedness											
	OMXH25	OMXC20	OMXS30	OSEAX	EUR	DKK	SEK	NOK	FROM Stocks	FROM FX	FROM Others
OMXH25	12.21	2.21	3.73	0.79	0.44	0.35	0.56	0.40	6.73	1.75	8.48
OMXC20	1.26	9.68	4.62	1.47	0.94	0.82	0.84	0.78	7.35	3.38	10.73
OMXS30	1.71	3.50	9.92	1.45	0.85	0.70	0.71	0.50	6.66	2.76	9.42
OSEAX	0.80	2.25	3.01	13.04	0.59	0.65	1.00	1.34	6.06	3.58	9.64
EUR	0.12	0.56	0.66	0.23	7.08	6.13	3.52	3.52	1.57	13.17	14.74
DKK	0.10	0.49	0.55	0.28	6.32	6.59	3.70	3.73	1.42	13.75	15.17
SEK	0.22	0.62	0.73	0.55	3.98	3.76	8.01	4.16	2.12	11.90	14.02
NOK	0.14	0.71	0.58	0.69	4.11	3.88	4.39	7.99	2.12	12.38	14.50
TO Stocks	3.77	7.96	11.36	3.71	2.82	2.52	3.11	3.02			
TO FX	0.58	2.38	2.52	1.75	14.41	13.77	11.61	11.41	**Total Spillover Index 12.09%**		
TO	4.35	10.34	13.88	5.46	17.23	16.29	14.72	14.43			
Long-term Connectedness											
	OMXH25	OMXC20	OMXS30	OSEAX	EUR	DKK	SEK	NOK	FROM Stocks	FROM FX	FROM Others
OMXH25	10.12	6.40	10.52	2.59	1.99	1.65	2.10	1.57	19.51	7.31	26.82
OMXC20	3.56	16.87	14.74	4.43	3.72	3.20	3.37	2.88	22.73	13.17	35.90
OMXS30	4.69	11.49	24.45	4.82	3.87	3.22	3.36	2.51	21.00	12.96	33.96
OSEAX	2.48	7.31	10.35	13.94	2.72	2.59	3.43	3.64	20.14	12.38	32.52
EUR	0.57	2.12	2.77	0.97	8.84	7.59	5.33	5.22	6.43	18.14	24.57
DKK	0.49	1.86	2.37	1.01	7.87	7.60	5.35	5.31	5.73	18.53	24.26
SEK	0.83	2.57	3.29	1.76	6.39	5.89	10.12	6.66	8.45	18.94	27.39
NOK	0.66	2.59	2.86	1.93	6.54	6.03	6.98	10.01	8.04	19.55	27.59
TO Stocks	10.73	25.20	35.61	11.84	12.30	10.66	12.26	10.60			
TO FX	2.55	9.14	11.29	5.67	20.80	19.51	17.66	17.19	**Total Spillover Index 29.13%**		
TO	13.28	34.34	46.90	17.51	33.10	30.17	29.92	27.79			

Table 5.11: Frequency Decomposition of NET Volatility Connectedness

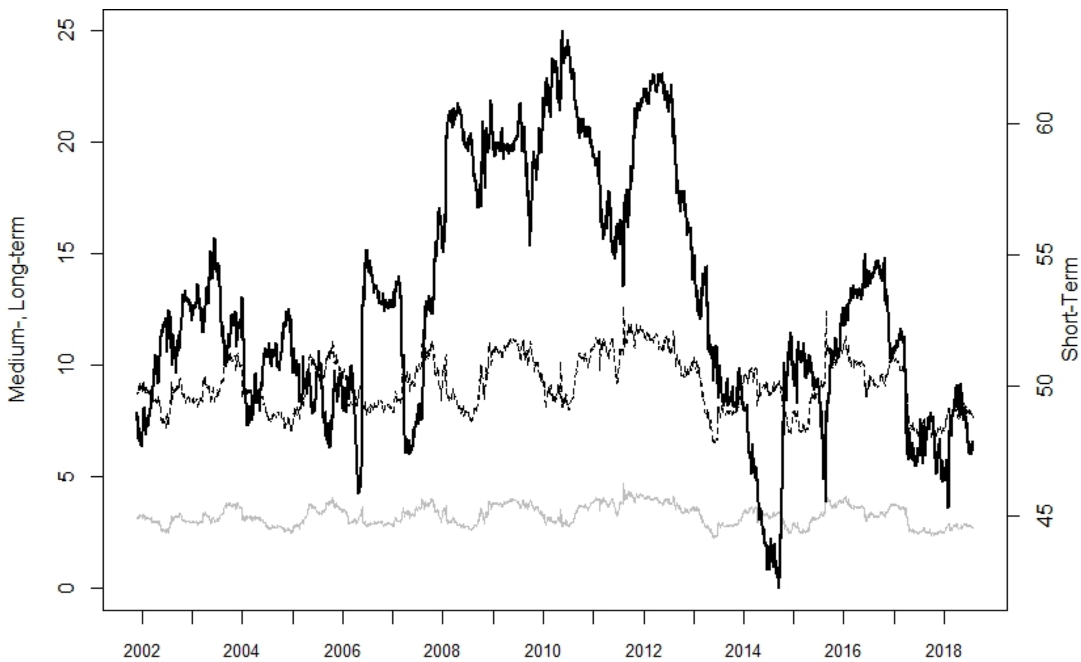
OMXH25	OMXC20	OMXS30	OSEAX	EUR	DKK	SEK	NOK
Short-term Connectedness							
-3.21	-0.28	3.14	-0.84	2.06	0.68	-0.86	-0.69
Medium-term Connectedness							
-4.13	-0.39	4.46	-4.18	2.49	1.12	0.7	-0.07
Long-term Connectedness							
-13.54	-1.56	12.94	-15.01	8.53	5.91	2.53	0.2

volatility transmitter in long-run. All other markets behave the same way in all frequencies. The highest volatility transmitter in short-run is OMXS30 (3.14%), followed by EUR (2.06%), while the highest receiver is OMXH25 (3.21%). On the other hand, in long-run horizon the pattern changes slightly. While again OMXS30 and EUR dominate as net volatility transmitters, the most is received by OSEAX (15%), followed by OMXH25 (13.54%).

