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Financial connectedness of the Nordic banking sector: examining time and frequency connectedness in return volatilities of bank shares

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ABSTRACT

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This thesis aims to analyze the volatility connectedness found between Nordic publicly listed banking institutions between 2004 and 2020. Assessment of connectedness is done on multiple levels of granularity, from system-wide connectedness to connectedness between specific banks. Static full sample connectedness and dynamic over time connectedness measures are achieved using the spillover index framework of Diebold and Yilmaz (2012). These measures are added upon with the frequency decomposition of connectedness methodology of Barunik and Krehlik (2018). The first framework allows us to assess general connectedness and its time-varying dynamics and the latter is used to understand whether connectedness is more long- or short-term in nature.

Our results show that, on average, about 51 % of the variation in a 10-day forecast is due to volatility spillover from other Nordic banks. This connectedness varies over time, and an increase in connectedness is associated with market turbulence. The overall connectedness varies between 36 and 75 %. Generally, Swedish banks seem to be central in the system, as they both emit and receive the most volatility. While they tend to be on the bigger side, we also don't find conclusive evidence supporting that larger banks are more connected. However, connectedness in the Nordics does seem to be higher within countries than across them. Finally, we find that the connectedness in the banking sector seems to be long-term in nature as most of the connectedness is created at low-frequency cycles, which means that shocks don't dissipate immediately but persist.

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Tämän Pro Gradu -tutkielman tarkoituksena on arvioida Pohjoismaisten pankkien keskinäisriippuvaisuutta ja volatiliteetin leviämistä 2004 ja 2020 välisenä aikana. Keskinäisriippuvaisuutta arvioidaan sekä systeemitasolla että yksittäisten pankkien välillä. Koko aikavälin kattavaa ja liikkuvaan otokseen perustuvaa keskinäisriippuvuutta arvioidaan Dieboldin ja Yilmazin (2012) ”spillover” indeksillä. Lisäksi keskinäisriippuvuutta arvioidaan eri taajuuksilla ja taloudellisissa sykleissä Barunikin ja Krehlikin (2018) metodologialla. Ensimmäisellä metodologialla arvioimme keskinäisriippuvuutta yleisellä tasolla sekä sen tyypillisiä yli ajan ominaisuuksia. Jälkimmäinen metodologia mahdollistaa arvioin siitä, onko keskinäisriippuvaisuus lyhyt vai pitkäaikaista.

Tuloksemme osoittavat, että keskimäärin noin 51 %:a variaatiosta 10 päivän ennusteessa voidaan osoittaa olevan lähtöisin muista pankeista levinneistä volatiliteetti shokeista. Keskinäisriippuvuus muuttuu yli ajan ja kasvava riippuvuus liittyy yleensä markkinatilanteen heikkenemiseen. Levinneiden volatiliteettishokkien osuus variaatiosta vaihtelee 36 ja 75 prosentin välillä. Yleisesti ottaen ruotsalaiset pankit sekä levittävät että vastaanottavat eniten volatiliteettia. Vaikka ruotsalaiset pankit ovatkin keskimäärin suurempia, ei pankin koon ja sen levittämän volatiliteetin välillä ole selkeää yhteyttä. Sen sijaan maiden sisäinen keskimääräinen keskinäisriippuvuus on suurempaa kuin maiden välinen. Viimeisenä tulokset osoittavat, että Pohjoismaisten pankkien välinen riippuvuus on pitkäaikaista matalilla taajuuksilla esiintyvää, eivätkä shokit katoa nopeasti.

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As I’m finishing my Master’s thesis, and with it my studies, I have to say that the prevailing emotion is that of relief. While most of my studies flew by, the same can’t be said about the thesis process, which has had its ups and down. Trying to complete a thesis alongside work proved to be a futile effort, but thankfully I was able to take some time off and after a slow start I was able to get the wheels rolling.

I want to acknowledge my thesis supervisor Jan and thank him for all the discussions and feedback along the way. It was great to have such an approachable and helpful supervisor.

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Helsinki 4th of December 2020

Matias Hällström

Table of Contents

List of Figures

List of Tables

Abbreviations

ADF	Augmented Dickey-Fuller test
AML	Anti-Money Laundering
ARCH	Autoregressive Conditional Heteroskedasticity
CoVaR	Conditional Value-at-Risk
ECB	European Central Bank
EGARCH	Exponential Generalized Autoregressive Conditional Heteroskedasticity
ES	Expected shortfall
FEVD	Forecast Error Variance Decomposition
FI	Financial Institution
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GFEVD	Generalized Forecast Error Variance Decomposition
IMF	International Monetary Fund
JB	Jarque-Bera test
KYC	Know Your Customer
MES	Marginal Expected Shortfall
VAR	Vector Autoregression
VaR	Value-at-Risk

1. INTRODUCTION

Modern-day global markets are increasingly interconnected and as such, the world we live in is, in a way, much smaller than it once was. Events on the other side of the planet don’t feel so far away when we can read about them as they are happening, while not so long ago, we might have never known about them. Not only do we know about what’s happening worldwide, but those far away events affect our lives. Many different factors have driven this interconnectivity. Technological advancements have allowed for instant transfer of information and communication across the planet. Political drivers such as the European Union, United Nations and the world trade organization have encouraged international dialog and brought countries to the negotiation tables. Domestic markets have become more saturated and the nations beyond national borders have become more attractive and available as businesses have sought room to grow. The increased ease and speed of transferring goods and information has done its part to pave the way for an interconnected global economy. Companies across the world form networks with varying degrees of connectedness between them.

Naturally, this interconnectivity is not just limited to more traditional markets with tangible products, but the financial markets too, where local shocks can have international consequences. Exceptional times often highlight how shocks can spread. The financial crisis of 2008 and onwards is still in recent memory and is a prime example of how shocks disperse across connected markets. This phenomenon, where a crisis in one market can spread to another, is referred to as financial contagion. Contagion is inherently related to the integration of markets and the spread of information across them. (ECB, 2005)

Contagion and connectedness are distinct but related concepts. Contagion refers to a spread of run-like behavior in a system, which can be intensified through connectedness. Connectedness itself can be defined as the degree of interconnectivity between institutions, enabling a failure in one to spread to another. Two main types of connectedness relate to balance sheet links. The party who owns debt, equity, or derivatives is exposed through asset connectedness to the issuing institution's failures. In turn, liability connectedness is realized when an institution depending on another for funding suffers from failures of the funder due to disruptions in the funding stream. (Scott, 2016)

Much attention has been paid to researching linkages between markets and firms, especially after the recent crisis periods. Often spillover effect is the focus of such studies. Spillover can be defined as the impact an event, even a seemingly unrelated one, has on a particular financial market or economy. Studies of spillover effects often focus on mean return spillovers and volatility spillovers. In simplistic terms, these are the effects a change in financial returns or volatility somewhere has on returns and volatility somewhere else. Regardless of the asset type or financial market, the global financial crisis of 2008 seems to be the peak in interconnectedness and the spillover effect. For example, Angkinand, Barth and Kim (2010) find an increasing degree of interconnectedness over time in stock market returns between advanced economies. Spillover effects were found to be highest just after the US subprime mortgage meltdown in 2007. Diebold and Yilmaz (2012) find a similar increase in the spillover of volatility between four different US asset classes: stocks, bonds, foreign exchange and commodities, during crisis periods.

Shocks do not just spread between international markets, but within industries too, be they global or local. The financial sector and its subindustries are a common subject in connectedness studies. So much of the world’s day to day operations depend on the sector that it deserves the increased scrutiny. Banking for example is a crucial piece of the puzzle that is the global economy and its failures can have significant consequences. We need not look any further than the global financial crisis, for a banking system lead crisis. The widely agreed-upon cause of which was the combination, along with other factors, of excessive risk-taking by banks and the burst of the real estate market. The trigger for the crisis in 2008 was the bankruptcy of the US investment bank Lehman Brothers. (Aliber and Zoega, 2019)

This thesis also focuses on banking and its interconnectedness. We focus specifically on the Nordic banking sector and its systematic connectedness and cross spillovers. The region is often overlooked and to our knowledge, there are no previous peer-reviewed published studies that focus primarily on measuring connectedness in the Nordics. This offers an attractive research gap to fill. The area is often thought to be calm and well regulated, but it is not immune to contagion and systematic risks. Iceland for example experienced the largest systemic bank collapse relative to its size by any country ever during the financial crisis (the economist, 2008). Our study aims to shed light on how vulnerable the Nordic banking sector is to such an event in one of the Nordic banks.

The methodological choice of this thesis is the spillover index framework of Diebold and Yilmaz (2009, 2012, 2014). The relatively recent framework for measuring connectedness allows us to look at the linkages between Nordic banks on multiple granularity levels, which is a feature not found in many other models. We not only look at systematic connectedness, but pairwise as well as connectedness between specific banks and the system. To provide an even more comprehensive look at connectedness, we also utilize the frequency connectedness framework of Baruník and Křehlík (2018). The next section provides more detail on the subject and the motivations behind why such research is essential. Later chapters detail the methodological choices and their alternatives.

1.1. Motivation and background

Financial connectedness is a somewhat elusive term with competing definitions and alternative measurements. Generally, when we refer to connectedness, we speak about the ways and the degree to which individual variables are linked: how they affect each other and by how much. In the previous section, we touch on asset and liability connectedness, for example. The concept of spillover is also related to connectedness. For example, a shock to one countries economy affecting a seemingly unrelated country’s economy is referred to as the spillover effect. Spillovers can be thought of as a symptom of high connectedness. You would be surprised to find significant spillovers between Sweden and Peru, but one might expect it between the much more connected Sweden and Finland. In this thesis, we define connectedness as the state of being connected to other variables and measuring connectedness as a measurement of how interconnected those variables are, i.e. how much past values of variables affect the variation in other variables through existing connections. In our chosen methodology, this is done with variance decomposition, which measures how much information each variable contributes to others. For the most part, we take no stand regarding what those connections and linkages are. For example, whether there are some specific asset or liability-based connections between the Nordic banks.

Connectedness is also a critical factor in risk measurement. For example, return and portfolio connectedness relate to market risk, default connectedness to credit risk, connectedness due to contractual obligations to counterparty risk and most importantly, system interconnectedness is a significant factor in systematic risk (Diebold and Yilmaz, 2014). The last is reflected by the fact that the Basel committee recognizes connectedness as one of the five critical factors in identifying systematically critical banks, the other factors being bank size, the degree of cross-jurisdictional activities, substitutability and complexity. (Basel committee on banking supervision, 2020). It's no wonder that the concept of “too connected to fail” exists, and connectedness measures continue to be proposed.

So why study volatility instead of returns, for example? As we are especially interested in crises and the spread of shocks, volatility presents a better alternative as it's more crisis sensitive, as noted by Diebold and Yilmaz (2009). Volatility can be thought of as an indicator of investor fears and its connectedness as the fear connectedness (Diebold and Yilmaz, 2015). These fear dynamics are of particular interest to us as we look at the time-varying nature of connectedness. Additionally, volatility dynamics are typically such that they support our methodological choice. This is explained later when requirements for the generalized framework are discussed. Some attention is also paid to a relatively overlooked factor in measuring connectedness, the choice of volatility proxy.

The Nordics themselves are a group of relatively small export-dependent economies, which makes them vulnerable to global economic fluctuations. Their economies are also intertwined as they make up a significant portion of each other's imports and exports. (Ahoniemi and Putkuri, 2020) The region was susceptible to the financial and the European debt crises, and Finland, Sweden and Denmark especially suffered a deep recession. Since the crisis period, Nordic banks, in general, have been more profitable than their European counterparts. Their capital adequacy is also comparatively strong. (Koskinen, Putkuri, Pylkönen and Tölö, 2016) While Iceland is a part of the Nordics, in this thesis, when we refer to the Nordics, we mean specifically the countries in the dataset: Finland, Sweden, Norway and Denmark. There are no Icelandic banks in the set as none of them remained publicly listed through and after the country's banking crisis.

While the current banking and financial system is stable, according to Koskinen et al. (2016), some structural vulnerabilities can pose a systemic threat. First of all, the banking sector is very large relative to the Nordic economies. For example, according to IMF data, Denmark, Sweden and Norway ranked in the top 3 in Europe in bank assets as a percentage of GDP in 2017. (TheGlobalEconomy.com, 2020) The pure number of banks is also significant. While there are many banks, the sector is also relatively concentrated, as a few large banks dominate the system. Especially Nordea, Danske Bank and Handelsbanken hold significant market share in this thesis's four Nordic countries. There are also other notable more, although not fully, local institutions such as DNB, SEB and Swedbank. The third major vulnerability is related to a special characteristic in the Nordic banking sector: the importance of mortgage credit institutions and cover bonds, especially in the funding of housing loans, which make up a significant portion of the Banks' balance sheets when compared to European banks in general. This makes the system especially vulnerable to housing market risks. (Koskinen et al., 2016) The COVID-19 pandemic has aggravated this vulnerability as data indicated a decline in both property sales and prices (Ahoniemi and Putkuri, 2020). While the Nordic covered bonds are considered safe, therein lies another vulnerability. Firstly, the banks are very dependent on market funding as 35-45 % of it is market-based, which opens the sector up to changes in the global financial markets. The banks also play an important role as market makers for covered bonds, which has led to Nordic banks holding 20-30 % of them. Refinancing of the bonds held by banks in the short-term money markets also further subjects them to disruptions in the markets. Finally, because a large portion of investors in the covered bonds are domestic, their systemic importance is further amplified. These are also all factors that increase the interconnectedness of the Nordic banking system. (Koskinen et al., 2016)

In any case, the Nordic countries are thought to be stable with prudent financial regulations and supervision, which should deviate risk. Paltadis, Gounopoulos, Kizys and Koutelidakis (2015) show the northern eurozone banking sector's systemic risk to be less apparent, whereas the banking sector in the southern eurozone is more prone to bank failures due to contagion. While only Finland is part of the euro area, it is not farfetched to assume that systemic risk in the other Nordics is similar. Even though the risk is not apparent, it doesn't mean there isn't any. We might argue that the unknown presents an even more significant threat than the known. In any case, attention needs to be paid to the Nordics as well, who form a culturally and economically tight-knit group of countries, which at the very least could experience a systematic local crisis and at worst affect the broader European or global economy.

Such a connectedness study could also benefit a variety of interest groups. Connectedness, first of all, is inherently related to risk, especially of the systematic kind. This naturally is useful to risk managers and financial supervisors alike. Knowledge of the connectedness level can also benefit portfolio managers as they make diversification choices: highly interconnected assets make for poor diversification options. Heightened connectedness can also act as a signal for regulators to act as it tends to signal market turbulence. In any case, providing new information on the connectedness in the Nordic banking sector benefits many parties.

1.2. Research objectives

This thesis aims to assess and analyze the financial connectedness found within the Nordic Banking system, between listed banks from Finland, Sweden, Norway and Denmark. The study's timeline spans from before the global financial crisis up until the very recent events related to the global Covid-19 pandemic and its economic consequences. This allows us to pay special attention to the over-time dynamics of connectedness as the period contains many financial ups and downs. Aside from time, we also focus on the lesser understood frequency dynamics of connectedness to better understand at which frequencies is connectedness created and at which times. We also assess whether size is a factor in bank connectedness.

To summarize, we touch upon time, frequency and size dynamics of connectedness and upon systematic risk factors in general. We also offer a Nordic perspective to the questions as a point of comparison to research done elsewhere. The main research questions are as follows:

1) *How connected are the Nordic Banks?*
2) *Is the connectedness between banks time-varying?*
3) *Which banks are the major exporters of Volatility? Which are its primary receivers?*
4) *Is there a significant correlation between a bank's size and its effect on others? Is there a correlation between size and a bank's susceptibility to spillovers originating from others?*
5) *Is the connectedness higher within countries than across them?*
6) *Is most of the connectedness created at low, medium or high frequencies?*

1.3. Scope of the study

This study focuses on the financial connectedness found in the Nordic banking sector, on a system level as well as from, to and in between individual banks. The set of banks is limited to only publicly listed banks in the Nordic countries. While this does encompass most major banks in the respective countries, it does rule out some systematically important banks from the dataset due to the lack of available share price data. For example, the Finnish OP Group is a non-listed co-operative bank, which holds the biggest market share domestically in many key categories. The bank has a 40 % share in private housing loans and corporate loans and a 39 % share of deposits (vs. the second largest Nordea with 29, 30 and 27 % in those categories). (Suomen pankki, 2020) This limitation also rules out any Icelandic banks from the set as none of them were publicly listed for a sufficiently long period to be included in the study. These exclusions might affect how representative of the Nordic banking landscape the results are. The full set of 9 banks is introduced later in the paper.

Timewise the scope of this paper is focused on relatively recent history. More specifically, we focus on the period between 2.1.2004 and 4.9.2020. These limits are set to include the most up to date price observations and the most important events in recent history. Most importantly, the goal was to include the period of the financial crisis and the great recession of 2007 to 2009 and the run-up to that. The European debt crisis also lands within this timeframe. By including the most recent available data, we can also assess the effects of the 2020 Covid-19 global pandemic on connectedness. Timeframe selection was limited by bank listing dates as if we were to choose a very long period, it would limit the number of banks included, as some of them were listed later than others. On the other hand, if we were to choose a shorter period to include more banks, we might miss something in the time-varying nature of connectedness. The selected timeframe covers a sufficiently long period and allows us to include a decent number of banks.

As we choose to focus on return volatility connectedness and spillover, we face a key limitation. As volatility itself is not observable in the same way as for example returns, we need to choose a way to estimate it somehow. The estimation is done using a volatility proxy calculated from daily opening, closing, high and low prices. Because we need to estimate volatility, we might introduce some additional measurement error to our connectedness measure. This is something we have to accept and a later section delves deeper into volatility estimation and its accuracy.

Additionally, we are limited to daily data, as high-frequency intraday data was not available to us. We try to compensate for this by choosing a volatility estimation method that considers daily highs and lows, which are much more readily available. However, some intraday volatility might be missed by our estimation.

1.4. Outline of the paper

From this point on, the thesis is divided into five main sections. We start by providing context to the methodological choices of this thesis in the theoretical framework chapter, which covers literature and methodologies on volatility and its proxies, measurement of connectedness with a focus on the spillover index framework of Diebold and Yilmaz (2009). Finally, we introduce the frequency connectedness framework of Baruník and Křehlík (2018). The theoretical framework also provides important context to the literature review chapter after it, which gives a summary of the existing literature on connectedness within the financial sector. Chapter 4 covers the data and methodology used in the thesis. First, the data is introduced and descriptive statistics for it are reported. The methodology section goes into detail on methodological parameters and on how the empirical results are achieved. In the fifth chapter, the empirical results are introduced and analyzed. In the final chapter, conclusions are drawn from the results and the thesis is summarized. We also look at the implications of the study. Finally, some further lines of research are discussed.

2. THEORETICAL FRAMEWORK AND MODELS

We begin with a chapter on the theoretical framework, which introduces the relevant tools and methodologies used in this thesis in particular and gives context to the broader field of connectedness and spillover research. Thus, the chapter is also relevant to the literature review conducted in the following chapter 3, where we summarize studies that also use the same models and frameworks introduced here. The first section of this chapter concerns volatility, in which we measure connectedness. After introducing volatility and its characteristics, we look at how this seemingly unobservable variable can be estimated and a volatility proxy can be created for use in modeling. The second section concerns financial connectedness and the methodological choices for measuring it. After a wider look at alternative approaches, we focus on the connectedness framework of Diebold and Yilmaz (2009, 2012, 2014), which is the methodological choice of this thesis. Finally, we look at a more recent extension to that framework, the frequency connectedness framework of Baruník and Křehlík (2018).

2.1. Volatility and its proxies

To be able to measure volatility spillover in a particular system of variables using the methodology introduced by Diebold and Yilmaz in their 2009 and subsequent papers, we need a way to first model or, in some other way, represent the level of volatility over time. In practice, one needs to have a time series of, for example, daily, weekly or monthly volatilities.

Let us first define what volatility is to give context to the variety of methods that could be used to produce the required time series. To put it simply, volatility is a measure of the variation in a given instrument's returns over time. For a particular dataset, it measures the dispersion relative to its mean. With a volatile instrument, we expect the movement in price to deviate further from the mean, whereas the value of a low volatility instrument might just barely change over time. (Ursone, 2015) Risk is often closely associated with volatility, as a highly volatile instrument is more unpredictable than a low volatility alternative and is therefore considered riskier. While risk is often thought to be related to negative outcomes, volatility makes no difference between the two opposites. (Poon, 2005) Risk can also be thought of as purely the existence of uncertainty.

Volatility has been the focus of countless scientific studies and through extensive research, several particular characteristics have been identified in asset returns. First of all, volatility tends to cluster up, meaning there are periods where volatility is high and periods where it’s low. This was first documented by Benoit Mandelbrot (1963, 418), who noticed that large price changes are not isolated but tend to be followed by more large changes of either sign. In summary, any movements are likely to be followed by movements of similar size.

The second important feature of volatility is the asymmetric nature of it. Return volatility is different in response to a large price increase than to a similarly sized drop. Large positive returns don’t affect overall volatility as much as negative returns. (Bekaert and Wu, 2000) While there is no absolute consensus on the cause, there are alternative explanations for the phenomena. One of these is the leverage effect hypothesis, which is based on the fact that negative returns increase financial leverage, which in turn increases risk and volatility (Christie, 1982). An alternative hypothesis is the volatility feedback effect. This relies on the fact that if volatility is priced and it increases, the required return of the underlying increases and as a result, the asset price immediately drops (İnkaya and Yolcu Okur, 2014).

Other known characteristics are that volatility evolves in a continuous manner over time and that volatility does not diverge into infinity. The first refers to the fact that sudden jumps in volatility are rare, although when they happen, they often happen in a series, e.g. volatility clustering. The latter means that there exists a range in which volatility usually varies and is often, therefore, stationary. (Tsay, 2002)

The above-mentioned properties of volatility often play an important role in models and measurements for volatility. A common approach to take clustering into account is to use an ARCH-type model in modeling a price process. Some models have even been specifically created to address specific characteristics of volatility and to correct modeling errors they might cause in more conventional approaches. For example, the EGARCH model was created to take asymmetric volatility into account. (Tsay, 2002)

As the section title implies, we often use proxies to represent volatility. This is because volatility as such is not directly observable, unlike returns, for example. There are a wide variety of approaches for estimating and representing volatility, such as observation-based GARCH models, parameter-based stochastic models, implied volatility and realized volatility. (Diebold and Yilmaz, 2015) Of these, we'll focus on estimating realized volatility. Optimally we would use high-frequency intraday data. For example, with 5-minute returns, we could calculate an efficient estimate of daily volatility. (Tsay, 2002, 80) However, in the absence of high-frequency data, other alternatives need to be explored to achieve a measure of volatility as accurate as possible. Therefore, we'll focus on methods that utilize more readily available data such as daily open and close, as well as daily high and low prices.

The simplest way to calculate historic or so-called realized volatility is to calculate the standard deviation of daily returns. The standard deviation is often expressed as annualized volatility, which is calculated by multiplying the standard deviation by the square root of the number of trading days, commonly 252.

$$annualized\ volatility = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n-1}} \times \sqrt{252} \tag{1}$$

Annualized volatility is widely utilized as a volatility parameter, but it does not provide enough granularity for the purposes of this paper. To capture the effect of volatility spillover, we need to see immediate reactions in the volatilities. Even if we were to calculate annualized volatility on a rolling basis, daily, weekly or even monthly volatility changes would not be visible enough as the weight of a new observation entering into the sample would be minuscule. This formula can, however, be adapted for shorter periods and daily close-to-close volatility can be calculated with the following equation:

$$\sigma_{CC} = \sqrt{\frac{F}{N-1}} \sqrt{\sum_{i=1}^{N} (x_i - \bar{x})^2}\,, \tag{2}$$

where F is the number of periods in a year, N is the number of periods used in the estimation, $x_i$is the log return calculated with adjacent closing prices and $\bar{x}$ is the mean return. As one can see, this is essentially the same formula (1)

We have now introduced one possible estimation method, which can produce the required proxy. There does not seem to be a generally agreed-upon practice on which method to use. Therefore, the major choices and their advantages and disadvantages are introduced in the following subsections. It is worth noting that even Diebold and Yilmaz, and the broader field of connectedness research, have chosen to use different proxies in different articles on the spillover methodology they introduced.

As volatility can't be directly observed and high-frequency data has just recently become more accessible, several alternative methods have been proposed. Historically, many researchers have resorted to using very simplistic ways of estimating volatility. Because a daily closing price series is perhaps the most readily available type of dataset, it is attractive to many researchers. This has led to the so-called close-to-close estimations of volatility, of which we already introduced one. Squared, or less commonly absolute, daily returns are an even more simple proxy for daily volatility. (Poon, 2005) The use of squared returns has been criticized, and for example, Lopez (2001) finds it to be problematic as a proxy due to it being a "noisy" or imprecise estimator because of its asymmetric distribution. It might be palatable on average bases, but on any specific day, the estimate might be far from the truth.

A problem with using only one data point per day, the closing price, is that it completely ignores intraday volatility. Let's say that there is a lot of volatility during the day, but the closing price is still very near the previous day's close. In such a case, we would see almost no volatility in the proxy. This could be addressed by using intraday squared returns, which would be a true measure of daily price movements. The problem is that even today, high-frequency data is often expensive or not readily available. Because of this, close-to-close methods remain somewhat popular. In the context of this study, the optimal choice would be high-frequency tick data. Unfortunately, this was not feasible as it was only available for part of the dataset and even then for only short periods. Fortunately, we don't have to settle for squared returns or any other estimate only based on closing prices. The range-based estimators introduced in the following sections represent better alternatives.

The earliest example of range-based estimation of volatility was introduced by Michael Parkinson (1980). In the method he referred to as the extreme value method, later dubbed as High-low estimation or Parkinson's estimation, we utilize the daily extreme values of a particular asset. The required daily high and daily low prices are readily available for a wide range of asset classes and listed securities, making Parkinson's estimation an attractive option. Citing a large body of previous literature setting a precedent, even Diebold and Yilmaz (2012) use Parkinson's estimation with their model. Parkinson himself noted that depending on the method of measuring the difference, his extreme value method produces an estimate about 2,5 to 5 times more accurate than the traditional close-to-close method and is much more sensitive to variation in volatility. (Parkinson, 1980) Parkinson's extreme value method can be expressed as below:

$$\sigma_{Park} = \sqrt{\frac{F}{N}}\sqrt{\frac{1}{4\ln(2)}\sum_{i=1}^{N}\left(ln\frac{h_i}{l_i}\right)^2}, \tag{3}$$

where F is the number of periods within a year, commonly the number of trading days 252, N, in turn, is the number of periods used in the estimation, h_i is the intraday high on day i and finally l_i is the corresponding intraday low price.

A clear upgrade compared to the close-to-close methods is the fact that Parkinson's model takes some intraday volatility into account. It, however, does still have some shortcomings that are addressed by later models. For example, the resulting proxy does not capture close to open or overnight volatility, and it assumes geometric Brownian motion with zero drift. Researchers such as Kunitomo (1992) and Fiszeder and Perczak (2013) have shown that alterations that allow for non-zero drift produce more efficient volatility estimations.

The second major model for estimation of volatility is the Garman-Klass model from 1980, the same year in which Parkinson released his research. The creators Mark Garman and Michael Klass aimed to create a model with universally accessible data, mainly with that which was available in the newspapers of the time. To the high and low daily prices used by Parkinson, they added open and closing prices as well. Their aim was not to create “the correct” model for asset fluctuation but to provide a proxy with readily available data. As does Parkinson’s model, the Garman-Klass model also assumes geometric Brownian motion with zero drift, meaning price changes over any interval have a mean of zero. Although not perfect, this new model can be up to eight times more efficient than classical close-to-close methodology. (Garman & Klass, 1980) The model can be formulated as follows:

$$\sigma_{GK} = \sqrt{\frac{F}{N}}\sqrt{\sum_{i=1}^{N}\left(Ln\frac{h_i}{l_i}\right)^2 - (2Ln(2)-1)\left(Ln\left(\frac{c_i}{o_i}\right)\right)^2}\,, \tag{4}$$

where F and N are, as in the Parkinson formula, the number of periods within a year and periods used in the estimation, h_i is again the daily high and l_i is the daily low and finally alongside these we have the closing price c_i and the opening price o_i of the day i.

The Garman and Klass model has many of the same shortcomings as the Parkinson’s model. Even with the inclusion of open and close prices, it doesn’t capture nighttime volatility, which the authors also recognize. Assuming Brownian motion with zero drift also introduces bias when drift exists in the data.

The next advancement in volatility estimation came from Rogers and Satchell (1991), who set out to create a model to address a shortcoming in the previously existing alternatives. Their goal was to create a model that does not assume zero drift with the same readily available data used in other models.

$$\sigma_{RS} = \sqrt{\frac{F}{N}}\sqrt{\sum_{i=1}^{N} Ln\left(\frac{h_i}{c_i}\right)Ln\left(\frac{h_i}{o_i}\right) + Ln\left(\frac{l_i}{c_i}\right)Ln\left(\frac{l_i}{o_i}\right)} \tag{5}$$

Where F is the number of yearly periods, N is the number of periods used in the estimation, $h_i$is the intraday high, l_i is the intraday low, c_i is the closing price of day i and finally o_i is the opening price of the same day. As we see, the data needed is the same as in the Garman-Klass volatility estimation method.

Rogers and Satchell (1991) find that their methodology outperforms the previous models when the underlying process follows geometric Brownian motion with a non-zero drift, a finding corroborated by others, who have included drift terms to previous models (Kunitomo, 1992; Fiszeder and Perczak, 2013). While the Rogers and Satchell model addresses one shortcoming in previous literature, it still ignores the existence of price jumps overnight between trading sessions.

The final and seemingly most comprehensive, widely used measure of realized volatility is the so-called Yang-Zhang estimator. Unlike the others, it can handle both non-zero drift and overnight jumps. It also produces the least amount of variance among the introduced estimators. (Yang and Zhang, 2000). Essentially the produced proxy is the sum of volatility overnight and the weighted average of open-to-close and Rogers-Satchel volatility (Bennett and Gil, 2012). The estimator is calculated as follows:

$$\sigma_{YZ} = \sqrt{F}\sqrt{\sigma_{overnight\ volatility}{}^2 + k\sigma_{open\ to\ close\ volatility}{}^2 + (1-k)\sigma_{RS}{}^2}, \tag{6}$$

where F is again the number of trading days in a year, the overnight volatility is presented in formula (8), open to close volatility in formula (9) and σ_{RS} is the Rogers-Satchel estimate in its entirety as seen in formula (5). Finally, the variable k is calculated as:

$$k = \frac{0.34}{1.34 + \frac{N+1}{N-1}}, \tag{7}$$

where N is the number of periods used in the estimation. The variable k is used to minimize the variance of the volatility estimate and in practice, we use it to calculate a weighted average of the open-to-close volatility and the Rogers-Satchel volatility (Yang and Zhang, 2000).

The overnight volatility can be formulated as follows:

$$\sigma_{overnight\ volatility}{}^2 = \frac{1}{N-1}\sum_{i=1}^{N}\left(Ln\left(\frac{o_i}{c_{i-1}}\right) - \overline{Ln\left(\frac{o_\iota}{c_{\iota-1}}\right)}\right)^2, \qquad (8)$$

where N is the same as in formula for k, o_i is the opening price on day i and c_{i-1} is the closing price of the previous day. The second term within the sum represents the average of overnight volatilities

Finally, the open to close volatility can be formulated as follows:

$$\sigma_{open-to-close\ volatility}{}^2 = \frac{1}{N-1}\sum_{i=1}^{N}\left(Ln\left(\frac{c_i}{o_i}\right) - \overline{Ln\left(\frac{c_\iota}{o_\iota}\right)}\right)^2, \qquad (9)$$

where the notation is very similar to the overnight volatility formula, the difference being that we calculate the volatility from opening to closing price and not the form the previous close to the following open.

Having introduced some of the most well-known volatility estimation methods, we are left with the decision of which to use. By looking purely at the features of the estimators, Yang-Zhang seems to be the most attractive, as it is the only choice that handles both drift and overnight jumps, both of which real-world data regularly exhibits. There are two standard metrics to assess the quality of volatility measures: the efficiency and the bias of the measure. Efficiency is defined by Garman and Klass (1980) as the ratio between the variance of our estimator to the variance of a benchmark estimator, which is commonly the close-to-close estimation of volatility. Therefore, by definition, close-to-close estimation has an efficiency of 1, against which all others are compared to. Bias, in turn, refers to the difference between estimated variance and the average volatility. For example, Bias is caused by overlooking drift or overnight jump when they exist in the data. Table 1 contains a summary of the main range-based estimators of realized volatility. In the required data column, C stands for closing, O for opening, H for high and L for low price. The last column describes the maximum efficiency of each estimate. It is worth noting that excess efficiency decreases when we increase the sample size. Therefore, maximum efficiency is achieved in small samples.

Table 1: Summary of volatility estimation methods

Estimate	Required data	Handles drift?	Overnight jumps?	Efficiency (max)
Close-to-close	C	No	No	1
Parkinson's	HL	No	No	5.2
Garman-Klass	OHLC	No	No	7.4
Roger-Satchel	OHLC	Yes	No	8
Yang-Zhang	OHLC	Yes	Yes	14

Note: Bennett and Gil, 2012

Based on all the factors mentioned above, we opt to use the Yang-Zhang estimator of realized volatility. The methodology does not have much precedent in connectedness studies as most seem to choose either Parkinson's or Garman-Klass estimation, following the example set by Diebold and Yilmaz (2009, 2012). However, they give no substantiated reasons for the choices and Yang-Zhang seems to be the more efficient proxy. In any case, we compare a rolling estimation of connectedness measure achieved with different volatility proxies in the result robustness section. To the best of our knowledge, such a comparison hasn't been shown previously.

2.2. Financial connectedness

At the core of this thesis is the concept of financial connectedness and spillover. The goal is to measure and interpret connectedness within a specified system of variables, in this case, the return volatilities of a set of Nordic banks. While we recognize that connectedness plays a significant role in the financial markets, there isn't a natural definition of connectedness and, therefore, no singular measure of it. Much has still been researched when it comes to financial interdependence and there are multiple alternative methodologies to uncover and measure the effects different variables have on each other. They all have their purposes and limitation, but most don't present a comprehensive picture of connectedness, but instead focus on specific aspects. Some of these methodologies are summarized below and finally, the Diebold and Yilmaz framework, which promises a more comprehensive approach to connectedness, is introduced.

As an example, many papers approach return and volatility spillovers with multivariate GARCH models, a common choice being a bivariate GARCH BEKK model first introduced by Engle and Kroner (1995). These kinds of models are especially suited for measuring pairwise directional connections between variables. Saleem and Fedorova (2010), for example, investigate pairwise linkages in stock and currency markets in eastern Europe and Maghyereh and Awartani (2012) measure return and volatility spillovers within the financial markets of Dubai and Abu Dhabi. While these pairwise connections are an important aspect of connectedness, they do not tell us how the variables interact with the system as a whole. Another shortcoming of multivariate GARCH models is that the coefficients of the estimated model themselves are not directly interpretable and there is no intuitive way of presenting them aside from tables, which grow in size significantly with additional lags and variables.

Aside from GARCH based approaches, there are generally two types of common connectedness measures: correlation-based ones and more modern extremes-based ones that focus on tail events. Correlation is a well-known measure, which in terms of connectedness, mainly focuses on the pairwise relationship between two variables. In general, it is a linear and nondirectional measure of dependence, although some nonlinearity can be captured by conditional time-varying correlation. As with GARCH models, correlation in its typical cases is only a measure of a pairwise connection. (Diebold and Yilmaz, 2015, 24-25) However, Engle and Kelly (2012) have proposed a way of aggregating correlations between multiple variables to achieve a system-wide correlation, the so-called equicorrelation, which can be thought of as a measure of system correlation, similar to the concept of total connectedness in the methodology used in this paper.

The second set of connectedness measures, the so-called extreme or tail-based measures, approach connectedness on a high system level, whereas correlation typically is a low-level pairwise measure. These system connectedness measures are built upon the familiar notions of value-at-risk (VaR) and expected shortfall (ES), widely used especially by risk managers and financial supervisors. First of the measures is the conditional value-at-risk (CoVaR, not to be confused with CVaR, which is also referred to as conditional value-at-risk aka expected shortfall) of Adrian and Brunnermeier (2016). Essentially CoVaR measures the contribution of a single firm to the VaR of a particular system. In the context of this thesis, it could be used to calculate how much risk a single bank contributes to the VaR of the whole set of Nordic banks.

On the other hand, the marginal expected shortfall or MES measures an individual firm's exposure to the entire market, meaning the expected loss of a particular firm when the whole market experiences extreme events (Idier, Lame and Mesonnier, 2014). These measures are similar to the “to others” and “from others” connectedness measures of the framework used in this paper. They are referred to as extreme or tail-based measures because they are usually calculated from the firm or system-specific tail of the distribution of profits and losses. Both CoVaR and MES are often used as measures for systemic risk.

As previous sections outline, there are multiple different ways to measure aspects of connectedness, be it pairwise or system-wide. However, a comprehensive measure of connectedness is attractive for the purposes of deep dives on interconnectivity within specified systems, as is the case in this thesis. Connectedness exists on many levels and it is more straightforward to be able to measure them with a unified framework instead of a collection of different models that are not necessarily directly comparable.

In 2009, Diebold and Yilmaz proposed a simple and intuitive measure for financial connectedness and interdependence dubbed by them as the spillover index. Their measure of connectedness allows us to decompose system-wide connectedness into lower-level aspects of connectedness. We are able to not only look at directional pairwise connections, but connections of individual variables to the system and vice versa, and we are able to divide the system-wide connectedness into subsystems. Diebold and Yilmaz built upon and expanded their original framework in a series of papers and a book. (Diebold and Yilmaz, 2009, 2012, 2014, 2015)

At its core, the spillover index framework is based on the vector autoregression (VAR) framework of Sims (1980). VAR is a multivariate linear autoregression model where n number of variables are explained not only by k number of their own past values, lags, but by the k past values of all other remaining variables in the model. Usually, we are not directly interested in the VAR model results: coefficients, their significances or R^2 statistics. Due to the complicated dynamics of VAR, they don’t have straightforward implications. Thus the model is often interpreted from Granger-causality tests, impulse response functions or variance decompositions. (Stock and Watson, 2001) Of these, the spillover index framework is built upon the variance decomposition of VAR.

Variance Decomposition, also commonly referred to as forecast error variance decomposition (FEVD), is a tool for interpreting variable relationships in fitted VAR models. It essentially tells us how much of the forecast error variance of a variable is caused by shocks to other variables in the VAR model. The variance is often analyzed for multiple forecast horizons, as some variables might affect others more in the long term than in the short. (Luthkepohl, 2012) By aggregating these connections between variables, Diebold and Yilmaz (2009) published the first iteration of their spillover index framework. Essentially, for each variable i we sum up shares of the error variance of its forecast coming from shocks to variable j, where $i \neq j$, and finally, we add across all the variables. For obtaining the variance decomposition, the original methodology relies on so-called Cholesky factorization, which like VAR, traces back to Sims (1980). The downside of the Cholesky method is that it is not invariant to variable ordering in VAR. This means that the results are sensitive to the order of variables in the dataset. While Diebold and Yilmaz (2015) note that the range of total spillover across different orderings is usually quite small, they recognized the need for an approach that produces the same result for any order of variables. Also, directional connectedness is more sensitive to ordering (Diebold and Yilmaz, 2015).

To address the issue of variable ordering, we look to the generalized forecast error variance decomposition (GFEVD) of Pesaran and Shin (1998) built, in turn, on the generalized impulse response of Koop, Pesaran and Potter (1996). Based on this, Diebold and Yilmaz (2012) proposed an order invariant framework, which alongside total connectedness measures, includes robust directional measures for spillovers. We have to note that the generalized variance decomposition does not come without its drawbacks. While it is invariant to ordering, it introduces the requirement for normality. Assessing spillover of returns, which are rarely normally distributed, is therefore, better done with Cholesky factorization. GFEVD is better suited for log-return volatilities, as is the focus in this thesis, which are well-approximated as Gaussian. (Diebold & Yilmaz, 2015)

Now that we have introduced the foundation for the Diebold and Yilmaz spillover index framework, let us move on to how the model is actually calculated. As mentioned, the process begins with an N variable autoregression with p lags. We note the covariance stationary VAR, based on the notation in the 2012 Diebold and Yilmaz paper, as:

$$VAR(p), x_t = \sum_{i=1}^{p} \phi_i \, x_{t-i} + \varepsilon_t, \tag{10}$$

where we have $\phi_1, \dots, \phi_p$ coefficient matrices and where $\varepsilon \sim (0, \Sigma)$ is the error process, which contains identically and independently distributed disturbances. Essentially, we have a regression model where each variable is explained by p lags of all variables, their own and all the others'. The infinite-order moving average representation of the VAR process is as follows:

$$x_t = \sum_{i=0}^{\infty} A_i \, \varepsilon_{t-i}, \tag{11}$$

where we have $N \times N$ matrices of coefficients noted by A_i, which follow the recursion $A_i = \phi_1 A_{i-1} + \phi_2 A_{i-2} + \cdots + \phi_p A_{i-p}$, where A_0 is an $N \times N$ identity matrix and $A_i = 0$ when $i < 0$. The coefficients of the moving average are crucial to recognizing the key system dynamics. For this, we use the forecast error variance decomposition to identify forecast variance errors rising from shocks to the variables in the system. To construct the order invariant spillover index, we use the generalized forecast error variance decomposition framework.