5.4.2 Dynamic Frequency Connectedness

In the previous section, we performed static analysis of frequency return and volatility connectedness, which gives us an average information about interconnectedness between the markets under analysis. Now we will proceed with dynamic frequency connectedness analysis. To get the dynamics, we used 200 days of rolling window and forecasting horizon of 100 days. Thus, our data points decrease by 200 days.

Figure 5.9: Total Return Frequency Connectedness



Notes: The frequency connectedness at short-term horizon defined at $d_1 \in [1; 5]$ days in bold line (right axis), medium-term horizon defined at $d_2 \in (5; 20]$ days in dashed line (left axis) and long-term horizon defined at $d_3 \in (20; 200]$ days in grey line (left axis). All lines through the frequency bands sum to the total connectedness.

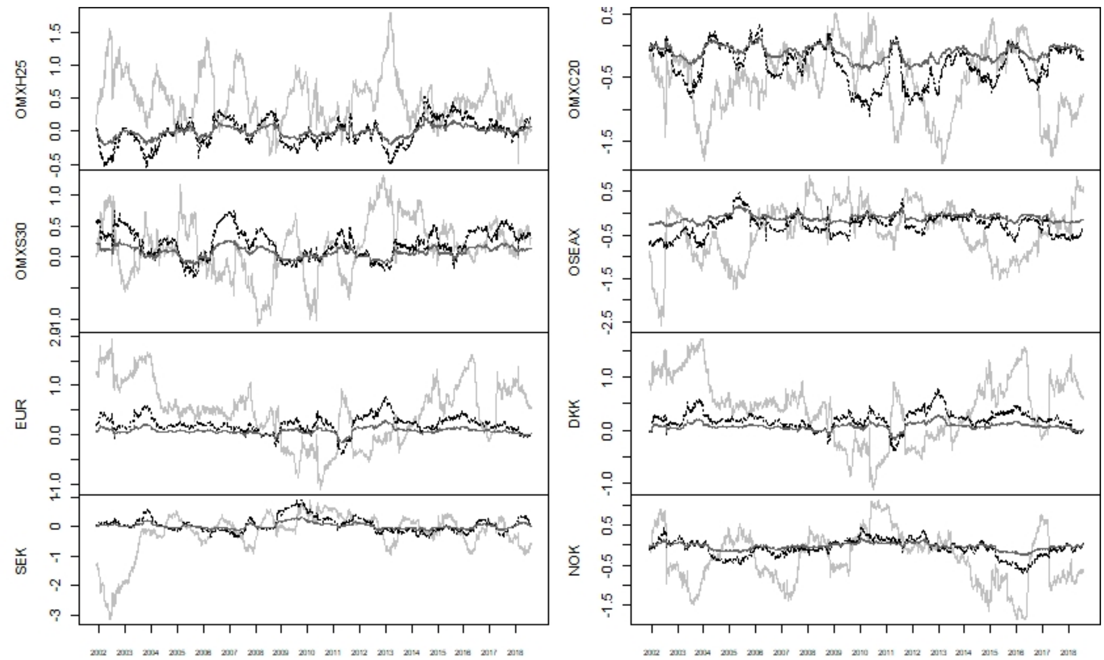
Figure 5.9 presents the dynamic total frequency connectedness for returns. We can easily observe that short-term connectedness highly prevails over connectedness in medium- and long-term horizons. This is in line with our previous finding from static analysis for returns. The long-run connectedness is the smoothest with rather small cycles during the whole period under analysis. Although the connectedness is much tighter in medium-run, the volatility of the volumes are rather low too. However, we can still notice some spikes corresponding to turmoil periods, such as global financial crisis in 2007-2009, European sovereign debt crisis in 2010-2013, Black Monday in China in 2015, for both medium-term and long-term connectedness. The dynamics are more saturated in short-run. We observe spike in return spillovers from 47% to 61% in 2008. That high spillovers volume persists until the end of 2010. Afterwards, we examine spike of similar magnitude during 2010-2013 period, corresponding to European debt crisis. Another round of high spillover transmissions is 2016-2017 period, when Britains voted for Brexit. In 2018 the spillover volumes returned to their pre-crisis periods, consequently suggesting rather calmer times.

What is also important is that the connectedness in all horizons reach their peaks during sovereign debt crisis in 2012, rather than during global financial crisis. Moreover, both medium- and long-run connectedness have downward sloping trends after Brexit referendum in 2016, while short-run connnectedness reaches its second peak.

To save some space we will proceed directly to NET dynamic spillover analysis for returns. Figure 5.10 presents the NET dynamic spillovers for returns in three frequencies. For all markets, we observe rather low connectedness dynamics in long-run. This supports the notion that directional spillovers FROM and TO other markets are not significantly different from each other in long-run. Although, similar patterns are observed in medium-run NET spillover dynamics, we can still reveal some distinct patterns. OMXS30, EUR and DKK are net spillover givers, with exception of two periods, from 2008 till 2009 and from 2011 till 2012 for the latest two. The latest period corresponds to European debt crisis. Other stock markets are dominated by negative values in medium-run for the whole period under analysis.