Variance decomposition allows us to separate H-step ahead forecasting error variance to $own\ variance$ and to $cross\ variance$ also known as $spillover$. We define the first as the share of the error variance in forecasting variable x_i caused by shocks to itself. The latter in turn is the share of forecasting error variance caused by shocks to x_j where $j = 1,2, \dots, N$ and $i \neq j$

Using the GFEVD of Pesaran and Shin (1998), we create an H-step forward variance decomposition matrix $D^{gH} = [d_{ij}^{gH}]$ in which the entries are calculated as:

$$d_{ij}^{gH} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \sum e_j\right)^2}{\sum_{h=0}^{H-1} (e_i' A_h \sum A_h' e_i)}, \tag{12}$$

where $\sum$ is the variance matrix of the error term vector ε, σ_{jj} represents its jth equation's standard deviation and e_i is the selection vector with zeros aside from one for the ith element. Finally, A_h is a matrix of the moving average coefficients at lag h.

The resulting matrix contains, for each variable, the own variance share and the individual cross variance shares of forecast error variance coming from each variable in the system. As the shocks in the GFEVD environment don't need to be orthogonal, the variance contributions (own and cross) don't always sum up to one, as is the case with the standard Cholesky factorization method. To address this, Diebold and Yilmaz (2012) suggest normalizing each row by the row sum. Therefore, instead of the matrix $D^{gH} = [d_{ij}^{gH}]$, we use $\widetilde{D}^{gH} = [\tilde{d}_{ij}^{gH}]$ for the spillover index where:

$$\tilde{d}_{ij}^{gH} = \frac{d_{ij}^{gH}}{\sum_{j=1}^{N} d_{ij}^{gH}} \tag{13}$$

Due to normalization $\sum_{j=1}^{N} \tilde{d}_{ij}^{g} = 1$ and $\sum_{i,j=1}^{N} \tilde{d}_{ij}^{g} = N$, because we have N number of rows that all sum to 1. We can now use the matrix $\widetilde{D}^{gH}$ to construct a so-called connectedness table and to calculate the spillover index measures.

From the results of the variance decomposition, we create a *connectedness table*. A basic schematic of such a table can be seen below in table 2. The connectedness table is at the core of the framework and from this table, we can derive the measures of connectedness. On the upper-left of the table, we have the $N \times N$ matrix $\widetilde{D}^{gH}$, which contains the normalized results of the forecast error variance decomposition. The left-most column containing $x_1, x_2, \dots, x_N$ describes the destination of the spillover and the top row containing $x_1, x_2, \dots, x_N$ the source of it. The Diagonal elements where $i = j$ contain the own variance share of the forecast error variance. The *From others* Column contains the sum of elements where $i \neq j$ and together with the diagonal element they sum to one.

Table 2: Connectedness table Schematic

	x_1	x_2	...	x_N	$From\ Others$
x_1	d_{11}	d_{12}	...	d_{1N}	$\sum_{j=1}^{N} d_{1j}, j \neq 1$
x_2	d_{21}	d_{22}	...	d_{2N}	$\sum_{j=1}^{N} d_{2j}, j \neq 2$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
x_N	d_{N1}	d_{N2}	...	d_{NN}	$\sum_{j=1}^{N} d_{Nj}, j \neq N$
$To\ others$	$\sum_{i=1}^{N} d_{i1}$ $i \neq 1$	$\sum_{i=1}^{N} d_{i2}$ $i \neq 2$	...	$\sum_{i=1}^{N} d_{iN}$ $i \neq N$	$\frac{1}{N}\sum_{i,j=1}^{N} d_{ij}$ $i \neq j$

Note: Diebold and Yilmaz, 2015

In turn, the bottom *to others* row is the sum of the off-diagonal elements in the column. Finally, the bottom-right element contains the grand-average of all off-diagonal elements in the matrix.

Now let us define how different connectedness measures are calculated from the variance decomposition matrix. The degree of pairwise directional connectedness is the simplest of the measures to interpret, as it is directly included in the variance decomposition matrix. We have also already defined how it is calculated in equations (12) and (13). We can abbreviate the $\tilde{d}_{ij}^{gH}$ notation to a more intuitive connectedness notation $C_{i\leftarrow j}^{H}$, where C stands for connectedness, H tells us the H-step forecast horizon and the subscript describes the source and destination of shocks. (Diebold and Yilmaz, 2015) We can read the same information from the table as:

$$C_{i\leftarrow j} = d_{ij}, \tag{14}$$

where i is the row number and j is the column. For example, the cross variance share of x_2 to x_1 is d_{12}. To use a trade analogy, this is similar to import and export. x_2 imports d_{12} volatility from x_1. (Diebold and Yilmaz, 2015) Note that $C_{i\leftarrow j} \neq C_{j\leftarrow i}$. We can calculate the "balance of trade", the net pairwise directional connectedness, between them as:

$$C_{ij} = C_{j\leftarrow i} - C_{i\leftarrow j}, \tag{15}$$

where a negative result implies that variable i contributes less to j than it receives from it and vice versa. The balance of trade is interpreted from the point of view of the first index i.

From the pairwise connectedness, we can move up a level to a less granular measure. The off-diagonal N number of row and column sums also tell us an important story. The row and column labeled “to others” and “from others” tell us the total directional connectedness measures. These are essentially the total export and total import of a variable. If, for example, the first-row sum was 0.25, it would mean that 25 percent of its variation comes from others. The normalized total directional connectedness to market i from all other markets j can be represented as follows:

$$C_{i\leftarrow\bullet} = \frac{\sum_{j=1,j\neq i}^{N} \tilde{d}_{ij}^{gH}}{\sum_{i,j=1}^{N} \tilde{d}_{ij}^{gH}} \times 100 = \frac{\sum_{j=1,j\neq i}^{N} \tilde{d}_{ij}^{gH}}{N} \times 100 \tag{16}$$

And the connectedness to all other markets j from market i as:

$$C_{\bullet\leftarrow i} = \frac{\sum_{j=1,j\neq i}^{N} \tilde{d}_{ji}^{gH}}{\sum_{i,j=1}^{N} \tilde{d}_{ji}^{gH}} \times 100 = \frac{\sum_{j=1,j\neq i}^{N} \tilde{d}_{ji}^{gH}}{N} \times 100 \tag{17}$$

Similarly, to the net pairwise measure, we can calculate the net contribution of variable i to the system, the net directional connectedness as:

$$C_i = C_{\bullet\leftarrow i} - C_{i\leftarrow\bullet} \tag{18}$$

This tells us whether the variable contributes more to the system variation than the system to the variation of variable i. When $C_i < 0$ variable i is a net importer of volatility and when $C_i > 0$ it exports more volatility to the system than it receives.

Finally, we have the highest level of connectedness measure, the total system-wide connectedness. It describes how much of the total system variation is due to cross variable variance, meaning variance originating from external sources rather than the variable itself. It is usually expressed as a percentage of the total variation, which in practice, is calculated as the share of off-diagonal entries to all entries in the decomposition table. We express the total connectedness as follows:

$$C = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{d}_{ij}^{gH}}{\sum_{i,j=1}^{N} \tilde{d}_{ij}^{gH}} * 100 = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{d}_{ij}^{gH}}{N} * 100 \qquad (19)$$

Using the same trade analogies, the total connectedness can be compared to total world imports and exports (Diebold and Yilmaz, 2015)

Up until now, we have only discussed the static approach to the spillover index framework. While a single measure of connectedness in a sample of a particular length tells us a lot about the average levels of interactions between the system variables, it is unlikely that the same levels of connectedness exist between them all the time. We would assume that connectedness and the amount of spillover changes overtime. Markets go through upturns and downturns; companies succeed and fail and the way we do business evolves with new policies and technological advancements. All of these could affect the level and type of connectedness, which we would miss by only using a static measure. To better capture connectedness dynamics, we can estimate the same measurements on a rolling sample basis. Instead of just using the full sample, Diebold and Yilmaz (2009) also introduce a measure of daily connectedness using a moving window estimation of their measures. All the above-mentioned measures can be estimated daily using a specified window length to parse information about the time-varying nature. Rolling window estimation also adds another valuable aspect to the framework, the ability to time events and to see how they affect connectedness.

At their core, all the different connectedness measures are derived from the connectedness table and more specifically from the variance decomposition matrix, be it estimated from the full-sample or on a rolling basis. They hold a wealth of information about the connections between the chosen variables and the systems they form. Usually, the variables are asset returns or return volatilities, but they can also be real fundamentals such as sales or earnings. Connectedness may also be measured across different asset classes as well as within them. (Diebold and Yilmaz, 2015) Different aspects of connectedness may interest different parties. Regulators might find the total system connectedness to be interesting, maybe as a measure of systemic risk, companies might want to know how vulnerable they are to their sector or investors might find pairwise measures of connectedness to be useful for diversification and hedging decisions.

Whatever the case may be, the spillover index framework's financial connectedness measures offer valuable insights on system dynamics and interconnectivity for a variety of applications.

2.3. Frequency Dynamics of Financial Connectedness

While this thesis's primary focus is on the generalized connectedness framework of Diebold and Yilmaz (2012), we are also interested in a less researched aspect of connectedness; its frequency dynamics. Baruník and Křehlík (2018) have developed a time-frequency connectedness framework based on the Diebold and Yilmaz approach to measuring connectedness. Whereas the standard connectedness framework allows us to analyze connectedness over time, the Baruník and Křehlík approach adds the ability to decompose connectedness into different frequencies as well. This allows us to measure connectedness at different frequency bands and to, for example, assess the short-, medium- and long-term frequency responses to shocks. Essentially, instead of just measuring the variation in variable a caused by a shock to variable b, the methodology reveals the variation in a due to a shock to b at a specified frequency band. Generally, shocks that have lasting effects measure higher at lower frequencies. This points to long-term connectedness between the variables. (Baruník and Křehlík, 2018) Long-term connectedness may arise from changes that are perceived as permanent or otherwise long-lasting, for example, a change to a company's dividend paying policy which is assumed to last for the foreseeable future (Balke and Wohar, 2002)

Baruník and Křehlík (2018) base their framework specifically on the generalized forecast error variance decomposition introduced by Pesaran and Shin (1998) and used in the connectedness measure framework of the 2012 paper from Diebold and Yilmaz. In order to produce their frequency connectedness measure, Baruník and Křehlík (2018) define a spectral representation of the GFEVD based on frequency responses instead of impulse responses to shock. This is done with a Fourier transform, a method of decomposing a function into frequencies of the impulse response functions.

Following the notation of Baruník and Křehlík, we consider the following frequency response function:

$$\Psi\left(e^{-i\omega}\right) = \sum_h e^{-i\omega h}\,\Psi_h, \tag{20}$$

which is the Fourier transform of the impulse response coefficients Ψ_h, with $i = \sqrt{-1}$. Ψ_h is the $N \times N$ matrix of coefficients at lag h from the vector moving average representation of the VAR process. Following this, the spectral density of x_t at frequency ω is defined as the Fourier transform of an infinite-order moving average series:

$$S_x(\omega) = \sum_{h=-\infty}^{\infty} E(x_t x'_{t-h}) e^{-i\omega h} = \Psi\left(e^{-i\omega}\right)\Sigma\Psi'\left(e^{+i\omega}\right) \tag{21}$$

$S_x(\omega)$ is the key to frequency dynamics and is referred to as the power spectrum. It shows us how the variance of x_t is distributed across the frequency components ω. Using this, we arrive at the frequency domain counterpart of the generalized variance decomposition:

$$\left(f(\omega)\right)_{i,j} = \frac{\sigma_{jj}^{-1}\left|\left(\Psi\left(e^{-i\omega}\right)\Sigma\right)_{i,j}\right|^2}{\left(\Psi(e^{-i\omega})\Sigma\Psi'(e^{+i\omega})\right)_{i,i}} \tag{22}$$

$\left(f(\omega)\right)_{i,j}$ signifies the share of the spectrum of ith variable at given frequency ω resulting from changes in the jth variable. We can interpret the result of the function as the within frequency causation, as on the denominator, we have the spectrum of variable i at frequency ω. For a natural decomposition of the generalized variance decomposition into different frequencies, we have to weight $\left(f(\omega)\right)_{i,j}$ by the frequency share of the variable i. The weighting function is defined as follows:

$$\Gamma_i(\omega) = \frac{\left(\Psi\left(e^{-i\omega}\right)\Sigma\Psi'\left(e^{+i\omega}\right)\right)_{i,i}}{\frac{1}{2\pi}\int_{-\pi}^{\pi}\left(\Psi(e^{-i\lambda})\Sigma\Psi'(e^{+i\lambda})\right)_{i,i}\,d\lambda} \tag{23}$$

$\Gamma_i(\omega)$ denotes the power of the ith variable at a given frequency. Summing through all frequencies, we arrive at a constant value of 2π. In economics, we are rarely interested in connectedness at a specific single frequency, but rather sets of frequencies that, for example, correspond with short- medium- and long-term connectedness. We refer to sets of frequencies as frequency bands. By using the weighing function $\Gamma_i(\omega)$ and the function $\left(f(\omega)\right)_{i,j}$ we can calculate the amount of generalized forecast error variance contributed by a specified frequency band d, where $d = (a, b)\colon a, b \in (-\pi, \pi), a < b$:

$$(\theta_d)_{i,j} = \frac{1}{2\pi}\int_d \Gamma_i(\omega) f(\omega)_{i,j}\, d\omega \tag{24}$$

Summing over disjoint frequency bands that cover the whole range between $-\pi, \pi$ results in the original variance decomposition achieved in the standard Diebold and Yilmaz. Function (24) can also be used to create similar connectedness tables for different frequency bands. As mentioned in the previous chapter on the standard framework, generalized variance decompositions don't have to add to unity. Baruník and Křehlík (2018) address this by normalizing each entry by the row sum of each frequency band decomposition:

$$\left(\tilde{\theta}_d\right)_{i,j} = \frac{(\theta_d)_{i,j}}{\sum_j (\theta_\infty)_{i,j}} \tag{25}$$

The scaling is done in a way that the row sums of variable i, sum up to one across all frequency bands. As we can create connectedness tables for each band, we can naturally calculate all the same connectedness measures as introduced in the previous chapter. However, Baruník and Křehlík (2018) introduce two different notions of connectedness. The first of them is the so-called $within\ connectedness$. We define it on the frequency band d as:

$$C_d^W = 100 \times \left(1 - \frac{Tr\{\tilde{\theta}_d\}}{\sum \tilde{\theta}_d}\right) \tag{26}$$

And the second notion of the $frequency\ connectedness$ is defined on the frequency band d as:

$$C_d^F = 100 \times \left(\frac{\sum \tilde{\theta}_d}{\sum \tilde{\theta}_\infty} - \frac{Tr\{\tilde{\theta}_d\}}{\sum \tilde{\theta}_\infty}\right) = C_d^W \times \frac{\sum \tilde{\theta}_d}{\sum \tilde{\theta}_\infty} \tag{27}$$

in both $Tr\{\cdot\}$ is the trace operator. For a square matrix, it is the sum of the elements on the diagonal, which in this case are the $own\ variance$ shares. $\sum \tilde{\theta}_d$ in turn, is the sum of all elements of matrix $\tilde{\theta}_d$ and $\sum \tilde{\theta}_\infty$ is the total sum across all different frequency matrices that cover the entire range $(-\pi, \pi)$. The $within\, connectedness$ is the measure of connectedness that occurs within a specific frequency band is exclusively weighted by the power of the series on that frequency. $Frequency\, connectedness$ is the Diebold Yilmaz overall connectedness measure decomposed into parts that sum up to the overall connectedness. Each band is weighted by its spectral density.

While it is possible to calculate all the connectedness measures of the standard spillover index framework for each frequency band, we limit the focus of this thesis to just the total connectedness at different frequency bands. Including all the measures for both the standard and frequency-based approaches would inflate the number of resulting metrics and increase the analytical burden in such a way that it is not within the scope of this thesis. The total connectedness at different frequencies also provides adequate information about the frequency dynamics of connectedness in the Nordic banking system.

3. LITERATURE REVIEW

In this section, we provide a brief literature review of previous studies relevant to the research topic of this thesis. Previous research provides us with the groundwork on which to build our further research as well as a point of comparison to assess our results against. It is normal to form assumptions based on past research and to either confirm or reject those assumptions based on the evidence gathered in one's own independent research. The chapter focuses on giving a comprehensive overview of research on connectedness and spillover, specifically in the financial and banking sector. We summarize the relevant results, which provides context to what to look out for in the empirical section. The literature review draws from information provided in the theoretical framework chapter, which includes background information on different connectedness and spillover methodologies. Here we mainly cover the relevant research findings of past published works instead of focusing on methodological literature.

3.1. Connectedness and spillovers in the financial sector

Interconnectedness has long been a topic of interest in financial literature, but the financial crisis of 2007-2009, alongside the introduction of new methodologies, seems to have raised even more questions about vulnerabilities and contagions in the global financial markets and institutions. Connectedness is widely thought of as a key enabler of contagion and the spread of shocks throughout the system. The Basel committee on banking supervision recognizes connectedness between financial institutions as one of five key factors in assessing systematic risk and identifying systematically significant institutions (Basel committee on banking supervision, 2020). Studies have even shown connectedness to be the most significant explanatory factor in developments of systemic risk (Barroso, Silva and Souza, 2018). While connectedness literature for the Nordics is sparse, there are lessons to be learned from elsewhere. The following paragraphs summarize some of the previous connectedness studies.

The connectedness measures of Diebold and Yilmaz fit a multitude of purposes and research areas. It is no wonder that the framework has also been applied to banking and the wider financial sector. These studies cover a wide range of geographical locations, some focusing on localized systems and some on huge global datasets. Diebold and Yilmaz themselves have recognized the natural fit to the financial sector by studying connectedness between US financial institutions (Diebold and Yilmaz, 2014) as well as between major global banks (Demirer, Diebold, Liu and Yilmaz, 2016). The first study focuses on connectedness before and during the global financial crisis. The results show that between 1999-2010, connectedness is very high in the financial sector, especially between investment banks as well as between government enterprises Fannie Mae and Freddie Mac, which were subject to a federal takeover during the subprime mortgage crisis. After them, the second largest pairwise connectedness was from Morgan Stanley to Goldman Sachs. The dynamic rolling sample measure shows that connectedness of the financial institutions reaches its highest level during the first half of 2007, after a period of decreasing connectedness following the previous high aligning with the burst of the IT bubble. (Diebold and Yilmaz, 2014). The latter study conducted by Demirer et al. (2016) is one of the largest spillover index connectedness studies in the financial sector. The researchers measure return volatility connectedness in a network of the 96 largest banks globally, which were listed during the period from 2003 to 2014. Static connectedness is found to have a significant geographic component in equities, but in the bond markets, geography does not play such a role. Overall, increased connectedness globally is caused more by changes in cross-country linkages rather than local ones. Dynamically, as in most other spillover index studies, connectedness in the system increases during crisis periods. The highest global total connectedness in banking aligns with the fall of Lehman brothers. (Demirer et al. 2016)

Also using the spillover index framework, Jentsch and Steinmetz (2016) study spillover in return volatilities calculated from high-frequency data in the German financial sector. They find the total connectedness to be 46.51 %. Compared to other studies, their total connectedness measure is relatively low, especially for a crisis period. Interestingly, they find that Deutsche Bank, by far the largest German financial institution, exhibits a low level of connectedness to other institutions in their data, which might indicate that Deutsche "plays in a different league" as a global financial institution.

Wang, Xie, Zhao and Jiang (2018) study the volatility connectedness of the Chinese banking system between 2008 and 2016 using the connectedness network specifications of Diebold and Yilmaz (2014). Using daily Garman-Klass-based volatilities, they find the Chinese banking sector to be highly interconnected as the *total connectedness* measure or the cross variance share of the total forecast error is 85.53 %. When measuring connectedness over time, Wang et al. note that connectedness is at its highest during turbulent times in the Chinese market. Their dynamic connectedness measure matches well with the findings of Huang, De Haan and Scholtens (2017), who find using CoVaR and MES that the systemic risk in Chinese banking decreased since the global financial crisis but increased after the Chinese banking liquidity crisis of 2013 and peaked in 2014. The Wang et al. (2018) study also shows that state-owned banks contribute less volatility to the whole banking system than Chinese joint-stock and city commercial banks, the last group being the largest contributor of volatility to the total connectedness of the system. Finally, the paper finds a significant negative rank correlation between bank size and *from-connectedness* and, to a lesser degree, a positive one between size and the *to-connectedness*. This seems to exist mostly on average bases as the rank correlation loses significance in a rolling window estimation. (Wang et al., 2018)

In another study on how size affects the type of connectedness, Elyasiani, Mansur and Pagano (2007) find significant size-varying properties in return and volatility spillovers across US financial institutions. Their findings suggest that return spillovers are more prominent across smaller firms and risk or volatility linkages are stronger withing larger institutions

While there are many spillover index framework studies, the literature focusing on the frequency dynamics of connectedness is limited as the fairly recent framework of Baruník and Křehlík (2018) hasn't had the time to achieve wider popularity. Even more, at the time of this thesis, peer-reviewed literature focusing on the financial sector is almost nonexistent aside from the seminal paper, which like Diebold and Yilmaz (2014), covers US financial institutions before and during the global financial crisis. To our knowledge, there are no papers that focus on frequency dynamic purely in the banking sector. In any case, Baruník and Křehlík's (2018) results indicate that connectedness increases at high frequencies when markets process new information rapidly but calmly. In such cases, shocks tend to have effects in the short-term. In turn, an increase in low frequency or long-term connectedness is associated with changes in investor attitudes and expectations, which tends to lead to persistent shocks. Averaging over the whole period, the high, medium and low frequencies contribute roughly the same to the overall connectedness. In contrast, the few studies on frequency connectedness not focused on the financial industry indicate that most of the connectedness, at least across different asset classes, is produced at higher frequencies (Tiwari, Cunado, Gupta and Wohar, 2018; Ferrer, Shahzad, López and Jareño, 2018). Because the available literature is limited, there is no clear consensus on the typical frequency dynamics of financial connectedness.

As we know, connectedness and spillovers can be studied in a variety of ways. Earlier studies, and especially studies that focus on the concept of spillover, tend to use GARCH models, especially the BEKK variant. For example, using a combination of multivariate GARCH models and a modified version of the generalized spillover index framework, Ribeiro and Curto (2016) study volatility spillover in the interbank money markets. According to their research, similar time-varying properties of connectedness can be found in the interbank money markets as in the stock markets found in other studies. This is to say that connectedness in the money markets is also responsive to market turbulence, highlighting the importance of monitoring it. In a GARCH model study focusing on Indian bank stocks, Shahani and Nagpal (2019) find that between 2013 and 2018, return spillovers are directional from private sector banks to public sector banks. However, in the case of volatility, the relationship is bilateral

Elyasiani, Kalotychou, Staikouras and Zhao (2013) use multivariate BEKK models to measure return and volatility spillovers in and between banking and the insurance industry in the US, UK, Eurozone and Japan. They find both volatility and return spillovers within and across the industries, which are strengthened even further in crisis periods. US financial institutions play a dominant role in exporting uncertainty to Europe, but the connection to Japan is weaker. Elyasiani and Mansur (2003) find similar directional spillover from US banks to German ones, but not to Japanese banks, suggesting tighter connectedness between the US and Europe. Expanding on the interconnectedness between banks and insurers, Niehaus, Rauch and Wende (2019) explore the effects of the regulatory environment on the relationship. They find that property and liability insurance companies' connectedness to the banking sector can be decreased by regulation that limits them from engaging in overlapping activities. However, the same regulations do not seem to affect connectedness between life insurers and banks.

In a study on credit risk volatility spillover in the European banking sector, Alemany, Ballester and González-Urteaga (2015) find different characteristics in the global financial crisis and the Eurozone debt crisis. They utilize an asymmetric multivariate BEKK model to measure volatility spillover in European CDS spreads of major banks between 2006 and 2013. They find that the global financial crisis exhibits unidirectional spillover from banks in the eurozone to European banks outside it. In turn, the European debt crisis does not exhibit the same type of spillover as banks outside the Eurozone seem to be better insulated from volatility within the Eurozone. After the Greek bailout, the unidirectional relationship of the financial crisis is no longer significant, but bidirectional spillover is found between banks in countries with debt problems and banks in the other eurozone countries. Based on the findings, a common currency does seem to be a factor in increased connectedness. (Alemany et al., 2015) Another study on credit risk spillover between European banks and sovereigns suggests that banks with smaller capital buffers, weak funding structures and less traditional activities are the most vulnerable to credit risk spillover. The study using excess correlation as a measure of contagion and connectedness also finds that direct capital injections effectively reduce spillover. (De Bruyckere, Gerhardt, Schepens and Vander Vennet, 2013)

On the risk spillover between banks and the wider European financial sector, Shahzad, Hoang and Arreola-Hernandez (2019) find asymmetric spillover effects depending on the market state. Their results implicate that during bearish markets, spillover flows form the financial industry towards banks and on the contrary, the direction is reversed during bullish markets.

Then there is literature using extreme or tail-based measures such as CoVaR and MES. These measures are typically thought of as measures of systemic risk rather than connectedness per se. However, they are comparable to the *to others* and *from others connectedness* measures in the way they measure either systems exposure to individual variables or their exposure to the system. Weiß, Neumann and Bostandzic (2013) research the effects of bank consolidation on systemic risk using marginal expected shortfall. They find supporting evidence for the “concentration-fragility” hypothesis, which says that bank mergers increase the system's total risk. The results indicate that a more concentrated system is a more interconnected and less stable one, as consolidated banks emit more risk to the system than the sum of its parts before the merger. In another study using MES, Idier, Lamé and Mésonnier (2014) assess its usefulness as a measurement of systemic exposure, the vulnerability of banks to risk spilling over from the whole system. Their findings don’t show MES to be any better at predicting equity losses and assessing the bank’s systematic vulnerability than more standard balance-sheet indicators of financial soundness.

Finally, there are the network studies, which inherently relate to connectedness as a typical network representation of data is just a way to measure things such as type, strength and direction of connections between variables. For example, Deev and Lyócsa (2020) use cross-quantilogram networks to assess the connectedness in stock market returns of European financial institutions. Like many others, they find connectedness to be higher during a crisis than during calm periods. Their network approach also displays other interesting characteristics of connectedness, such as that intra-country connectedness is higher than inter-country, despite the increasing integration in Europe. Similarly, they find that connectedness is stronger between institutions in older member states than in between newer EU members, and much like Alemany et al. (2015), they find that a common currency, such as the Euro, increases interdependence.

In another network study, Minoiu, Kang, Subrahmania and Berea (2015) explore the predictive power of connectedness, a source of potential systemic risk, on financial crisis. They use data on banking transactions in 210 countries between 1978-2010 to assess global connectedness trends, which they then use to predict banking crises. The results indicate that the level of interconnectedness has potential as an early warning signal. Crisis tends to be proceeded by an increase in a country’s *own connectedness* and a decrease in connectedness to its direct financial partners. Eng-Uthaiwat (2018) also finds evidence for the predictive power of connectedness, in a study on network topology and its use in predicting stock returns. They theorize that connectedness increases risk propagation and find evidence of it being able to predict excess returns. Billio, Getmansku, Lo and Pelizzon (2010), in turn, find predictive power in Granger-causality networks, another method of measuring connectedness when forecasting returns in the financial sector. Their results hold even when controlling for other key variables such as the Fama-French factors.

4. DATA AND METHODOLOGY

In chapter 4, we take a closer look at the data and methodology of this thesis in particular. The first section introduces the dataset used for obtaining the empirical results presented in a later chapter. Some light statistical analysis is conducted and the results are reported in tables containing key descriptive statistics. Series and their mutations are also visually presented in graphs. From data, we move on to the methodology section, which, relying on the methodology introduced in the theoretical framework chapter, delves deeper into how the actual research in this thesis is conducted.

4.1. Data

The core dataset of the thesis consists of daily high, low, opening and closing prices of nine Nordic banks, which were listed on their respective stock exchanges before the global financial crisis of 2008 and up until the summer of 2020. All banks that met those criteria were chosen. The set contains two Finnish banks Ålandsbanken (ALB) and Nordea (NDA), although the latter was a Swedish bank up until the tenth of October 2018, when it re-domiciled to Finland (Nordea, 2018). It also contains three Swedish banks: Swedbank (SWED), Svenska Handelsbanken (SHB) and Skandinaviska Enskilda Banken (SEB), three Danish banks: Danske Bank (DANSKE), Jyske Bank (JYSK) and Sydbank (SYDB) and finally one Norwegian bank DNB (DNB). In brackets is the bank's stock ticker, which is used to identify banks in figures, tables, and text from this point forward. Unfortunately, there were no Icelandic banks that were listed throughout the Icelandic banking crisis between 2008-2011 and therefore, Iceland is unrepresented in the set of Nordic banks. In total, the dataset of prices runs from 2.1.2004 to 4.9.2020 and consists of 4081 observations in total. Price data was collected from Yahoo finance and is denominated in the respective Nordic currencies. Data on daily exchange rates for Nordic currencies against the Euro was used to convert all prices to the Euro. Daily exchange rates for the full period of prices were retrieved from the publicly accessible statistical data warehouse of the European central bank.

Figure 1 below depicts the evolution in the euro-denominated stock price of each bank in the dataset. Similar patterns can be interpreted from all the series. We see peaks and valleys associated with events such as the global financial crisis, the European debt crisis and the most recent events related to the market turmoil caused by the global pandemic Covid-19. Each series, of course, has its characteristics and events, but this already reveals to us that none of the Banks exists in a vacuum and they are all in some way connected to other entities in the market. More sophisticated methods are, however, required to reveal their connectedness to each other.

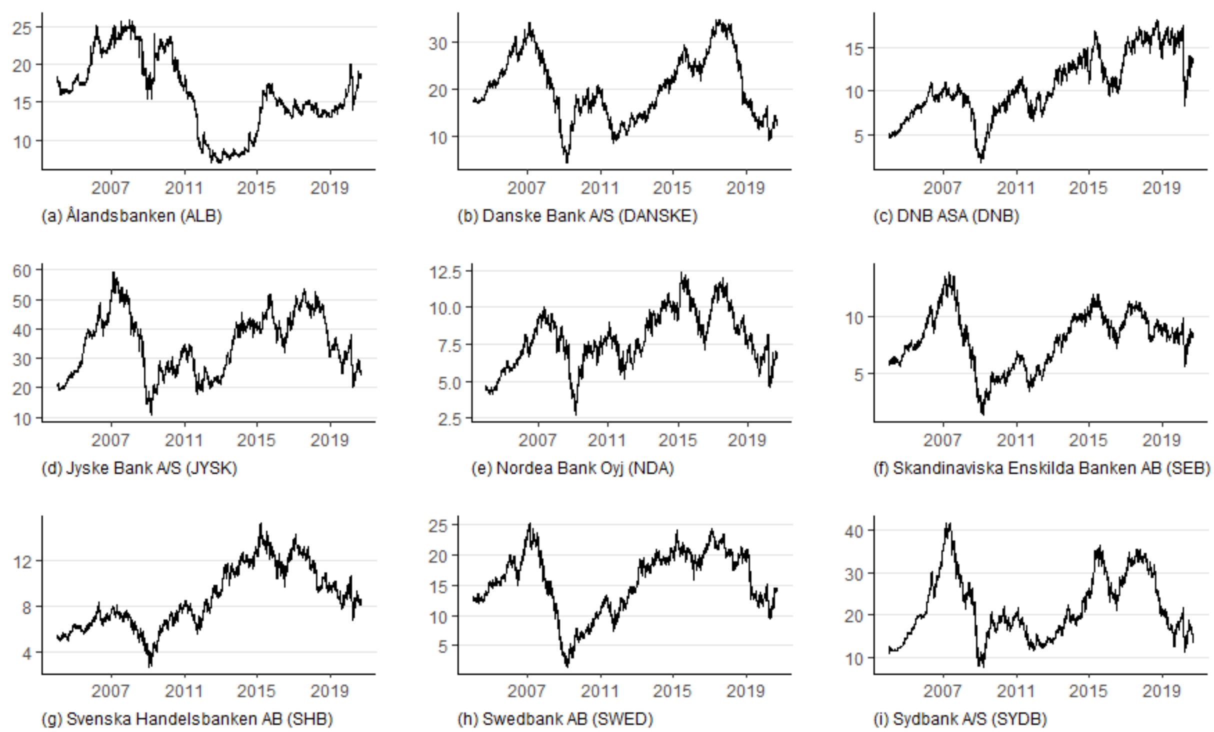


Figure 1: Bank equity prices

Table 3 below shows descriptive statistics corresponding to closing prices in figure 1.

Table 3: Descriptive statistics for bank equity prices

	ALB	DANSKE	DNB	JYSK	NDA	SEB	SHB	SWED	SYDB
Mean	16.121	20.423	10.770	34.920	7.876	7.958	8.712	15.594	21.794
Median	16.014	19.521	10.148	35.398	7.750	8.222	8.058	16.290	19.772
Maximum	25.890	34.625	18.218	59.412	12.420	13.901	15.277	25.294	41.648
Minimum	7.000	4.429	1.725	10.858	2.715	1.388	2.669	1.463	7.784
Std.Deviation	4.981	6.917	3.642	10.286	1.917	2.447	2.745	5.246	7.582
Skewness	-0.016	0.166	0.040	0.031	-0.001	-0.211	0.271	-0.526	0.511
Kurtosis	2.149	2.136	2.291	1.952	2.479	2.477	1.991	2.477	2.299
ADF	-1.149	-1.225	-3.045	-2.010	-2.270	-1.824	-1.372	-1.495	-1.694
JB	123.42***	145.59***	86.54***	187.50***	46.11***	76.71***	222.87***	234.73***	260.71***

*Note: The statistics are calculated from daily closing prices of the given equities from between January 2004 and September 2020 (obs. 4080). For the augmented Dickey-Fuller test (ADF) and Jarque-Bera test (JB): ***, ** and * represent significance at the 1 %, 5 % and 10 % levels in the given order.*

Although interesting and revealing in themselves, pure price series are not used in the methodology of this paper. Following Diebold and Yilmaz (2009, 2012, 2014), we might be more interested in returns and return volatilities. While this paper focuses mainly on return volatilities, we look at both, as returns may reveal something about the nature of volatility in the chosen equities.

First, we take a look at log-returns calculated from closing prices. These are shown in figure 2. From these graphs, we can identify clear periods where large consecutive changes in prices happen, resulting in large returns. This is referred to as volatility clustering, which means that large changes are followed by large changes of either sign and in turn, small changes follow small changes. In other words, they cluster up and dramatic changes tend to ripple and persist for a period. This phenomenon was first written about by Mandelbrot (1963, 418). These periods match well with times of economic and financial turmoil. The longest period of large returns happens between 2008 and 2010, where both the global financial crisis and the European debt crisis were in full effect. The coronavirus pandemic has also produced spikes second only to the highest daily returns of the aforementioned crisis. Assessing individual banks, we see that Ålandsbanken exhibits the smallest clusters and its peaks tend to be on the smaller side. On the other hand, Swedbank seems to have produced a lot of large returns in the 2008-2009 period. We can also see company-specific events here as in the previous price graph. An example of this could be the Danske Bank money-laundering scandal of 2018, which we see in figure 1 as a large drop in stock price and in figure 2 as a cluster of big negative and positive returns.

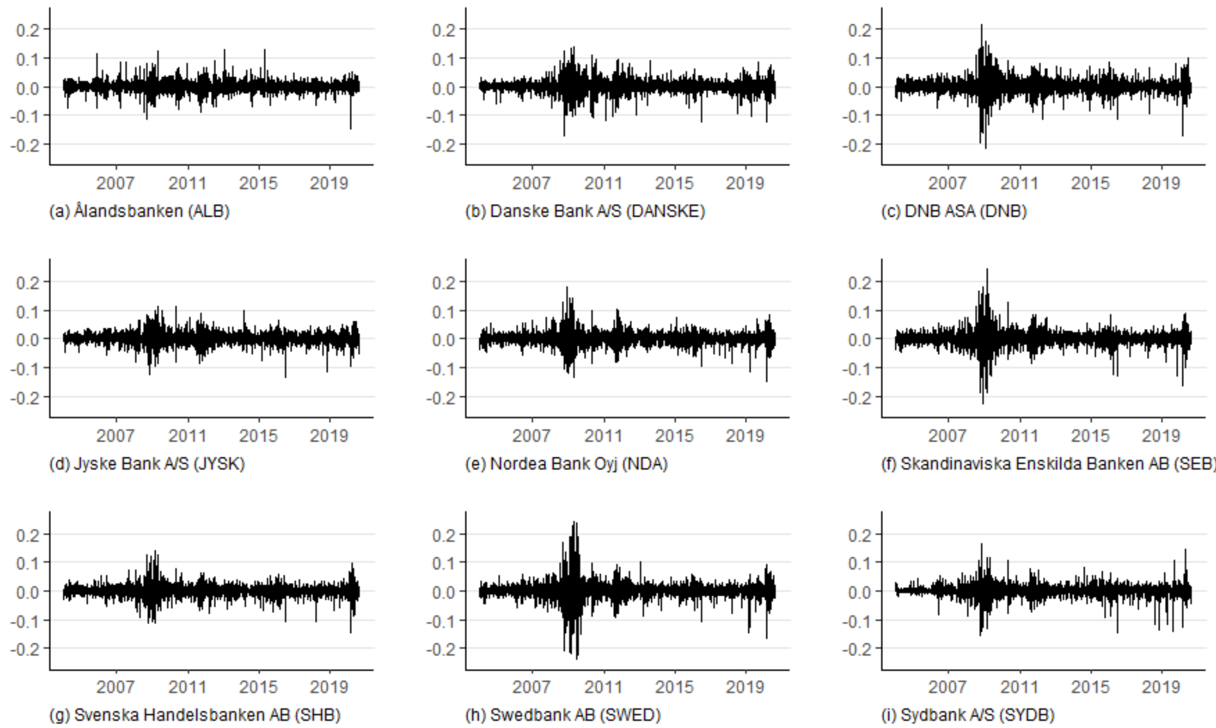


Figure 2: Bank equity log-returns

In Table 4 below we can see the same descriptive statistics for returns as in table 3 for closing prices. However, this time, they reveal more about potential volatility, which we are most interested in, and are also more appropriate for assessing how the chosen methodology would fit the data. We see that Swedbank has the largest standard deviation, followed by SEB and DNB. In turn, Ålandsbanken exhibits the lowest standard deviation. For model fit, we look at first the Augmented Dickey-Fuller test for the existence of a unit root. We reject the null in favor of stationarity for each series, which is essential for the methodology. We have achieved stationarity by taking first differences, as we can see that in table 3 the prices were not stationary and the results of the ADF test were insignificant. Now the ADF test shows significance at a 1% significance level. We can therefore say that the prices are integrated of order 1. The Jarque-Bera test for normality is conducted in order to assess which strategy of obtaining the variance decomposition suits best. In each case, the null of zero skewness and excess kurtosis is rejected. Looking at the pure skewness and kurtosis, we see that each series exhibits positive excess and are therefore leptokurtic with only a slight negative skew. Based on this, we should favor Cholesky factorization as in the original Diebold and Yilmaz paper (2009).

Table 4: Descriptive statistics for bank log-returns

	ALB	DANSKE	DNB	JYSK	NDA	SEB	SHB	SWED	SYDB
Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Median	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000
Maximum	0.127	0.139	0.215	0.111	0.182	0.241	0.142	0.320	0.163
Minimum	-0.149	-0.172	-0.213	-0.132	-0.150	-0.228	-0.144	-0.296	-0.155
Std.Deviation	0.017	0.021	0.025	0.019	0.021	0.025	0.019	0.029	0.020
Skewness	0.144	-0.112	-0.312	-0.205	0.221	-0.135	-0.058	0.181	-0.756
Kurtosis	11.180	9.891	13.161	8.252	10.930	15.987	9.990	27.165	14.557
ADF	-15.69***	-14.77***	-16.58***	-13.99***	-16.39***	-17.81***	-17.64***	-15.76***	-14.37***
JB	11387***	8079***	17615***	4715.9***	10722.3***	28677.5***	8306.7***	99269.7***	23088.9***

*Note: The statistics are calculated from daily log returns of the given equities from between January 2004 and September 2020 (obs. 4079). For the augmented Dickey-Fuller test (ADF) and Jarque-Bera test (JB): ***, ** and * represent significance at the 1 %, 5 % and 10 % levels in the given order.*

Finally, we move on to return volatility, which is the actual variable we want to use in the empirical section of this paper. As explained in chapter 3, volatility isn't something that can actually be observed, and therefore, it has to be estimated. We choose to utilize the Yang-Zhang volatility estimator as it has been shown to be the most efficient of the methods. It also captures overnight jumps, which are an important aspect of volatility. The calculation of the volatility is done as introduced in formulas (6) through (9). The resulting estimate is the daily return volatility, which we can see graphed below in figure 3.