On the other hand, the short-run dynamics have higher volumes and are more informative in our case. Those dynamics reveal that during the whole period under analysis EUR and DKK are net spillover givers, with exception of two pe-

Figure 5.10: NET Return Frequency Connectedness



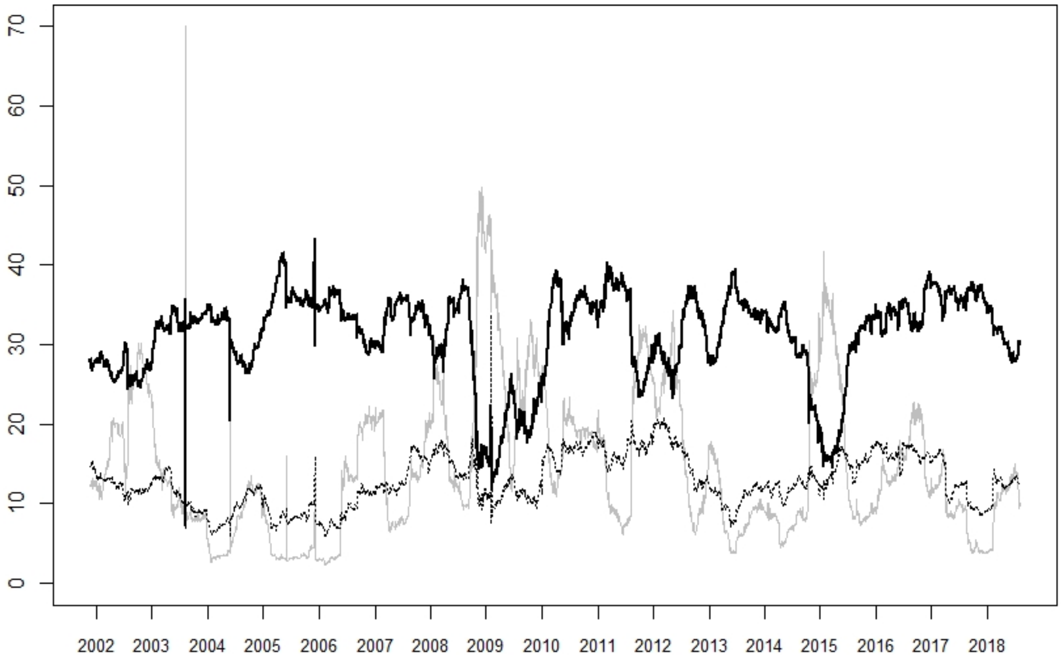
Notes: The frequency connectedness at short-term horizon defined at $d_1 \in [1; 5]$ days in light grey, medium-term horizon defined at $d_2 \in (5; 20]$ days in dotted line and long-term horizon defined at $d_3 \in (20; 200]$ days in bold grey line.

riod that corresponds to European debt crisis. Meanwhile, OMXC20, OSEAX and NOK are rather net spillover receivers. Other markets have more balanced spillover dynamics. We can conclude that Norwegian financial markets do not contribute much to return spillovers in short-run, rather receiving them from other markets during that period.

Now as we completed the dynamic analysis of frequency decomposition of connectedness for returns, we can proceed with the dynamic analysis for volatilities. Figure 5.11 presents the dynamics of total volatility connectedness decomposed into three frequency bands. We can easily observe rather higher volumes of volatility transmission, compared to those for returns, with exception of short-run connectedness. Moreover, the long-run and short-run connectedness have richer dynamics, while medium-run spillovers are rather smooth with three main periods of higher volatility transmission (2008-2009, 2010-2013, 2015-2017). Those periods correspond to main crisis and turmoil events discussed in previous sections.

From the dynamics of short- and long-term spillovers, we observe prevalence of short-term connectedness during normal times, while long-term connectedness

Figure 5.11: Total Volatility Frequency Connectedness

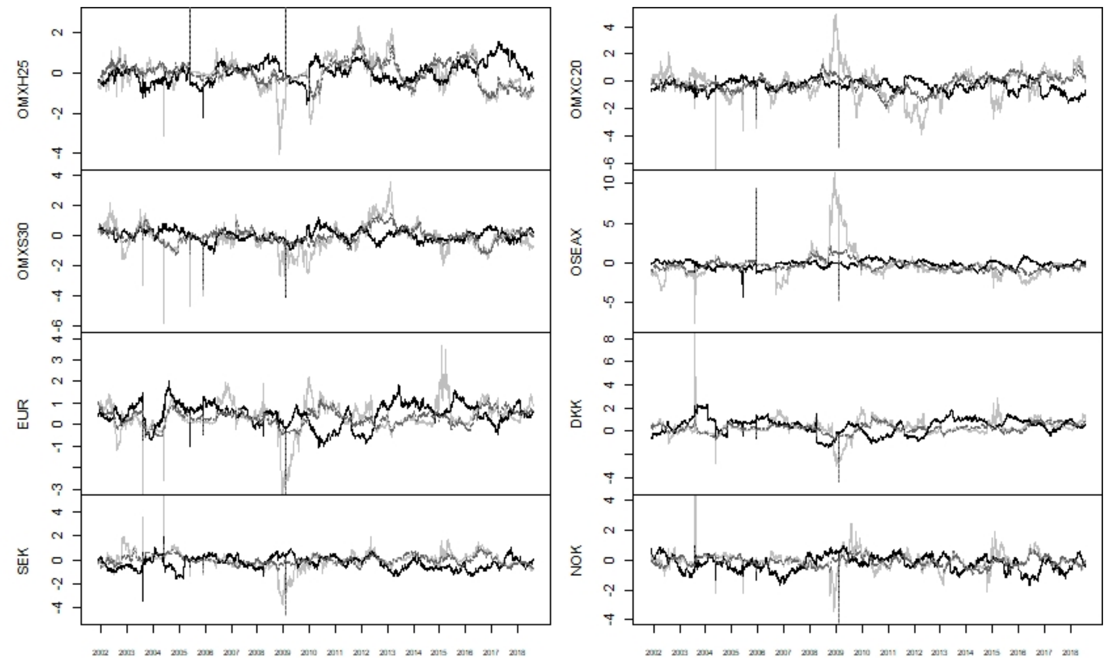


Notes: The frequency connectedness at short-term horizon defined at $d_1 \in [1;5]$ days in bold line, medium-term horizon defined at $d_2 \in (5;20]$ days in dotted line and long-term horizon defined at $d_3 \in (20;200]$ days in grey line. All lines through the frequency bands sum to the total connectedness.