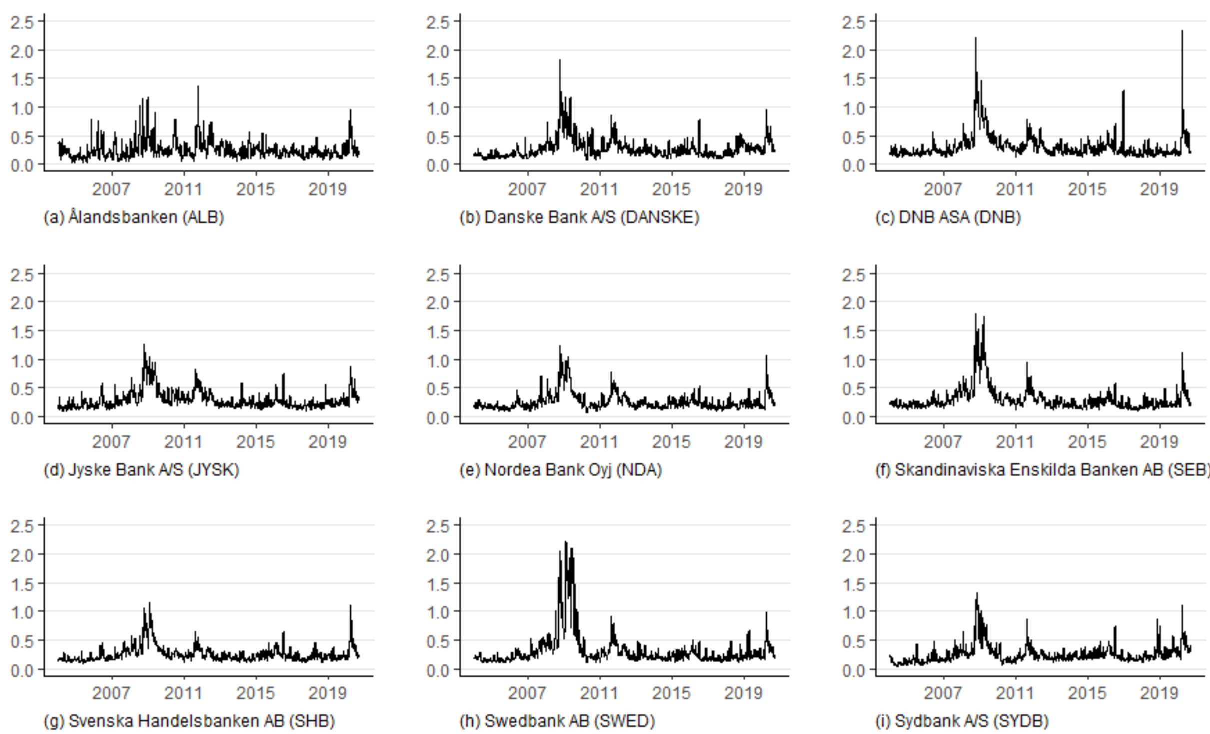


Figure 3: Bank return volatilities, Yang-Zhang

Figure 3 matches up well with the clusters found in the return series. Another aspect of volatility, the previously introduced asymmetric volatility, is also plain to see. Volatility is highest when the underlying economy is doing poorly, such as during the financial crisis of 2008. DNB and Swedbank seem to exhibit the highest volatility spikes, which can be confirmed from the descriptive stats table 5. Those are also the two most volatile banks in the set. While the returns might have suggested that Ålandsbanken is the least volatile bank, here we have a different story. The addition of intraday high and low prices and opening prices has clearly brought more information on volatility dynamics. For example, overnight jumps are not captured by closing prices only. Based on our volatility estimation, the actual least volatile bank is Svenska Handelsbanken.

On the topic of model fitness, we again reject the null hypothesis of the existence of a unit root according to the ADF test result. This means vector autoregression is suitable for pure return volatilities. However, the Jarque-Bera test null hypothesis is also rejected at a 1 % confidence level, meaning that the series is not normally distributed. Cholesky factorization could be the choice if pure volatilities were to be used. However, it is rare to use them in the context of the Diebold and Yilmaz model.

Table 5: Descriptive statistics for bank return volatilities

	ALB	DANSKE	DNB	JYSK	NDA	SEB	SHB	SWED	SYDB
Mean	0.262	0.279	0.318	0.294	0.261	0.308	0.259	0.324	0.257
Median	0.222	0.224	0.251	0.244	0.215	0.239	0.214	0.224	0.216
Maximum	1.354	1.821	2.323	1.247	1.225	1.789	1.156	2.211	1.311
Minimum	0.034	0.069	0.115	0.089	0.066	0.102	0.086	0.099	0.033
Std.Deviation	0.162	0.186	0.232	0.165	0.156	0.221	0.145	0.313	0.169
Skewness	2.333	2.734	4.021	2.116	2.559	3.154	2.662	3.555	2.623
Kurtosis	10.891	14.101	25.052	8.464	10.945	14.965	12.025	16.867	12.046
ADF	-9.507***	-5.998***	-6.797***	-5.728***	-5.755***	-4.664***	-5.707***	-4.754***	-5.949***
JB	14140***	25765***	92701***	8036***	15028***	30780***	18472***	40862***	18397***

*Note: The statistics are calculated from daily range-based volatilities of the given equities from between January 2004 and September 2020 (obs. 4038). For the augmented Dickey-Fuller test (ADF) and Jarque-Bera test (JB): ***, ** and * represent significance at the 1 %, 5 % and 10 % levels in the given order.*

Following the large body of literature before us, we opt for log volatilities (Diebold and Yilmaz, 2009; Diebold and Yilmaz, 2012; Diebold and Yilmaz, 2014). Volatilities are often right-skewed and asymmetrically distributed, which is not optimal for the preferred choice of generalized variance decomposition. Therefore, we take the natural logarithm of the daily volatility estimate to achieve approximate normality. (Diebold and Yilmaz, 2012)

As we see in figure 4 below, this transformation alters the distribution. Peaks are much less dramatic, although we still see signs of asymmetry in the distribution. An interesting note is that Ålandsbanken distribution has a wider range but less defined peaks than others.

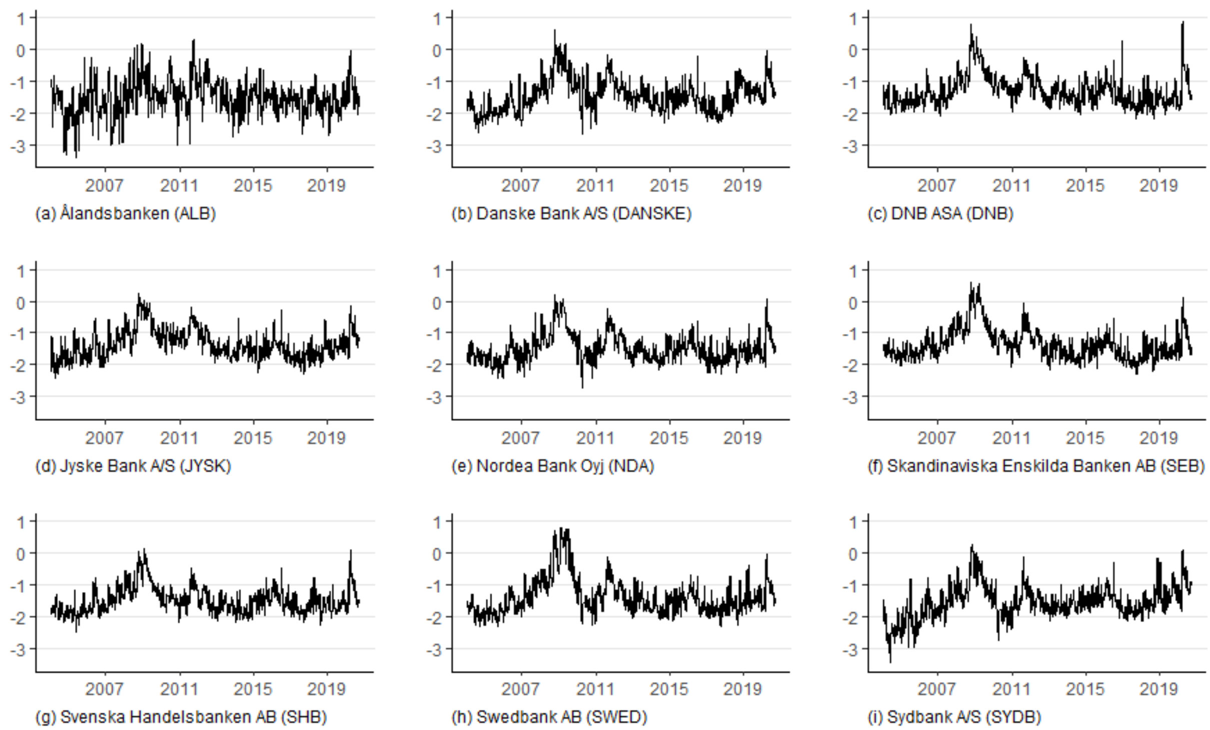


Figure 4: Bank log-return volatilities, Yang-Zhang

Descriptive statistics in table 6 confirm that based on standard deviation, Ålandsbanken is actually the second most volatile stock after Swedbank and that the least volatile is Svenska Handelsbanken. Now looking at the skewness and kurtosis, we see that the transformation has taken us reasonably close to the typical values for normality. However, Jarque-Bera still rejects actual normality for all variables. Still following previous studies, we opt to use the generalized variance decomposition introduced in the 2012 study by Diebold and Yilmaz, where they perform the same log transform and achieve similarly near-normal distribution.

Table 6: Descriptive statistics for bank log-return volatilities

	ALB	DANSKE	DNB	JYSK	NDA	SEB	SHB	SWED	SYDB
Mean	-1.486	-1.425	-1.287	-1.339	-1.462	-1.328	-1.458	-1.350	-1.510
Median	-1.507	-1.495	-1.382	-1.412	-1.537	-1.431	-1.541	-1.497	-1.532
Maximum	0.303	0.600	0.843	0.221	0.203	0.582	0.145	0.794	0.270
Minimum	-3.385	-2.680	-2.164	-2.416	-2.716	-2.285	-2.454	-2.315	-3.411
Std.Deviation	0.533	0.517	0.475	0.456	0.457	0.494	0.427	0.582	0.534
Skewness	0.128	0.696	1.293	0.747	0.933	1.217	1.034	1.410	0.287
Kurtosis	3.716	3.447	5.262	3.279	3.953	4.630	4.097	5.180	3.967
ADF	-8.969***	-5.582***	-6.125***	-5.873***	-5.984***	-5.116***	-5.78***	-4.675***	-5.633***
JB	97.29***	359.58***	1985.71***	388.79***	738.86***	1443.03***	922.71***	2138.26***	212.76***

*Note: The statistics are calculated from daily log volatilities of the given equities from between January 2004 and September 2020 (obs. 4038). For the augmented Dickey-Fuller test (ADF) and Jarque-Bera test (JB): ***, ** and * represent significance at the 1 %, 5 % and 10 % levels in the given order.*

Appendix 1 shows the actual distributions plotted against a normal curve. As we see the distributions are slightly skewed but close to the desired optimal distribution. Another argument in favor of the generalized forecast error version of the framework is the fact that the frequency connectedness methodology is specified for it. This means that the resulting measures are directly relatable to each other as the Baruník and Křehlík (2018) frequency connectedness results are essentially a frequency-based decomposition of the total connectedness measures of Diebold and Yilmaz (2012).

4.2. Methodology

The core objective of this thesis is to provide a comprehensive picture of the connectedness present in the publicly listed Nordic banking sector. Simultaneously we try to provide answers to specific questions about the nature of that connectedness. Measuring the interconnectivity is done with both the generalized version of the connectedness framework of Diebold and Yilmaz (2012) and the generalized frequency connectedness framework of Baruník and Křehlík (2018)

The process begins with estimating a nine-variable vector autoregression model. The variables on which the model is estimated for are the daily log return volatilities of the nine Nordic banks proxied with the Yang-Zhang estimator. The lag order of the VAR model is decided on with the help of a selection of different information criteria. The maximum lag order is set to be 10 to avoid an overspecified model before estimating the information criteria. The chosen criteria are the Akaike information criterion (AIC), Hannan-Quinn information criterion (HQ), Bayesian information criterion (BIC), and finally, Akaike's final prediction error criterion (FPE). Below in table 7 are the suggested lag orders

Table 7: Model selection, information criteria results

AIC(n)	HQ(n)	BIC(n)	FPE(n)
6	2	2	6

As we see, they are split between 6 and 2 lags. We choose 6 as removing the maximum order limit would result in larger suggestions in all criteria, suggesting that there is information in the older lags. In the robustness assessment, we check how the choice of order 2 would alter the connectedness measure. In any case, the main results rely on a VAR(6) model with a set of nine variables.

Once fitted, the model results are interpreted with the generalized forecast error variance decomposition represented in equation (12). Before that, we have to consider the predictive horizon H of the variance decomposition. We have to consider that not all connectedness is created immediately, and choosing a longer forecast horizon typically increases the amount of measured connection. In the standard connectedness measurement, we choose a horizon of 10 days. Although there is no inherently correct horizon choice from a risk management perspective, we can relate this choice to the 10-day value-at-risk required by the Basel accord (Diebold and Yilmaz, 2014). Sensitivity to the horizon is also explored in the robustness assessment.

Based on the variance decomposition results, we then build the connectedness table containing the key connectedness measures for the full sample. As noted before, the generalized decomposition does not always add up to unity, and therefore, we normalize the results row-wise. Based on the results, we analyze the average connectedness measures of the system, the total volatility spillover, directional spillover, net spillover and the net pairwise spillover.

The relationship between bank size and directional connectedness is also explored in the full sample connectedness. Following the precedence set by Wang et al. (2018), we use the same two non-parametric rank correlation tests: Spearman's rho and Kendall's tau, in order to dissect the relationship between bank size and connectedness measures. We test the relationship between the market capitalization of the banks based on their latest quarterly reporting (Q2/2020) and to-, from- and net-connectedness. The methodology of this thesis should be directly comparable to that of Wang et. Al (2018).

From analyzing the static full-sample connectedness measures, we move onto a dynamic rolling-sample connectedness to explore the time-varying nature of connectedness. All the same measures as for the static connectedness are calculated on a rolling basis. Essentially what we do, is choose a specified time window for which we estimate the connectedness. Then we move that window day at a time and estimate the connectedness for each given day. We choose the window length to be one year in line with many other studies. Choosing too short of a window results in noisy results, and increasing the length, in turn, smooths the daily changes. Window length choice is also assessed later on in the robustness analysis.

From then on, we move to the frequency side of connectedness. Using the same fitted nine variable vector autoregression model with six lags, we again interpret the results with a generalized forecast error variance decomposition. This time, however, the forecast horizon is set to be hundred days. This needs to be done in order to capture connectedness created at lower frequencies and to assess the long-term connectedness effects. We group the frequency scale into three distinct bands, which represent short-term, medium-term and long-term connectedness, equivalent to a week, a month and a year. With the resulting decomposition, we can build connectedness tables for each band and analyze their results. Frequency connectedness is also interpreted on a rolling-basis similar to the standard connectedness measure.

To help us better understand the frequency connectedness dynamics, we conduct a simple event study in which we examine the response in connectedness to significant events in the financial markets. The analysis is done on a visual basis, similar to what was done by Baruník and Křehlík (2018). Essentially, we highlight event dates and examining the response in the connectedness at different frequencies. We focus mostly on events associated with the European debt crisis. Specific events are introduced in the results section.

Finally, to assess the sensitivity of our results to many of the model parameters, we conduct a comprehensive robustness analysis, as referenced before. This is mostly done by means of sensitivity analysis, where individual model parameters are altered and the results and their ranges are recorded and visualized. This allows us to assess the consequences of choosing false or otherwise different model specifications. We test the effects forecast horizon, VAR order, rolling window length, the choice between generalized variance decomposition and Cholesky factorization, and volatility proxy has on total connectedness over time.

5. RESULTS

The results chapter focuses on analyzing the empirical results achieved by the methodological procedures summarized in the previous section. We start by looking at the full sample connectedness measures achieved by following the connectedness framework of Diebold and Yilmaz (2012). With the full sample results, we also assess their relation to the size of the financial institutions. From there on, we move to examine the dynamic nature of connectedness over time using rolling sample estimation of the same methodology. From the Diebold and Yilmaz framework, we change over to the Baruník and Křehlík (2018) frequency framework, again starting with a full-sample analysis followed by examining the frequency dynamics over time. We also employ a simple event study to understand the frequency dynamics better. Finally, we conduct a comprehensive robustness assessment in the form of sensitivity analysis.

Full sample connectedness

Table 8 below shows the aggregated results of the full sample 10-day ahead generalized forecast error variance decomposition from our fitted VAR(6) model. As we see, it resembles the one presented before in table 2 with some added measures such as the rows "*to others including own*" and "*net*". Let's first focus on the overall system connectedness, which is measured by the spillover index found at the bottom right of the table. Connectedness in the publicly listed Nordic banking sector seems to be at a medium to a high level when compared to the same metric reported in other studies using the same methodology. The spillover index in this case is 50.04 %, which essentially means that just above half of the forecast error variance in the system is caused by spillover from other banks in the system. This is a bit higher but similar to what Jentsch and Steinmetz (2016) find in German financial institutions, but smaller than is found in the US sector by Diebold and Yilmaz (2014) and Wang et al. in Chinese banks, respectively. The total connectedness is essentially an average of the directional connectedness measures, either to or from others connectedness.

Table 8: Total connectedness, full sample

	from									
to	ALB	DANSKE	DNB	JYSK	NDA	SEB	SHB	SWED	SYDB	from others
ALB	90.34	1.70	1.86	0.76	0.43	2.07	1.78	0.98	0.09	9.66
DANSKE	1.20	49.08	5.74	7.66	5.44	8.48	4.73	8.08	9.58	50.92
DNB	0.72	5.13	45.50	6.41	7.58	11.29	9.60	8.83	4.94	54.50
JYSK	0.44	6.62	6.79	55.05	3.38	8.45	3.22	6.13	9.94	44.95
NDA	0.32	6.56	7.56	4.95	34.84	13.59	11.01	13.93	7.25	65.16
SEB	0.08	4.34	8.19	6.24	7.83	39.09	13.43	16.08	4.73	60.91
SHB	0.40	5.21	7.57	5.35	6.98	18.22	37.04	13.23	5.99	62.96
SWED	0.16	4.52	5.51	4.30	6.28	19.56	12.14	42.84	4.69	57.16
SYDB	0.27	8.44	5.42	10.49	4.23	4.86	4.80	5.64	55.84	44.16
to others	3.60	42.52	48.64	46.16	42.14	86.52	60.70	72.90	47.21	450.39
to others including own	93.93	91.59	94.14	101.21	76.98	125.61	97.74	115.74	103.05	Spillover index
net (to - from)	-6.07	-8.41	-5.86	1.21	-23.02	25.61	-2.26	15.74	3.05	= 50.04 %

Note: The table is based on a variance decomposition obtained with a daily VAR with the order of 6 and the identification method of generalized variance decomposition. The (i,j) element of the 9x9 composition matrix represents the estimated 10-day-ahead stock return volatility forecast error to bank i coming from shocks to stock return volatility of bank j. Other elements in the table are derived from the 9x9 bank matrix as described in previous sections.

Because of this, it is affected by the inclusion of less connected banks. On the system level, we can see perhaps unsurprisingly that Ålandsbanken contributes to and receives very little variation from the rest of the system. It is by far the smallest bank in the system when measured by market capitalization, as seen in appendix 2. The relationship between size and connectedness is examined later.

Focusing on the pairwise measures in the 9x9 matrix in the upper left section, we find that for each bank, its own volatility share is the single most significant contributor to its forecast error variance. This can be confirmed by looking at the diagonal elements of the matrix. However, not for all, is it the majority of the variance as the diagonal percentages range from 90.3 % to 34.8 %. In the case of banks that exceed the 50 % threshold on the diagonal, we can say that they themselves are a more significant factor in their own 10-day ahead forecast variance than the remaining system put together. Again, Ålandsbanken stands out as a clear outlier as over 90 % of its variation is caused by shocks to itself. It also contributes very little volatility to others and only barely receives more from others, making it a net importer of volatility. On the other end of the scale is the largest bank in the Nordics Nordea, which has the smallest own variance share at 34.8 %. While it does exhibit average levels of spillovers to others, Nordea stands out as the biggest receiver of volatility in the whole Nordic banking system, causing it to be the largest importer of volatility.

Looking at other pairwise relationships, we find that the Swedish banks in the set: SEB, Handelsbanken and Swedbank, are the most interconnected. They are the biggest individual importers and exporter of each other's volatility, the only exception being that Nordea provides more spillover to Handelsbanken than Swedbank does. When we also include Nordea, which for most of the sample was a Swedish bank, we can say that no other pairwise relationship is as large as those within Sweden. Looking at the danish banks, we see similar evidence that the within-country spillovers are the strongest as they in general rank as the highest pairwise relationships although SEB is actually the second largest source of spillover to Danske and Jyske Bank. Also notable is that the pairwise connections are weaker in the Danish banks than in the Swedish ones. Table 9 shows these within-country connections in a more readable format

Table 9: country subsamples from full sample connectedness

	from		
to	DANSKE	JYSK	SYDB
DANSKE	49.08	7.66	9.58
JYSK	6.62	55.05	9.94
SYDB	8.44	10.49	55.84

a) Denmark

	from		
To	SEB	SHB	SWED
SEB	39.09	13.43	16.08
SHB	18.22	37.04	13.23
SWED	19.56	12.14	42.84

b) Sweden

To better understand the interconnectedness in the system, we present directional connectedness measures in table 10 below, ranked by the size of the connection measures. We present ranking for *to-, from- and net-connectedness* separately. In the *to-connectedness* ranking, we find the Swedish bank trio at the top, meaning that they contribute the most volatility to the system. The margin between the three and the rest is also quite large. The top three range from 86.5 % to 60.7 %, from number four to eight the range is 48.6 % to 42.1 % and lastly, the lowest *to-connectedness* is exhibited by Ålandsbanken at 3.6 %. SEB is, with a large margin, the biggest exporter of volatility shocks to the system.

The *from-connectedness* ranking distribution is much more uniform, again aside from the outlier Ålandsbanken at its 9,66 %. The more uniform distribution was also noted by Wang et al. (2018) in their results. The top eight ranges from 44.2 % to 65.2 %. The largest Nordic bank Nordea is ranked as the leading importer of volatility from the system, whereas it is the second to last origin of spillover to others. As possibly the most pan-

Nordic bank with significant market shares in each country in the set, it is reasonable to assume that Nordea is highly linked with most, if not all, other banks. Because of the pure number and significance of these connections, Nordea is exposed to most of the shocks in the system. The *to-connectedness,* in turn, is primarily increased by turbulence within the bank, meaning a more stable institution has less volatility to spillover. Judging by the descriptive statistics presented in table 6, Nordea has the second lowest standard deviation, which might lend credence to the theory that it has been less prone to shocks that have affected its own share price, which then might have spilled over to the others.

Finally, the last column presents the net directional connectedness ranking. The net is calculated as the difference of to others and from others connectedness in a way that a positive net means that the bank is a net exporter of volatility and a negative net means that it is a net importer of volatility. On one end of the spectrum, we have SEB as the largest exporter of volatility into the banking sector, and on the other end, Nordea as the largest importers of volatility. Another notable exporter of volatility is Swedbank.

Table 10: Directional connectedness rankings

Rank	To-connectedness		From-connectedness		Net-connectedness	
	Bank	$C_{\bullet\leftarrow i}$	Bank	$C_{i\leftarrow\bullet}$	Bank	C_i
1	SEB	86.52	NDA	65.15	SEB	25.61
2	SWED	72.90	SHB	62.96	SWED	15.74
3	SHB	60.70	SEB	60.91	SYDB	3.05
4	DNB	48.64	SWED	57.16	JYSK	1.21
5	SYDB	47.21	DNB	54.50	SHB	-2.26
6	JYSK	46.16	DANSKE	50.92	DNB	-5.86
7	DANSKE	42.52	JYSK	44.95	ALB	-6.07
8	NDA	42.14	SYDB	44.16	DANSKE	-8.41
9	ALB	3.60	ALB	9.66	NDA	-23.02

Note: The 9 Nordic banks ranked by the different directional connectedness measures calculated from the full sample.

We have already touched upon the relationship between size and connectedness before. To inspect further if there is indeed a correlation relationship between these factors, we employ rank correlation measures à la Wang et al. (2018). We use two different rank correlation measures: Kendall's tau (τ) and Spearman's rho (ρ), to compare the three different rankings in table 10 against the market capitalization of each firm found in appendix 2. Table 11 below presents the correlation coefficients and their p-values and statistical significances.

Table 11: Rank correlation testing

	To-connectedness	From-connectedness	Net-connectedness
Kendall's tau	0.167	0.833***	-0.167
p-value	(0.612)	(0.001)	(0.612)
Spearman's rho	0.317	0.900***	-0.200
p-value	(0.4101)	(0.002)	(0.613)

*Note: Rank correlation tests between market capitalization and the directional connectedness measures calculated from the full sample. Correlation coefficients and p-values are presented for both Kendall's tau and Spearman's rho. *, ** and *** indicate the rejection of the null hypothesis of no correlation at levels 10%, 5% and 1%.*

There seems to be a small but statistically insignificant positive rank correlation between market cap and *to-connectedness* (τ = 0.167 and ρ = 0,317), which would indicate that larger banks might contribute more spillover to the system. However, between market cap and from-connectedness, we find a much stronger and statistically significant positive rank correlation (τ = 0.833 and ρ = 0,900 at 1%), which means that larger banks are much more receptive to spillovers coming from shocks to other banks in the system. Larger banks are likely to be more exposed to the other institutions in the system, whether it be through contractual obligations, market-making activities or direct investments, for example. At least in the Nordic context, size goes hand in hand with exposures and links to the rest of the banking system. The biggest banks in the set operate in all of the four countries, at least in some capacity. The smallest banks Ålandsbanken, Jyske Bank and Sydbank in turn, mostly operate in their domestic Nordic markets. Finally, there is a slight negative statistically insignificant correlation between *net-connectedness* and size (τ = -0.167 and ρ = -0,200). This points to larger banks being more likely to be net importers of volatility. Contrary to what is found by Wang et al. (2018) in the Chinese banking sector, our results indicate a positive correlation of market cap with both *to-* and *from-connectedness*. Their results point to a negative relationship between market cap and *to-connectedness*.

Rolling sample connectedness

We cannot expect a single measure to capture the intricate dynamics of the Nordic banking sector as interbank relationships are likely to change over time. To capture the time-varying nature, we use a right-aligned rolling sample with a window width of a year and the same 10-day forecast horizon and VAR(6) model as in the static case. Our rolling daily estimate of total connectedness in the system starts in July 2005 and ends in September 2020. The rolling total spillover index measure can be seen in figure 5.

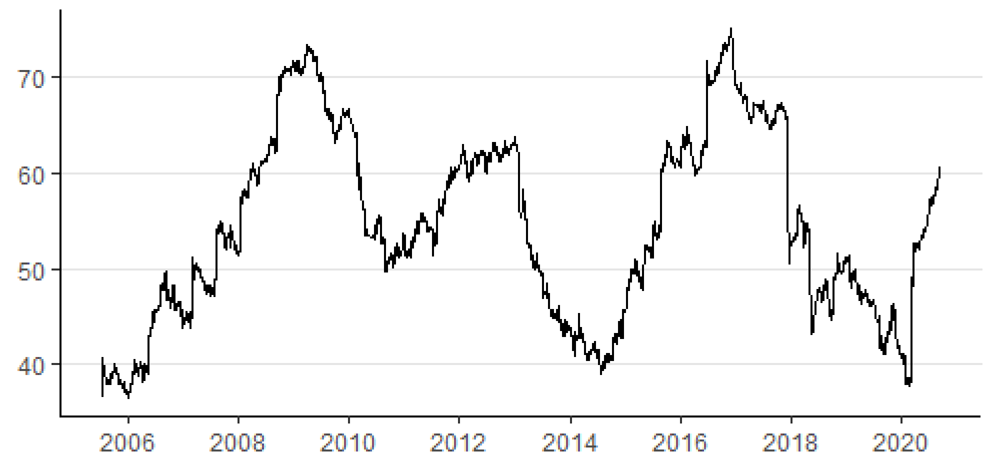


Figure 5: Total connectedness

The overall connectedness in the system starts at the lowest level in our sample history. At the beginning of 2006, spillover only accounts for 36.5 % of the forecast error variance. From this calm before the storm state, connectedness among the banks increases rapidly, as the global financial crisis takes over the markets, reaching a peak of 73.2 % during the first half of 2009. Looking at the broader picture, we can clearly identify defined cycles in the level of connectedness in the Nordic banking sector. The financial crisis peak is followed by the peaks of the late European Debt crisis, after which connectedness drops to a low level at the end of 2014. Again, a period of increasing connectedness follows, this time without such clear-cut market events to point to as the cause. The increase is likely to have been caused by multiple overlapping events, in the beginning by the market selloffs of 2015 and 2016, then the market turbulence caused by Brexit and at the latter part of the wave, by the uniquely Nordic banking scandals related to money laundering. The last explanation seems intuitive as we can see an increase in spillover from Danske bank, the institution at the center of the whole scandal, to the rest of the system. Other Danish banks also show above-average spillovers to the system, as they were likely to experience the most severe shocks from their largest domestic bank and then spill volatility forward. Others, such as Nordea and Swedbank, were also implicated by money laundering allegations and as a result, some of the largest banks, Danske, SEB, Nordea, Swedbank, DNB and Handelsbanken formed a joint KYC and AML initiative (Milne, 2019; Reuters, 2019). It is no wonder that this uniquely Nordic set of events aligns with the highest peak in our sample period. Connectedness reached a peak of 75 %

during the set of events. From there on, connectedness shrinks, before again suddenly rising due to the COVID-19 related market turbulence in March 2020.

For now, we have presented the total connectedness over time in figure 5. The directional measures of connectedness can also similarly be plotted over time. Below in figure 6, we can see the *to-connectedness* measures of each bank. The red dashed line indicates the average directional connectedness calculated from the full sample seen in table 7. From this figure, we can, for example, confirm the forementioned increase in spillover coming from Danske (b) and other Danish banks (d and i). The figure tells us from which banks spillovers to the system originate and when. For example, we see that SEB (f) was by far the largest origin of volatility during the European debt crisis. In recent history, we see that DNB (c) is exporting a lot of spillover. Alongside the COVID-19 pandemic, the bank's considerable exposure to the energy markets is also a likely cause, as the drop in oil prices caused by the Russia Saudi Arabia price war coincides with the increase in *to-connectedness* (Wass and Ahmad, 2020).

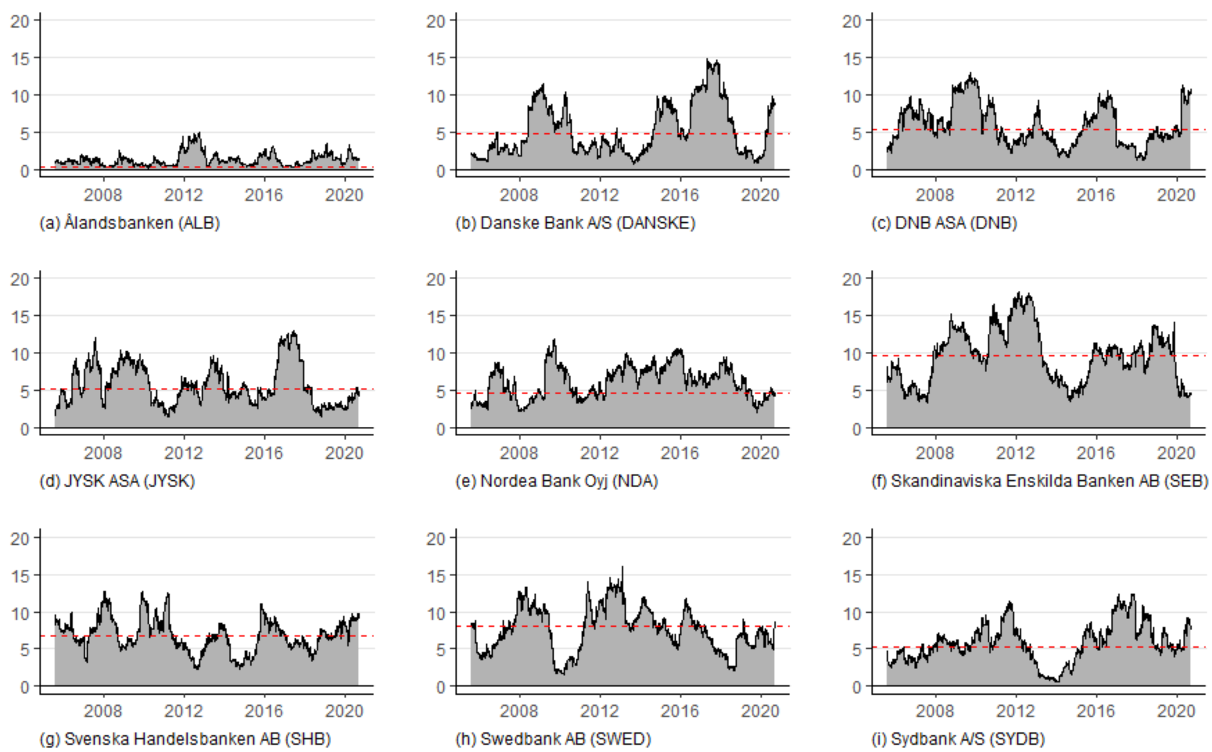


Figure 6: To others connectedness

Figure 7, in turn, shows the *from others connectedness* from our rolling sample estimation. Again, the red line designates the full sample *from-connectedness* in table 8. As we can see, the changes in the *from-connectedness* is much more gradual, which makes sense as this measure is essentially an aggregate of the spillovers coming from all the other banks in the system. If a bank is highly connected to many of the others, large comovements in their to-connectedness measures are needed for more defined peaks in the from-measure. Market cycles are still clearly visible, but they resemble mounds rather than mountain peaks. Looking at Ålandsbanken's (a) graph, we see much more defined and sudden changes. This matches our previous remarks about the bank being less connected to the system as a whole. If it only has a few significant connections, changes to those banks have a much bigger impact on Ålandsbanken.

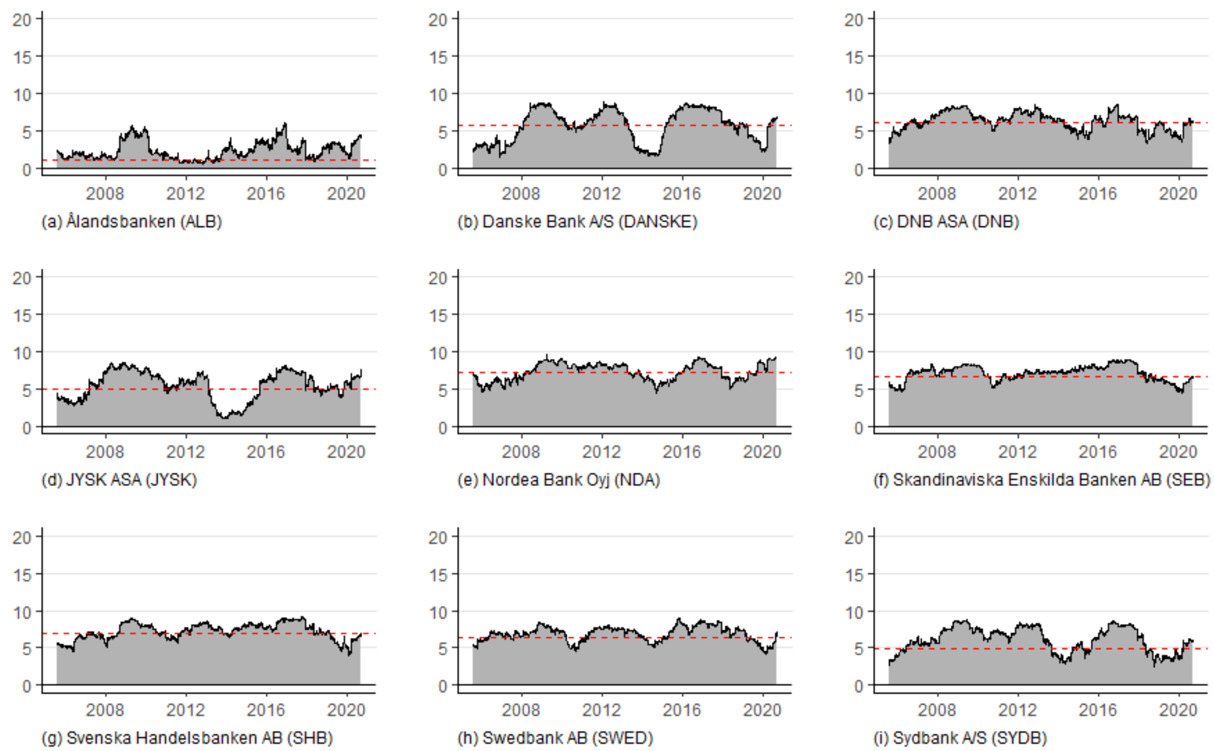


Figure 7: From others connectedness

Finally, we have plotted the net directional connectedness as the difference between to and from in figure 8 below. The red line is the full sample *net-connectedness*. When the curve is above zero, the bank is exporting volatility and when it is below zero, it is importing more than exporting. From the figure, we can interpret which banks are exporting and which are importing at any given moment, which helps us get a better idea about where shocks in the system originate and where they end up. All banks in the dataset experience times where they are a net importer and a net exporter of volatility. Reflecting the graphs to the known financial cycles, we see that during the financial crisis and the European debt crisis, spillovers originate predominantly from Swedish banks. Especially SEB is a major exporter of volatility during the latter end of the debt crisis, reaching the highest peak of any bank at over 10 %. In the latter part of the 2010s, the origin of shocks to the system shifts more towards Danish banks. Looking at the whole period, we see that SEB is the most significant importer over time. In turn, Ålandsbanken very rarely gives more to the system than it receives from others.

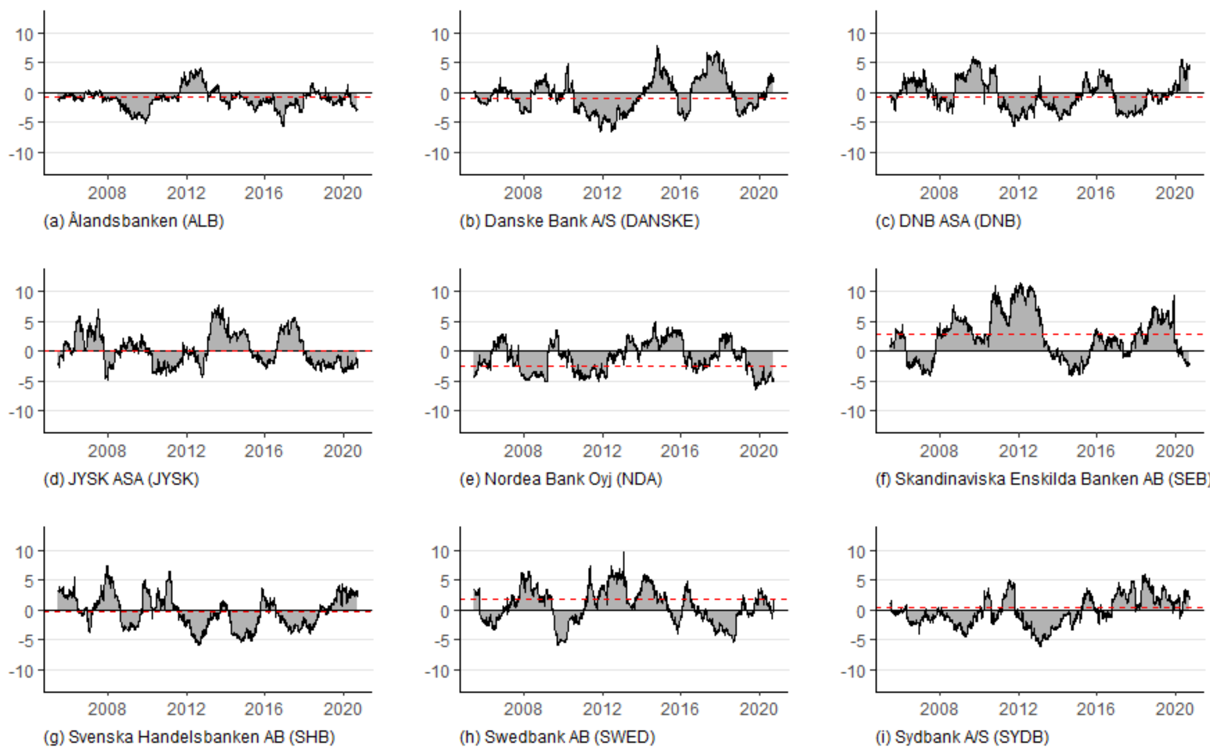


Figure 8: Net-connectedness

We could also plot the net pairwise connectedness measures, but the resulting graph would be quite large. Nine variables make 36 unique sets of pairs to plot. The rolling net pairwise connectedness would, however, be a good way to delve deeper into relationships between individual banks.