prevails during turmoil periods. Such a pattern is observed during 2009-2010 crisis period and during 2012-2013 period. Moreover, during those periods decrease in short-term connectedness is observed. On the other hand, Brexit referendum did not lead to the same pattern, but dominance of short-term connectedness is observed. Another period of prevalence of long-term connectedness over short-term is the end of 2014 till the end of 2015. This may be attributed to decline in oil prices and Chinese Black Monday during those times. Such findings are in line with the existing literature (Baruník & Křehlík, 2018; Baruník & Kočenda, 2018).

Figure 5.12 presents the dynamic NET volatility spillover decomposed into three frequency bands. First thing that can be easily observed is that short- and medium-run connectedness are rather low and close to zero, while long-term connectedness has rich dynamics for all markets. Still in short-run, we can observe prevalence of positive net spillovers for EUR and DKK during the whole period under analysis, with exception of crisis periods of 2009 and 2012, when the dynamics reverse. NOK, OSEAX and OMXC20 exhibit negative short-term spillover

Figure 5.12: NET Volatility Frequency Connectedness



Notes: The frequency connectedness at short-term horizon defined at $d_1 \in [1;5]$ days in black line, medium-term horizon defined at $d_2 \in (5;20]$ days in dotted grey line and long-term horizon defined at $d_3 \in (20;200]$ days in grey line.

prevalence over the whole period. The other markets exhibit rather balanced dynamics. In medium-run no discernible patterns can be observed.

In long-term horizon the net connectedness measures are rather abruptly changing from positive to negative in all markets. Consequently, rather high and non-persistent spikes can be observed. Even though, some distinctive patterns are examined. EUR and DKK exhibit positive net spillover values in long-run, while OSEAX is net spillover receiver for the whole span, with exception of 2008-2009 period, when the pattern reverses. NOK also performs similarly as OSEAX, which is in line with our previous finding, suggesting that Norwegian forex and stock markets exhibit rather similar patterns. Other markets exhibit balanced patterns of net volatility spillovers in long-run.

Chapter 6

Conclusion

In this thesis, we aim to analyze the return and volatility spillovers using the approach based on spillover index, proposed by Diebold & Yilmaz (2009) and further evolved by Diebold & Yilmaz (2012). This approach is based on generalized vector autoregressive (GVAR) model. In such a model forecast error variance decomposition is invariant to the ordering of the variables, which allows us to estimate total, directional and net spillovers. Furthermore, we employed the new methodology proposed by Baruník & Křehlík (2018), that is based on decomposition of spillover indices for returns and realized volatility into frequency bands, that represent short-, medium- and long-term horizons. Those frequency bands correspond to daily, weekly and monthly frequencies, respectively.

All the estimations are performed in statistical software R using its supplemental package Frequency Connectedness. The analysis is performed for four Scandinavian stock and forex markets for the period of February 2002 till the end of July 2018. This period covers various turmoil periods, such as the downturn of global stock markets in 2002, global financial crisis in 2007-2009, European sovereign debt crisis in 2010-2013 and Brexit referendum in mid 2016. Hence, there is enough data to cover pre- and post-crisis periods for all events.

The empirical results consist of several sections. First, we performed spillover analysis for both returns and realized volatility over the whole period, thus, static analysis. Afterwards, we employ 200-day rolling window and estimate the total and directional spillover dynamics through the 18-year span under analysis. This method enables us to examine the evolution of the spillover indices over time and to reveal the differences between distress and normal times. Finally, we performed similar analysis on our sample employing newly developed methodology of frequency connectedness. This methodology allows us to decompose the spillover indices into frequency bands and examine the evolution of spillover indices in short-, medium- and long-term horizons. Using this new framework we performed first the static analysis and then delved into the evolution of the spillover indices in various frequencies.

The static analysis of spillover indices reveals that inter-market spillovers are of higher magnitudes than the cross-market spillovers for both returns and realized volatility. As opposed to our first hypothesis we determined less contribution to return and volatility spillovers by Norwegian stock and forex markets, which has floating exchange rate regime. On the other hand, SEK turns out to be the highest contributor of cross-market spillovers in case of both returns and volatility, while EUR has the highest spillovers to other markets in total. Furthermore, OMXS30 is the highest contributor in cross-market spillovers among stock markets for both returns and volatility. Meanwhile, OMXH25 contributes the most in total return spillovers and the least in total volatility spillovers among stock markets. Additionally, we reveal that in net terms OMXC20, OSEAX and NOK are only net return spillover receivers, while OMXH25 is the highest return spillover transmitter, followed by EUR. The pattern changes slightly in case of volatility spillovers. The list of net spillover receivers remains the same with addition of OMXH25 as the highest net volatility receiver from other markets, while OMXS30 is the highest volatility transmitter, followed by EUR. All other markets are net spillover givers.