Frequency dynamics of connectedness

Up until now, we have addressed the standard connectedness measure of Diebold and Yilmaz on a few different levels of granularity. Here we move on to decompose these connectedness measures to different frequencies based on the spectral representation of the generalized forecast error variance decomposition proposed by Baruník and Křehlík (2018). As mentioned, we divide the spectrum of frequencies into three distinct bands and assess connectedness in short-, medium- and long-term cycles. Our bands roughly correspond to a week ($d_1 \in [1,5]$), a month ($d_2 \in [5,20]$) and a year ($d_3 \in [20,300]$). These, along with other model specifications, match those of Baruník and Křehlík (2018) when possible in order to provide us with a point of comparison. Literature using their methodology is quite limited, and therefore, we are also interested in seeing whether their findings about the frequency dynamics of connectedness hold in the Nordic banking sector.

We'll focus on the time-varying frequency dynamics instead of static measures. However, the static measures are calculated and the results for each frequency band can be found in appendices 3 through 5. The tables present the within band frequency and the actual spectral density-weighted frequency connectedness is given before the table. The bands sum up to the standard static total connectedness of 55.3 %, which, as previously explained, means that spillover accounts for 55.3 % of 100-day ahead forecast error variance. When decomposed into separate bands, we find that the overwhelming majority of the full sample connectedness is created at low frequencies as the long-term connectedness is 47,3 % (85 % of the total). Medium-term connectedness in the sector is 7,4 % (13 % of the total), and finally, in the short-term, frequency connectedness is only 0,61 % (under 2 % of the total). Within the frequency bands, spillovers account for 19.6 % in high frequencies, 38.8 % in medium frequencies and 61.56 % in low frequencies. Looking at the results, we can say that the relationship between the Nordic banks is long-term in nature, which is reasonable as the firms operate within a relatively tiny geographic area, similar economies and the same sector. This is somewhat in conflict with what Baruník and Křehlík (2018) find in the US financial sector, as in their results, connectedness is much more evenly distributed across the bands. We'll discuss the possible source of this conflict later on.

The static measure in the previous section gives us only part of the story and very little about the actual dynamics of frequency connectedness. Therefore, we move on to the overtime rolling sample daily connectedness measures. Below in figure 9, we have two separate graphs, one for the actual frequency connectedness (a) and one for the within frequency band connectedness (b). The lines in graph (a) sum up to the corresponding daily total connectedness.

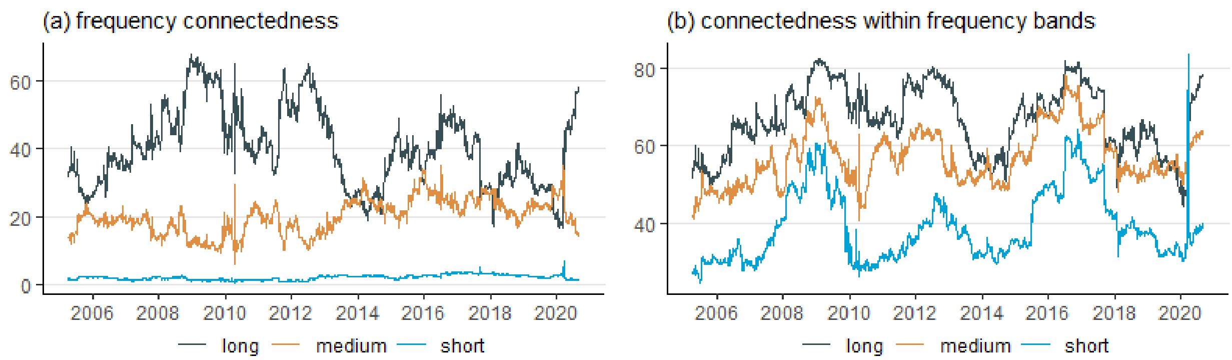


Figure 9: Total frequency connectedness, absolute and within

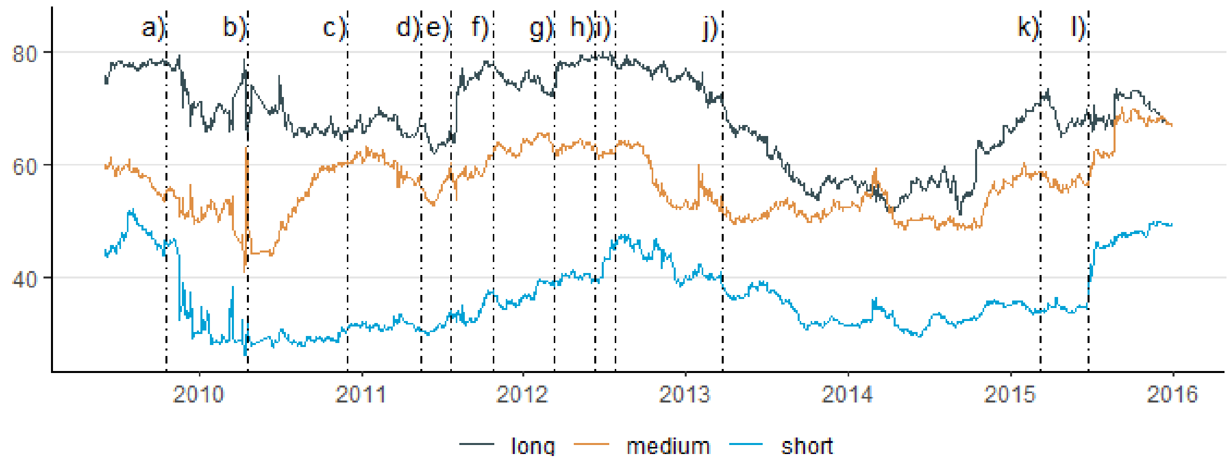
The over time frequency connectedness (a) matches the full sample analysis findings as connectedness in our dataset seems to be mostly created at low (long-term) and medium frequencies. Long-term connectedness ranges between 16 and 67 %, medium-term between 6 and 35 % and short-term between 0.6 and 7 %. The within connectedness graph (b) does tell us that spillovers play a role in the high frequencies as well, but when weighted, their contribution to the total connectedness is minuscule. Appendix 6 shows the total connectedness summed from the frequency decomposition (a). The slight differences between this rolling total connectedness and the one presented in figure 6 are explained by the different forecast horizons and rolling window lengths. If we were to use the same specifications, the summed-up frequencies would match figure 6 exactly.

Reflecting the total connectedness to its frequency decomposition, we can observe that during turbulent markets with increased connectedness, such as the global financial crisis and the European debt crisis, connectedness is created mostly at low frequencies, indicating changes in long-term expectations. In turn, the contribution of the two other frequency bands increases during calmer periods when overall connectedness is low. The dynamics in medium and short-term connectedness are similar, but the contribution to the total comes almost exclusively from medium-term connectedness. Appendix 7 shows each frequency band connectedness on its own axis, where changes over time are easier to discern. There we see that the two higher frequency bands behave similarly to each other. Our results regarding the time-varying dynamics of connectedness are in line with those of Baruník and Křehlík (2018). The clear difference, however, is the fact that in our system, almost none of the overall connectedness is created in the highest frequency band. This is either due to the fact that the nature of connectedness in the Nordic banking sector is heavily long-term created at low frequencies or that we are simply unable to capture it with our methodological choices. For the most part, our methodological choices are identical to those of Baruník and Křehlík with only one apparent deviation. Baruník and Křehlík use a daily logarithmic volatility calculated from high-frequency intraday returns, whereas we use a range-based estimation of daily log volatilities. Range-based proxies of volatility may lose accuracy in the short-term, which could mean that the variance decomposition doesn’t properly capture short-term connectedness. Unfortunately, we cannot test this hypothesis due to the lack of access to comparative high-frequency tick data. Existing literature doesn’t provide an answer either as to our knowledge no one has addressed this.

Frequency connectedness event study

Because frequency connectedness literature is limited and we’ve noticed some inconsistencies between our results and those in the seminal paper of Baruník and Křehlík (2018), we replicate a part of an event study in their research with our data. This is done to better see if our results behave similarly, aside from the already recognized difference that connectedness is not created equally in higher frequencies. A nice feature of the Diebold and Yilmaz (2012) connectedness framework is the ability to time events. We can see immediate changes in the measures once new significant events enter the sample. By adding the frequency decomposition of connectedness to the mix, we can also analyze the changes and their differences in the frequency bands. Borrowing from

Baruník and Křehlík (2018), we graph within connectedness during the European debt crisis against significant events during the period. This is presented below in figure 10. The note below the figure contains labels for the events.



Note: From left to right, the events are: a) the reveal of the Greek deficit, b) the first Greek bailout, c) the Irish bailout, d) the Portuguese bailout, e) the second Greek bailout, f) 50% write-off of Greek sovereign debt, g) the second Greek debt write off, h) the Spanish bank bailout, i) Mario Draghi's "whatever it takes" speech, j) the Cypriot bailout, k) the start of quantitative easing by the ECB and l) The expiration of the Greek bailout.

Figure 10: Within frequency connectedness, European debt crisis event study

Starting from the left with the reveal of the deficit by the Greek prime minister Papandreou (a), we see an immediate response in the short and medium-term connectedness and a delayed one in long-term connectedness. However, only in the medium-term is the connectedness increase sustained at all, which suggests that investors don't yet assume long-term uncertainty. The first Greek bailout (b) causes a tremble in all bands, especially in the medium-term connectedness where spillovers increase by almost 20 %. Afterward, the medium-term connectedness starts to increase the fastest and short-term connectedness much slower. However, long-term connectedness keeps decreasing. The Irish and the Portuguese bailouts have no significant, sustained effects in any of the bands. Only with the second Greek bailout (e) do we see a change in long-term connectedness, when the share of cross variance jumps by ca. 10 % and the increased level is sustained. This suggests a fundamental shift in investor expectations from shorter-term uncertainty to long-term uncertainty. Connectedness at all frequencies reaches their high-points around the time of Mario Draghi's "whatever it takes" speech in July of 2012, which is widely thought of as a turning point in the crisis. Our connectedness measures correspond to this notion as we see a decrease in all bands, especially in the one associated with long-term uncertainty as it drops even below the medium-term connectedness in 2014. Later on, when quantitative easing starts (k), we also see a drop in long-term connectedness, and the expiration of the Greek bailout (l) only has an increasing effect in the short-term.

Reflecting on the results of Baruník and Křehlík (2018) in the US financial sector, we can say that the big picture is very similar. The most significant events have comparative effects on the medium and long-term connectedness measures as the changes are similar in change and direction. However, again our short-term connectedness measure deviates. The connectedness does respond similarly to events, but the change is seldom sustained. We do see the same sharp responses, but they die down quickly. Again, this could mean that the Nordic banking sector has a low level of short-term connectedness and the banks affect each other only in short bursts at high frequencies, or that our methodology cannot capture high-frequency connectedness adequately.

Robustness assessment

Finally, we perform a simple robustness assessment by changing around model parameters and recording the response in the total connectedness measure. This is done to better understand the effects each parameter has and the possible consequences of choosing differently. The sensitivity analysis can also shed light on the significance of the results and their interpretations from the model on which the actual results are based on. In each separate test, the model parameters are as specified in the methodology section before unless otherwise stated.

In the first test, we assess the sensitivity of the total connectedness measure to the forecast horizon. We record total connectedness for horizons between 5 and 10 days and record the results in figure 11. Increasing the horizon increases the connectedness measure as it gives more time for spillovers to occur. The range also tightens slightly during times of heightened overall connectedness suggesting that spillover spreads faster at such times.

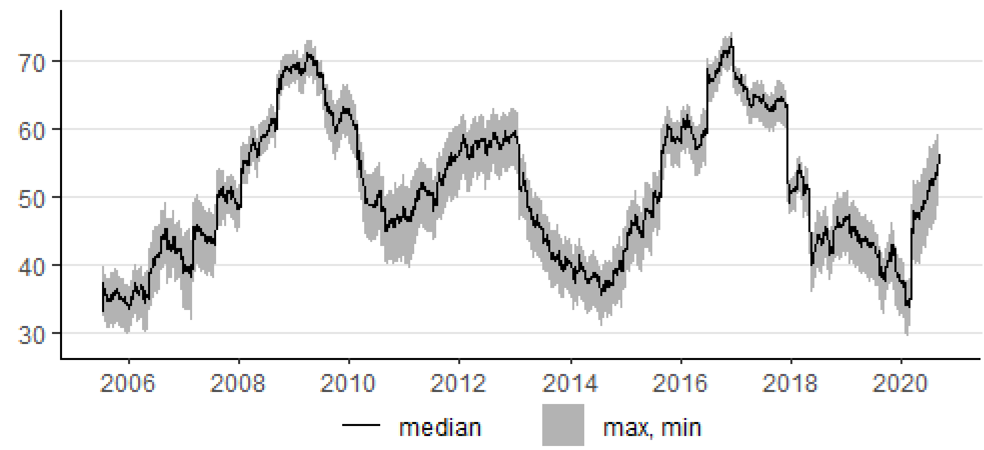


Figure 11: Horizon robustness

Although it is essential to understand and know how horizon affects the connectedness measure, the results don't actually need to be robust to the choice of horizon. There is no "correct" horizon as it is entirely a choice based on what we want to know. Choosing a short horizon focuses a study on the immediate future and choosing a longer one allows for a better understanding of long-term relationships. Therefore, it is preferable to anchor the horizon to some practical timeframe, such as the 10-day Basel VaR chosen here.

In the second test, we change the lag order of the VAR model. We measure connectedness for all lags between 2 and 6, the ones suggested by information criteria earlier. The resulting range of dynamic total connectedness is seen in figure 12 below.

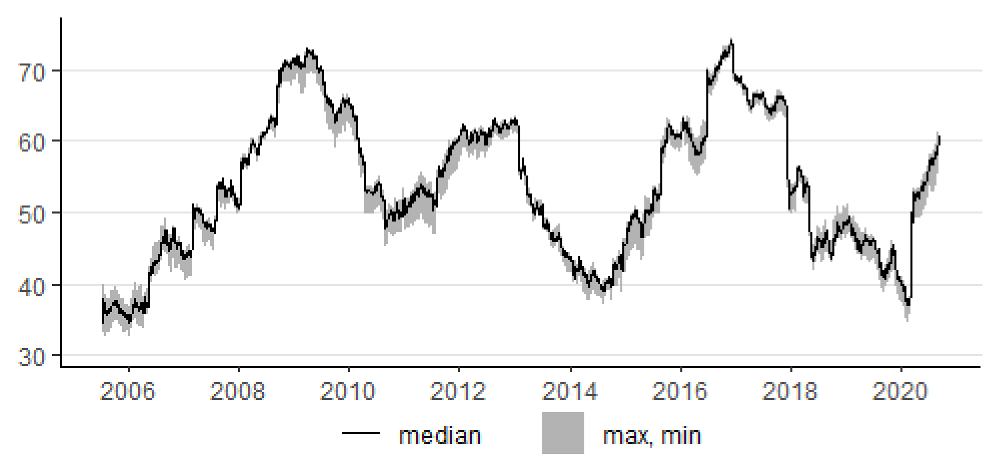


Figure 12: Lag order robustness

The total connectedness seems to be fairly robust to the lag number as the resulting range is small and the dynamics of connectedness do not change. The choice we made between lag order 2 and 6 is relatively inconsequential.

In the third test, we use the Cholesky factorization method instead of the generalized variance decomposition methodology. Because the Cholesky factorization is not invariant to variable ordering, we also record the range of total connectedness results from 16 randomly chosen variable orders. Firstly, comparing the dynamics of Cholesky based connectedness in figure 13 to our generalized results in figure 6, we find that they are very similar, moving in accordance with each other. However, the generalized connectedness measure runs significantly higher than the one based on Cholesky, a finding also corresponded by others (Diebold and Yilmaz, 2014).

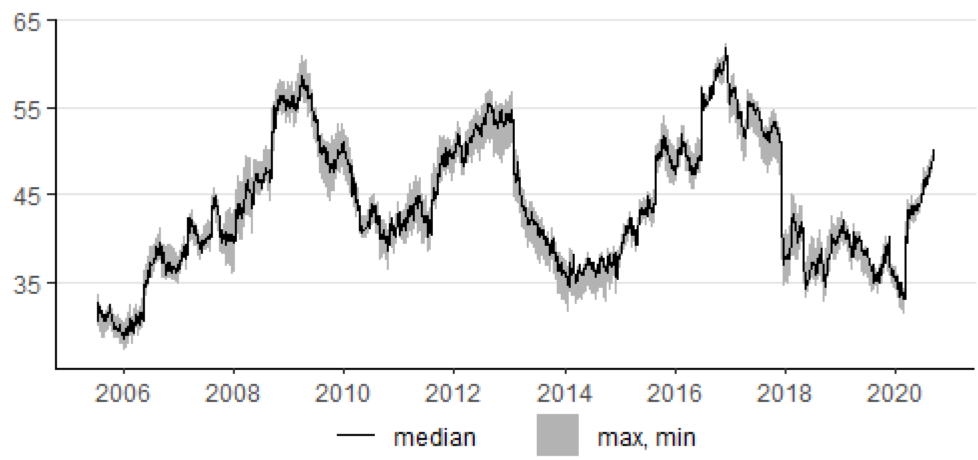


Figure 13: Cholesky factorization with 16 random variable orders

Finally, looking at the range from the 16 different variable orderings, the range seems to be fairly small and the variable ordering does not change our previous conclusions. Testing all possible orderings is not in our scope, but Klößner and Wagner (2014) estimate that the true range of connectedness across all possible orderings can be significantly larger than shown in such a small sample of orderings. We are confident in our choice of generalized variance decomposition as the dynamics are very similar and there is less uncertainty related to the method.

In the next robustness test, we look into the choice of the rolling window length. We test five different lengths from 100 days to 500 days with 100-day increments. Again, window length is something that has no inherent “correct” choice, but rather we must first decide our goal and then pick based on the features we find desirable. Figure 14 shows the total connectedness with different window lengths.

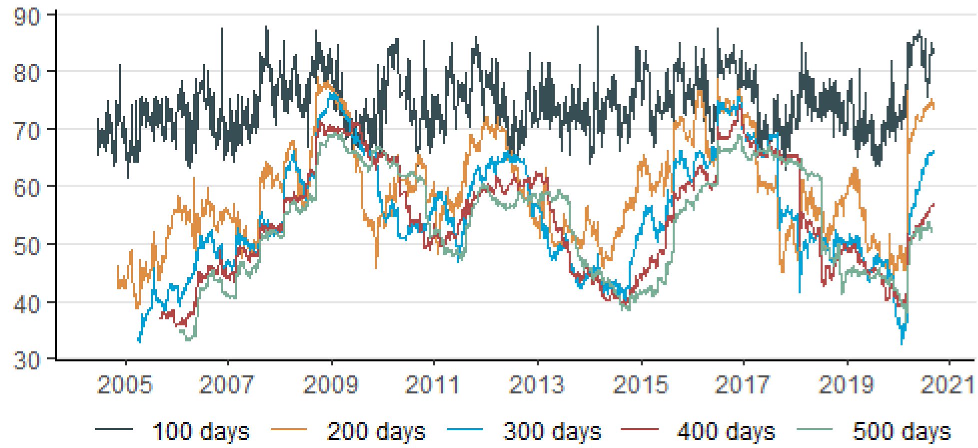


Figure 14: Window length robustness

The obvious observation from the figure is that increasing the length also increases the smoothness of the curve. This is natural, as when the window is short, new observations entering the sample have a larger weight than when the window is longer. This means that using a shorter window allows us to see a more immediate reaction to market events in the connectedness measure. Choosing the sample length is a balancing act between smoothness and clarity versus a faster response in the measure. Too short a window, like 100 days, leads to a very noisy measure, and alternatively a very long window erases possibly important shifts. If we were to use connectedness for forecasting, a shorter window would likely be a better early signal. In this case, however, we prefer a smoother connectedness curve as we are more focused on the over-time dynamics.

Finally, we look at how the choice of volatility proxy affects the total connectedness by comparing two popular alternatives: Parkinson’s and Garman-Klass volatility proxies, to Yang-Zhang-based connectedness. The three connectedness measures are shown in figure 15. Overall, the results across all three are very similar. Peaks and shifts seem to match each other in time, although sometimes their sizes differ a bit. During the most turbulent periods, Yang-Zhang appears to produce higher peaks, which could be due to it capturing more features of volatility, such as overnight volatility.