The dynamic analysis of spillover indices reveals higher spillover volumes during distress periods for both returns and volatility. Hence, we can reject our second hypothesis. Moreover, the dynamics indicate that Scandinavian financial markets are affected more by European sovereign debt crisis in 2010-2013, rather than by global financial crisis in 2007-2009. In case of return spillovers we observe that OMXH25, OMXS30, EUR and DKK exhibit smooth evolution of spillover transmissions during global financial crisis, while other markets have higher volumes of spillover transmissions TO other markets. However, for OMXH25 and OMXS30 the pattern changes in case of directional spillovers FROM others, while EUR and DKK exhibit downward sloping trend. Moreover, all markets, but SEK, exhibit high spikes compared to other markets during 2015-2017 period. From net directional spillovers, we observed that OMXH25, OMXS30, EUR and DKK are net return spillover transmitters for the whole time span, while others are net return spillover receivers. Hence, we concluded that Finnish financial markets contribute the most to return spillovers, while Swedish ones contribute the least.

The results from the dynamic volatility spillover analysis, reveal that cycles in all markets during the turmoil periods are of similar volumes. This suggests that the the level of uncertainty in all markets was the same during all crisis events. Moreover, OSEAX, OMXC20 and NOK return to their pre-crisis level faster after 2013, compared to other markets. This supports our finding that Norwegian financial markets and Danish stock market are not exposed to that much of volatility compared to others. Furthermore, EUR and DKK are the net volatility spillover transmitters during the whole period under analysis, while NOK, OSEAX and OMXC20 are net spillover receivers, with exception of global financial crisis periods, when the pattern inverses for all abovementioned markets.

The static frequency connectedness analysis shows that on average short-term connectedness is rather high, compared to medium- and long-term ones for return spillovers. However, the pattern changes for volatility spillovers. In that case long-term connectedness prevails over short-term connectedness, while medium-term connectedness is the lowest. Net spillover transmissions for returns show that Swedish financial markets are net spillover receivers in short-run, while they become net spillover givers in long-run. Other markets keep their signs the same for all frequency bands, with OMXH25 being the highest contributor of return spillovers in short-run, while OMXS30 is the highest in medium-and long-run horizons. The pattern changes slightly for volatility spillovers. All stock markets are net volatility receivers, except OMXS30, which is the highest volatility giver in all frequency bands, followed by EUR. Moreover, Norwegian financial markets are net spillover receivers in short- and medium-run, while NOK changes its sign in long-run.

Dynamic frequency connectedness analysis for returns reveals that short-term connectedness is rather too high compared to medium- and long-term connectedness during the whole period under analysis. Thus, we can reject our third hypothesis, which states that at higher frequencies the spillovers are not higher than in lower ones. Furthermore, we documented that connectedness in all frequencies reach their peaks during European debt crisis in 2012, rather during global financial crisis. Even after Brexit referendum in June 2016 medium- and long-run connectdness have downward sloping trend, while short-run connectedness reaches its second peak.

Dynamic volatility frequency connectedness analysis reveals that medium-run connectedness is the lowest for the whole period under analysis, while the dominance of short-run and long-run connectedness changes from time to time. In general short-run connectedness dominates over long-run during calm periods, while long-run connectedness takes over during distress periods, such as global financial crisis mid 2008-2010, sovereign debt crisis from the end of 2011 till the mid of 2012 and in 2015 corresponding to Black Monday in China. Moreover, during those turbulent periods we documented decrease in short-run conenctedness.

Finally, we see several directions of extension of the analysis performed in this thesis. First, similar analysis can be done using high frequency data, while we used only daily data. This may reveal some new patterns and also will enable to analyze asymmetric volatility spillovers. Additionally, further analysis of directional pairwise spillovers can be conducted, which will allow to examine the sources of spillovers received by the markets in the system more deeply. Last, but not least, more markets can be included in the analysis, such as bond markets of the same countries or financial markets of other countries, such as US, UK or other European or Asian country.

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Appendix

Descriptive Statistics for Level Data

Table A.1: Descriptive Statistics for Level Data

	Min	Mean	Max	S.D.	Kurtosis	Skewness	JB-stat	Ljung-Box Q-stat
OMXH25	1093.37	2433.71	4363.30	798.48	2.27	0.41	222.65***	35209.58***
OMXC20	169.04	506.43	1051.83	258.80	2.35	0.86	620.86***	35387.84***
OMXS30	421.01	1060.99	1719.93	323.49	2.08	0.15	173.91***	35297.81***
OSEAX	105.82	455.49	1028.41	214.25	2.52	0.27	96.15***	35239.80***
EUR	0.84	1.23	1.60	0.16	2.88	-0.44	143.36***	35141.26***
NOK	0.11	0.15	0.20	0.02	1.94	-0.12	218.45***	35127.21***
DKK	0.11	0.17	0.21	0.02	2.89	-0.44	145.95***	35138.12***
SEK	0.09	0.13	0.17	0.02	2.28	-0.27	150.44***	35068.63***

Notes: JB-stat stands for Jarque-Bera statistic. For Ljung-Box test we used 8 lags. ***, **, * represent significance level of 1%, 5%, 10%

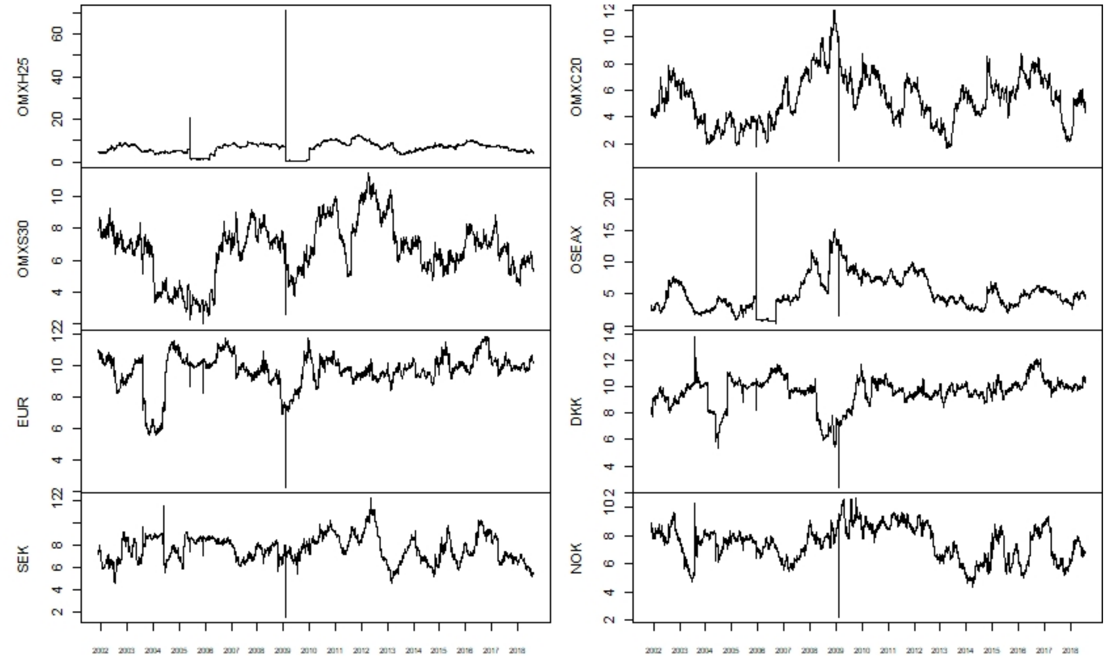
Table A.2: Stationarity Tests for Level Data

	ADF	KPSS	Phillips-Perron
OMXH25	-1.73	16.94***	-2.07
OMXC20	-1.91	22.35***	-2.07
OMXS30	-3.03	21.43***	-3.52
OSEAX	-1.51	22.39***	-1.45
EUR	-2.00	6.20***	-1.89
NOK	-1.84	5.40***	-1.79
DKK	-2.01	6.17***	-1.91
SEK	-1.80	5.17***	-1.72

Notes: ADF, KPSS and Phillips-Perron test lag orders are selected automatically and are 16, 15 and 10 for all series respectively. ***, **, * represent significance level of 1%, 5%, 10% respectively.

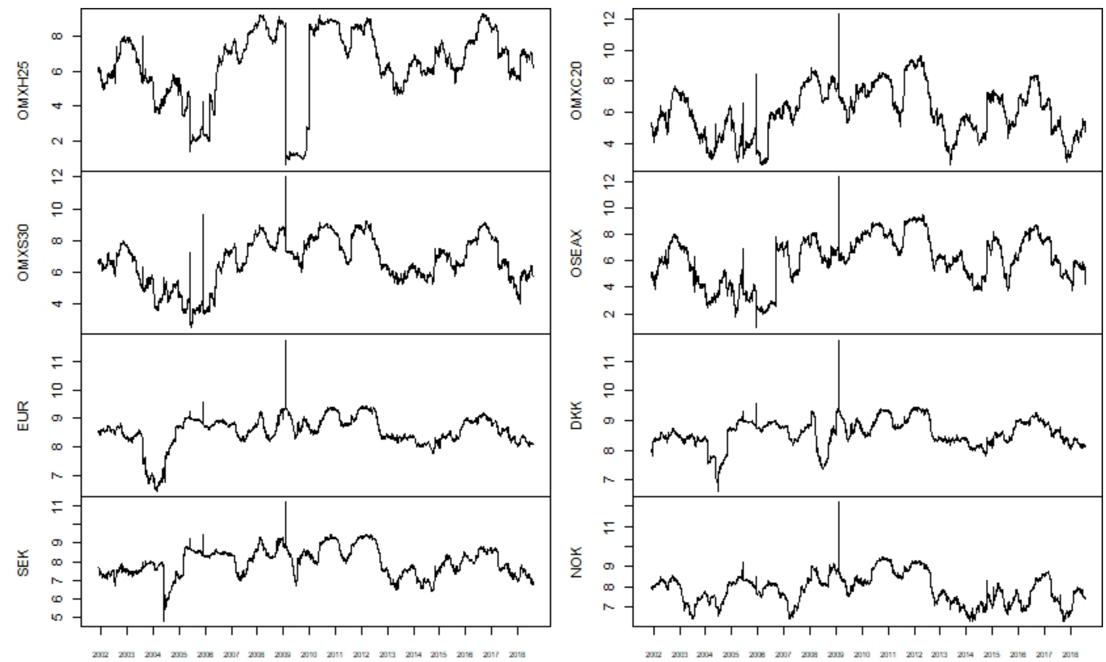
Full Volatility Spillover Figures

Figure A.1: Directional Volatility Spillovers TO others - Full



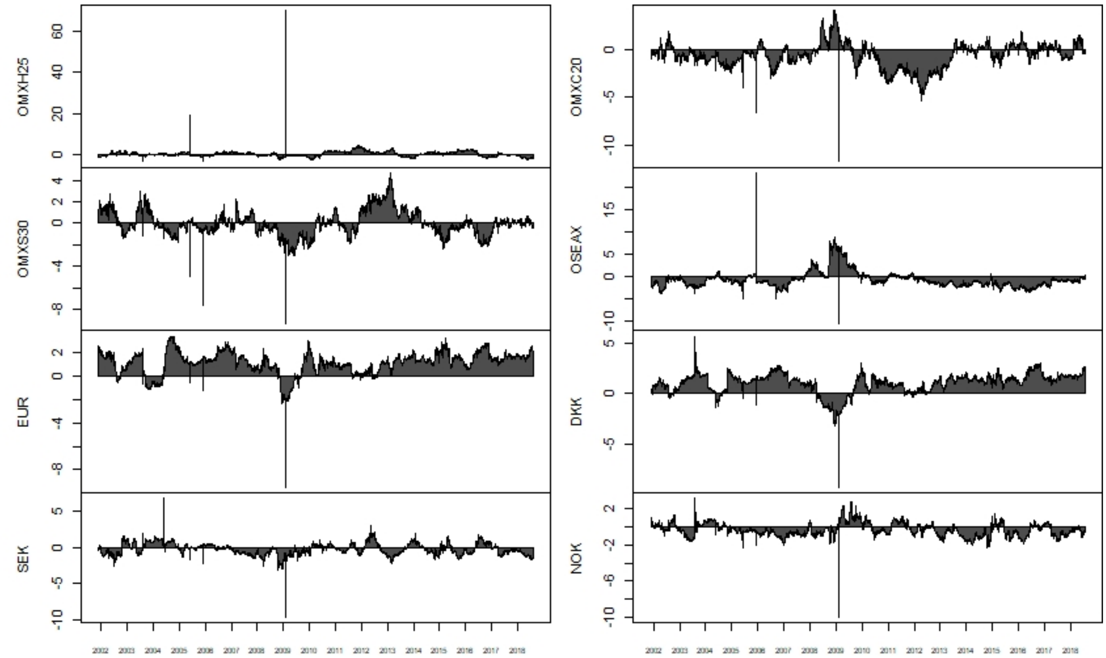
Source: Author's Estimations

Figure A.2: Directional Volatility Spillovers FROM others - Full



Source: Author's Estimations

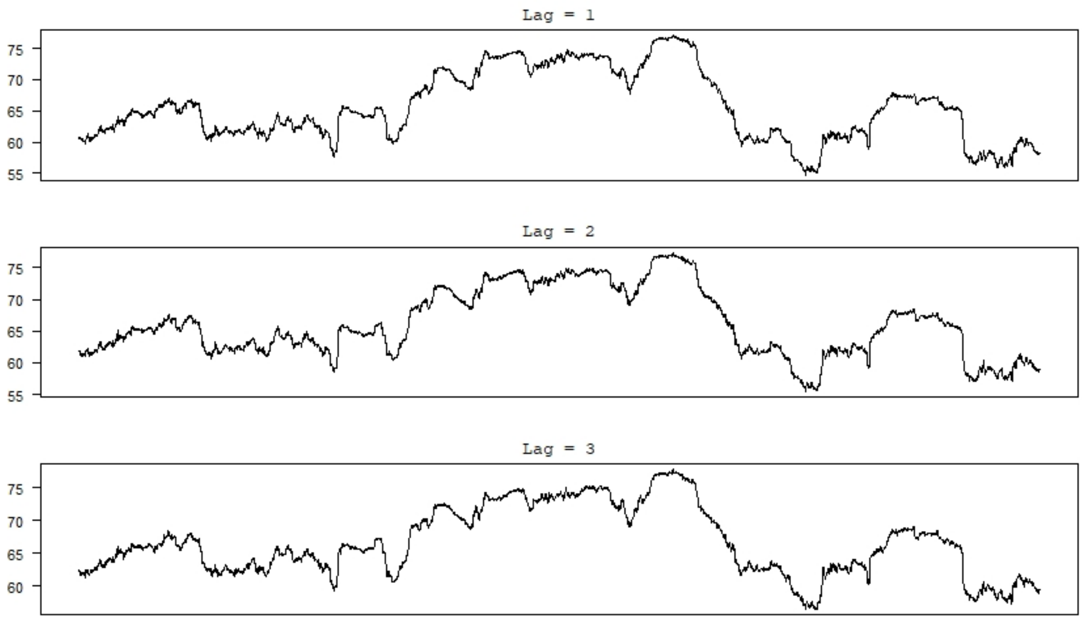
Figure A.3: NET Directional Volatility Spillovers - Full



Source: Author's Estimations

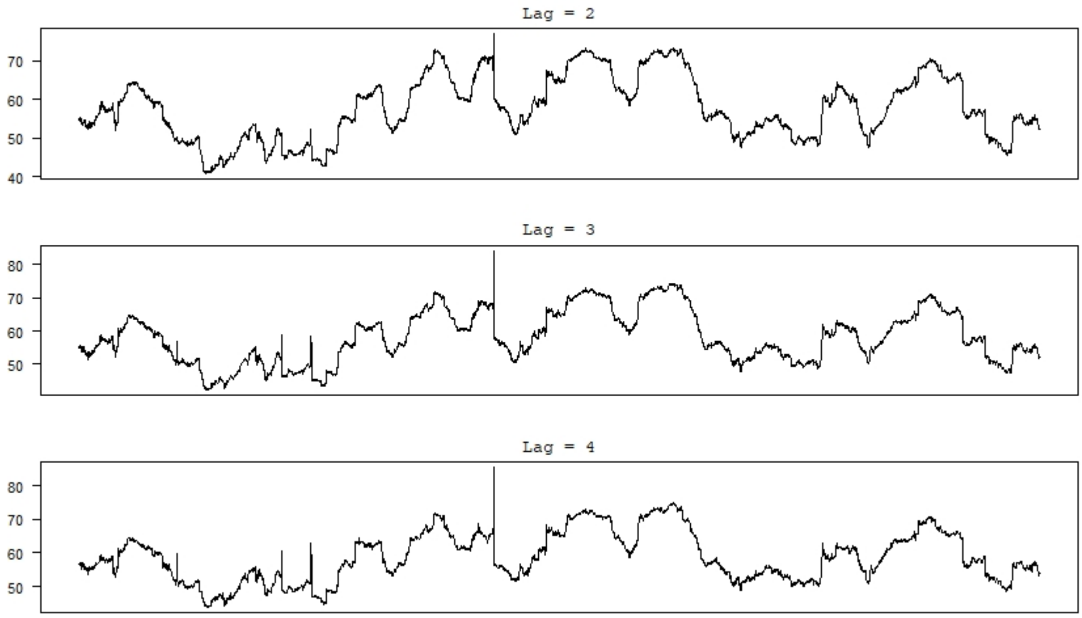
Robustness Check

Figure A.4: Robustness check for returns with respect to lag length



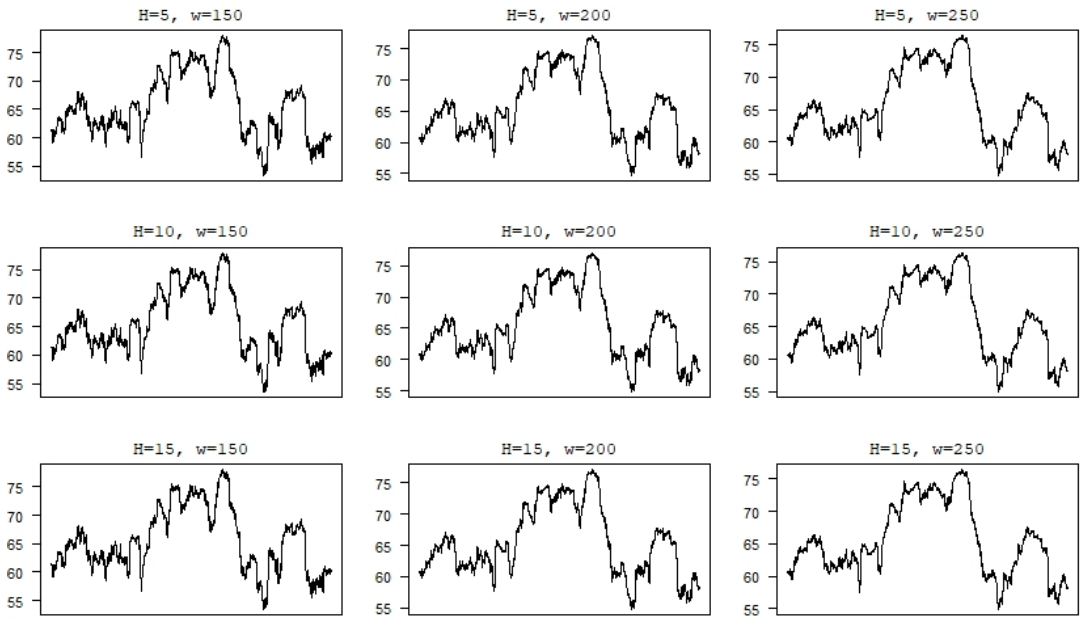
Source: Author's Estimations

Figure A.5: Robustness check for RV with respect to lag length



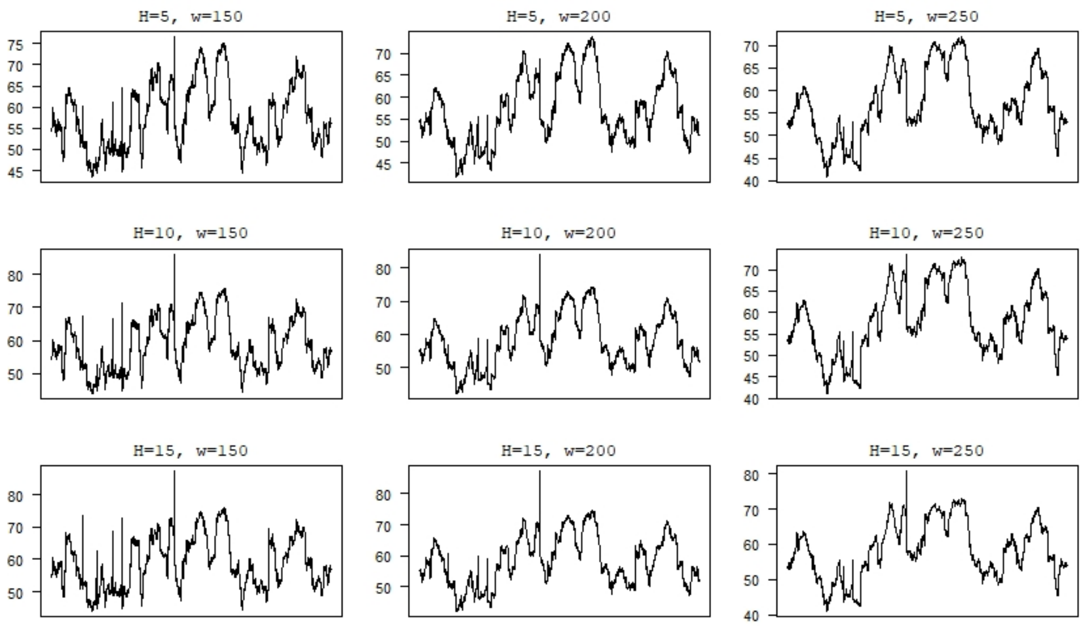
Source: Author's Estimations

Figure A.6: Robustness check for returns with respect to the window width, w, and forecasting horizon, H



Source: Author's Estimations

Figure A.7: Robustness check for RV with respect to the window width, w, and forecasting horizon, H



Source: Author's Estimations