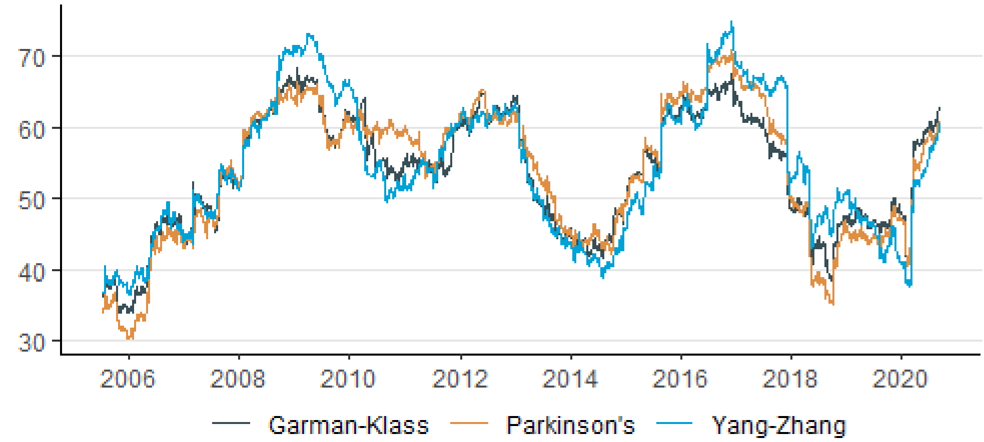


Figure 15: Robustness to the choice of volatility proxy

During 2010 and 2011, Parkinson’s based connectedness seems to deviate slightly as it stays relatively level while the other two drop. Aside from these and a few other noticeable deviations, the results seem to be very comparative. It is not in the scope of this thesis to assess which one is the most correct, but as we discussed earlier, Yang-Zhang should provide an accurate range-based proxy for volatility.

6. CONCLUSIONS

This thesis's stated goal was to measure and analyze connectedness and its time and frequency dynamics on a system scale and to assess pairwise connections between individual banks and between banks and the broader sector. Specifically, we focused on the publicly listed Nordic banking sector during a period from before the global financial crisis to the most recent data available in September 2020. With the generalized variance decomposition-based connectedness framework of Diebold and Yilmaz (2012), we assessed the static connectedness over the full sample and the time-varying dynamics of connectedness with a rolling sample. We then decomposed the connectedness into its frequencies with the recent extension of Baruník and Křehlík (2018), which utilizes the spectral representation of variance decomposition to divide connectedness into frequency bands corresponding to connectedness in different time intervals: long-, medium- and short-term. Finally, a comprehensive sensitivity analysis provided us with information on the robustness of our results.

6.1. Summary and implications

To summarize our key findings and results, we shall go through the research questions presented at the beginning of this thesis. The results are also further discussed here, and their potential practical implications are summarized. Finally, possible extensions as well as further research topics are presented.

1) *How connected are the Nordic Banks?*

Based on our results and those of others as a point of comparison, we can say that the connectedness found within the Nordic banking sector is relatively significant. As a benchmark for static connectedness, we can use the original results of Diebold and Yilmaz (2009), for example, who find the return and return volatility connectedness to be

35 and 39 % across general equity indices. In the Nordic bank stocks, we found that more than half of the 10-day ahead forecast error variance for the full sample period is attributable to spillover. In the daily rolling sample estimation, the overall connectedness, the share of variance caused by spillover, ranges from 36 to 75 %, with the average connectedness being 54 %. Comparing this to other connectedness studies done with similar datasets, but in different geographical areas, we find the connectedness to be lower than within the Chinese banking sector or the US financial sector, where the total connectedness index was 85 and 78 %, respectively (Wang et al., 2018; Diebold and Yilmaz, 2014). However, the connectedness between the Nordic banks is higher than the connectedness of 47 % in the German financial sector, according to the results of Jentsch and Steinmetz (2016). A high degree of connectedness seems to be typical for the banking and broader financial sectors. Also, it is worth noting that connectedness is typically lower across countries than within them (see question 5), which further highlights that the Nordic banks are significantly interconnected, as the results in comparison are from studies focusing solely on one economic area.

2) *Is the connectedness between banks time-varying?*

As the rolling sample analysis shows, connectedness is very much a time-varying measure. The share of spillover effect on the forecast error variation varies from the low of 36 % to the high of over 75 %. This variation tends to clearly align with market cycles, as turbulent periods overlap with periods of high connectedness. The measure is also sensitive to individual events entering the rolling window, as demonstrated by the event study done for the frequency connectedness measures. Individual cycles are clear to interpret because we see sustained, both high and low, levels of connectedness. Global events such as the financial crisis, the European debt crisis and most recently the onset of the Covid-19 pandemic can be clearly distinguished from the daily overall connectedness measures. This also applies to directional and pairwise directional measures of daily connectedness. This time-varying nature of connectedness is in line with the existing literature (Diebold and Yilmaz, 2009, 2012, 2014; Baruník and Křehlík, 2018; Wang et al., 2018; Jentsch and Steinmetz, 2016).

Surprisingly the highest period of connectedness occurs at the end of 2016, during a period without a widely recognized crisis. However, the peak is preceded by substantial market selloffs and the Nordic money laundering scandals, mostly, but not only, associated with Danske bank. The level of connectedness is almost matched during the global financial crisis, but the more localized events of 2015-2017 likely contribute to the higher level of connectedness during that period.

3) *Which banks are the major exporters of Volatility? Which are its primary receivers?*

The major exporters and importers of volatility can be dissected from the directional spillover results, the from others and to others connectedness measures. Looking at both static and rolling sample results, we see a few clearly dominant banks in both groups. Nordea arises as by far the biggest importer of volatility from others, followed by the Swedish banks. Although Nordea is no longer a Swedish bank, for most of the sample, up until 2018, it was. It is no surprise that Nordea, the only Nordic bank with a significant market share in all four countries, receives the most volatility from others. In turn, the by far biggest exporter of volatility to others is the Skandinaviska Enskilda Banken (SEB). The other two Swedish banks Handelsbanken and Swedbank, are also significant origins of volatility shocks in the system. Sweden and the Swedish banks seem to play a central role in the Nordic financial sector as they both emit and receive the most volatility.

4) *Is there a significant correlation between a bank's size and its effect on others? Is there a correlation between size and a bank's susceptibility to spillovers originating from others?*

On the relationship between the size of the institution and its net and directional connectedness measures, we find using rank correlation tests a statistically significant strong positive correlation between *from-connectedness* and market capitalization. This means that larger banks tend to receive more volatility from others. A statistically non-significant small positive rank correlation exists between the amount of volatility bank exports and its size. Finally, a non-significant negative rank correlation is found between *net-connectedness* and bank size, meaning a larger bank is slightly more likely to have a negative *net-connectedness* than a smaller one. Comparing our results to Wang et al. (2018), who use rank correlation test on Chinese banks, we find much less conclusive evidence supporting the hypothesis that larger banks are more connected ones. Whereas they find a significant relationship between all the above-mentioned measures and size, we find one only with *from-connectedness*. They also find the correlation between to-connectedness and size to be negative as opposed to a positive one in our data. In any case, connectedness is not a pure function of size and further research on explanatory factors of connectedness is needed.

5) *Is the connectedness higher within countries than across them?*

While the difference between within country and across country connectedness is not explicitly and statistically tested here, by looking at the pairwise directional relationships, we can interpret some trends. Our dataset contains two countries, Sweden and Denmark, with more than two banks within them. When we compare the connectedness measures those banks have, we see that the degree of connectedness tends to be bigger with banks in the same country than with those in any of the other ones with only small exceptions. This is especially clear in Sweden, where the strongest pairwise connections are found, but also applies to Danish banks. For more robust tests to make sense, a more extensive study with more within and across country counterparts for each variable is needed. However, the potential mitigating effect of national borders is corroborated by Deev and Lyócsa (2020), who also find that connectedness is higher between companies in the same country.

6) *Is most of the connectedness short-, medium- or long-term in nature?*

Finally, we have the results of the Baruník and Křehlík (2018) extension of the connectedness framework. Looking at both the static and rolling sample estimation of connectedness at short-, medium- and long-term frequency bands, we can make assessments of the type of connectedness found in the sector and when each of the types occurs over time. From both the daily connectedness and the full sample connectedness, it is clear that the overwhelming majority of connectedness is created at low frequencies, which suggests that the relationship between the banks is long-term and the transfer of volatility doesn't just happen in short distinct burst. This is especially the case during market unrest as the portion of low-frequency connectedness increases. Once markets calm down, connectedness at low frequencies decreases and the share of higher frequency connectedness is increased. However, this increase is mainly seen in the medium frequency band, which is equivalent to cycles over a week and up to a month. Almost none of the system's total connectedness is created at the highest frequency band, which roughly describes short-term connectedness. The time-varying dynamics of high-frequency connectedness are similar to that of medium frequencies, but the contribution to the overall connectedness is negligible.

Reflecting our results to the existing, although limited, literature using the framework, we see some similarities but also clear differences. The most obvious comparison is to the original Baruník and Křehlík (2018) paper, where they measure frequency connectedness in the US financial sector and from which many of the parameter choices are borrowed in this thesis. Their results also show that the share of long-term low-frequency connectedness increases when market turbulence increases. During such times, the clear majority of connectedness is created at low frequencies and when the turbulent period starts to pass, the share of higher frequencies increases. The dynamics of the long and medium-term bands are comparable to those in this thesis. However, a big difference is seen in short-term connectedness. We see very little short-term connectedness, while in the Baruník and Křehlík study, it contributes significantly to the overall connectedness. There are a few differences between the studies that could explain the deviations. First of all, their dataset has institutions from multiple subindustries within the US financial sector, while ours focuses on commercial banks. The relationship between an insurance company and an investment bank may be different in nature from a relationship between one commercial bank and another. The second major difference is their use of high-frequency 5-minute returns in approximating volatility, while we use a range-based proxy. It could be that high-frequency data allows for better capturing of high-frequency connectedness. (Baruník & Křehlík, 2018) However, a study conducted by Jiang, Piljak, Tiwari, and Äijö (2019), using range-based Garman-Klass volatility, finds that most of the across industry connectedness in China is created at higher frequencies. This could lend credence to the theory that connectedness within a specific sector is more long-term in nature, while it is more short-term across industries. Their results are corroborated by Wang and Wang (2019), who measure connectedness across Chinese industries and oil prices. They find that higher frequency bands contribute the most to across industry and asset class connectedness. Tiwari et al. (2018) study frequency dynamics across global asset class connectedness indices and while they find a low level of overall connectedness across them, what little connectedness there is, seems to be also mostly short-term in nature. Unfortunately, at the time of this thesis, there doesn’t seem to be any research focusing purely on one specific sector, like the Nordic commercial banks here, but the existing literature appears to show that across industries and asset classes, the connectedness is more short-term than what our within industry results show. However, the current literature does seem to agree with us on the time-varying dynamics of frequency connectedness, i.e., that lower frequency long-term connectedness increases during a crisis and in turn, higher frequencies contribute more to the overall during calmer periods (Baruník and Křehlík, 2018; Jiang et al., 2019; Wang and Wang, 2019 and Tiwari et al., 2018).

Moving on to a more practical side of things, we list some potential benefits and benefactors of the results obtained here. As we’ve mentioned before, connectedness is highly tied to risk, especially the systemic kind. Therefore, any new information on connectedness is of interest to those whose responsibility is to monitor risk. Potential interest groups should include regulators and financial supervisors, whose job it is to identify critical institutions. Our results not only show the level of overall connectedness in the Nordic banking sector but also identify the most interconnected institutions within the system. The overall connectedness measures, in turn, allow for comparisons against comparative subsystems in Europe and the world. The identification of potentially too connected to fail institutions enables regulators and supervisors to take proactive action. Bank risk managers in the institutions themselves also could benefit from knowing which banks they are most vulnerable to. While the connectedness measures of this thesis alone don’t contain dramatic revelations, we argue that such connectedness frameworks should be used alongside other monitoring tools or as early warning signals. For example, the IMF has utilized the connectedness framework of Diebold and Yilmaz in their global financial stability reports (International monetary fund, 2011). Increased knowledge of connectedness between publicly listed banks has some benefits for investors as well. The obvious use case of such information is in making diversification decisions. Our results show the banks to be highly connected in the long-term, which means they are unlikely to be good long-term diversification options for each other. In the short-term, however, the connection is not as significant. The pairwise connectedness measures also provide information on which institutions affect each other the least and the lower cross-border connectedness is also valuable information. Finally, our results add to the broader literature on connectedness, especially on the relatively recent and little-studied frequency side of connectedness. Our dataset is somewhat unique in the frequency domain as we focus on a relatively homogenous group of institutions, the Nordic commercial banks. These banks do have their own characteristics, but the frequency connectedness literature has mostly focused on cross-industry and cross-asset class connectedness. This has potentially revealed a disparity between which frequencies is most of the connectedness created at.

6.2. Potential further research

The focus of this paper is purely on connectedness itself found within the Nordic banking sector and less attention is paid to finding more practical uses for the connectedness measurements. Potential applications of the connectedness measures have received some attention, but there is still a lot to research. Using connectedness in early warning systems, for example, comes up in literature quite often when the time-varying nature of connectedness is noted. However, actual research on the topic is not as prevalent. As we ourselves note, connectedness increases in turbulent markets and some research points to its explanatory power on stock returns (Eng-Uthaiwat, 2018). Naturally, it leads to a question of whether the increase of connectedness precedes financial crisis and could therefore give early warning to financial supervisors and regulators as well as private institutions. As we've discussed, connectedness is inherently related to risk, especially systemic risk, and the use of the Diebold and Yilmaz (2012) connectedness, as well as the frequency connectedness of Baruník and Křehlík (2018), should be explored as a measure or a part of a composite measure for systemic risk.

As the frequency connectedness measure of Baruník and Křehlík (2018) is fairly recent and the literature is sparse at the time of this thesis, new questions are raised from our results, which to our knowledge, have not been answered in published research. First of all, the within industry versus across industry frequency connectedness should be further investigated as our within industry decomposition of connectedness differs from the connectedness found across industries. The same kind of comparisons should be done between within asset class and across asset class frequency connectedness. Finally, the potential effect the use of different methods of estimating realized volatility has on connectedness at different frequencies should be studied further. The main question is whether high-frequency price data is better at capturing high-frequency connectedness than range-based volatility proxies.

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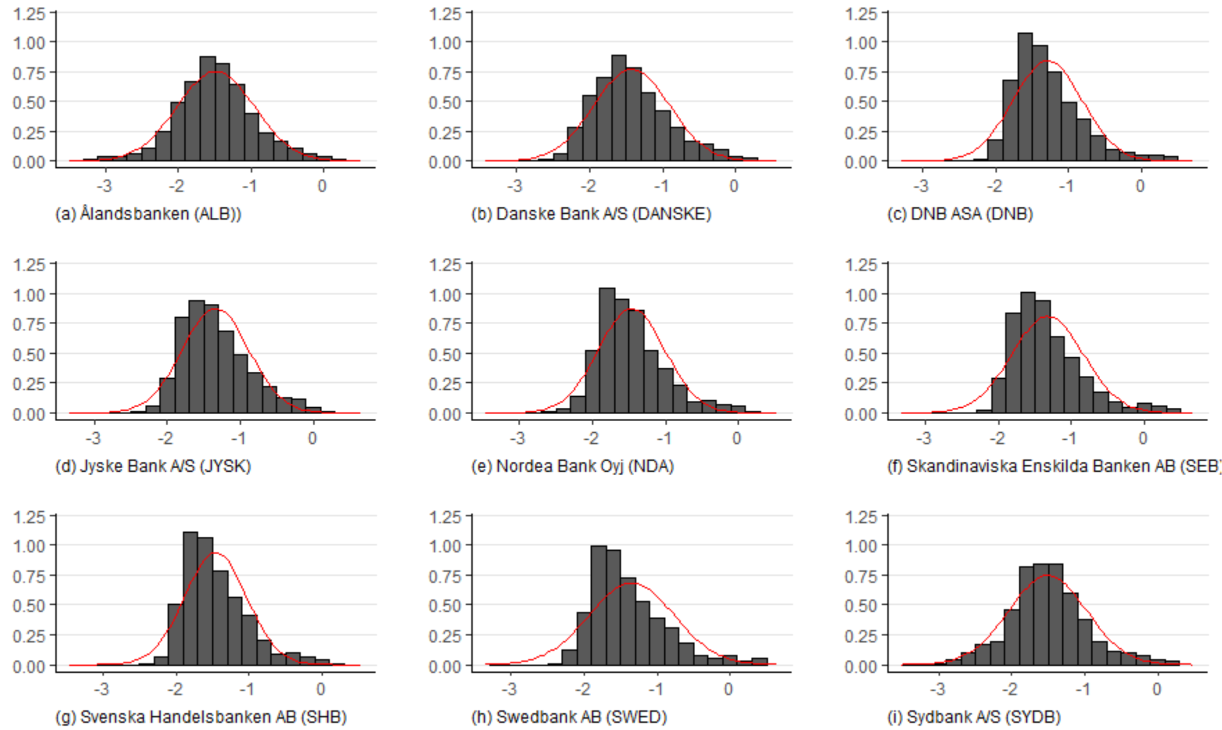
APPENDICES

Appendix 1: Distribution of Yang-Zhang log volatilities



Appendix 2: Market capitalization of Nordic banks, Q2/2020

	Q2/2020 price in EUR	shares outstanding	Market capitalization
NDA	6.15 €	4 040 000 000	24 837 920 000 €
DNB	11.65 €	1 550 000 000	18 053 976 989 €
SHB	8.43 €	1 980 000 000	16 685 520 826 €
SEB	7.69 €	2 160 000 000	16 609 367 832 €
SWED	11.38 €	1 120 000 000	12 742 310 691 €
DANSKE	11.85 €	852 640 000	10 099 972 942 €
JYSK	26.10 €	72 560 000	1 893 690 792 €
SYDB	16.50 €	59 090 000	975 239 514 €
ALB	16.85 €	9 110 000	153 503 500 €

Appendix 3: Short-term within frequency connectedness, a week.

Weighting by the spectral density of the frequency band, the short-term total frequency connectedness is 0.61 %. The table presents within frequency band connectedness.

	from									
to	ALB	DANSKE	DNB	JYSK	NDA	SEB	SHB	SWED	SYDB	from others
ALB	4.82	0.01	0.01	0.00	0.01	0.01	0.00	0.01	0.00	0.05
DANSKE	0.00	2.43	0.05	0.07	0.13	0.06	0.06	0.06	0.09	0.51
DNB	0.01	0.06	2.45	0.03	0.14	0.10	0.14	0.08	0.06	0.62
JYSK	0.00	0.13	0.05	2.73	0.05	0.05	0.07	0.02	0.13	0.50
NDA	0.00	0.10	0.09	0.02	2.25	0.19	0.25	0.14	0.04	0.85
SEB	0.00	0.03	0.09	0.03	0.16	1.62	0.26	0.23	0.03	0.83
SHB	0.02	0.03	0.09	0.03	0.17	0.30	2.25	0.21	0.03	0.89
SWED	0.01	0.05	0.06	0.03	0.12	0.26	0.28	1.65	0.02	0.84
SYDB	0.00	0.08	0.05	0.13	0.06	0.03	0.03	0.02	2.35	0.40
to others	0.05	0.50	0.49	0.35	0.85	1.00	1.09	0.77	0.40	5.50
to others including own	4.87	2.93	2.94	3.08	3.09	2.63	3.35	2.42	2.75	Spillover index
net (to - from)	-0.01	-0.01	-0.14	-0.15	0.00	0.17	0.20	-0.07	-0.01	= 19.59 %

Appendix 4: medium-term within frequency connectedness, a month.

Weighting by the spectral density of the frequency band, the medium-term total frequency connectedness is 7.39 %. The table presents within frequency band connectedness.

	from									
to	ALB	DANSKE	DNB	JYSK	NDA	SEB	SHB	SWED	SYDB	from others
ALB	27.26	0.23	0.29	0.04	0.07	0.34	0.29	0.14	0.03	1.43
DANSKE	0.23	13.10	1.11	0.99	0.93	1.13	0.53	0.87	1.43	7.23
DNB	0.08	0.70	12.75	0.76	1.44	1.40	1.39	1.01	0.66	7.44
JYSK	0.08	0.76	0.96	13.77	0.54	0.84	0.20	0.55	1.66	5.61
NDA	0.09	0.82	1.40	0.56	10.64	2.17	1.85	2.12	1.21	10.21
SEB	0.03	0.46	1.45	0.72	1.72	8.03	2.53	2.32	0.79	10.02
SHB	0.04	0.72	1.35	0.60	1.39	3.14	9.00	1.98	0.99	10.20
SWED	0.02	0.35	0.80	0.36	1.26	3.14	2.06	7.86	0.56	8.54
SYDB	0.02	1.06	0.90	1.56	0.62	0.56	0.58	0.54	11.61	5.84
to others	0.59	5.09	8.26	5.58	7.97	12.73	9.44	9.53	7.34	66.52
to others including own	27.85	18.19	21.01	19.35	18.61	20.76	18.44	17.39	18.94	Spillover index
net (to - from)	-0.84	-2.15	0.82	-0.03	-2.24	2.71	-0.76	0.99	1.50	= 36.84 %

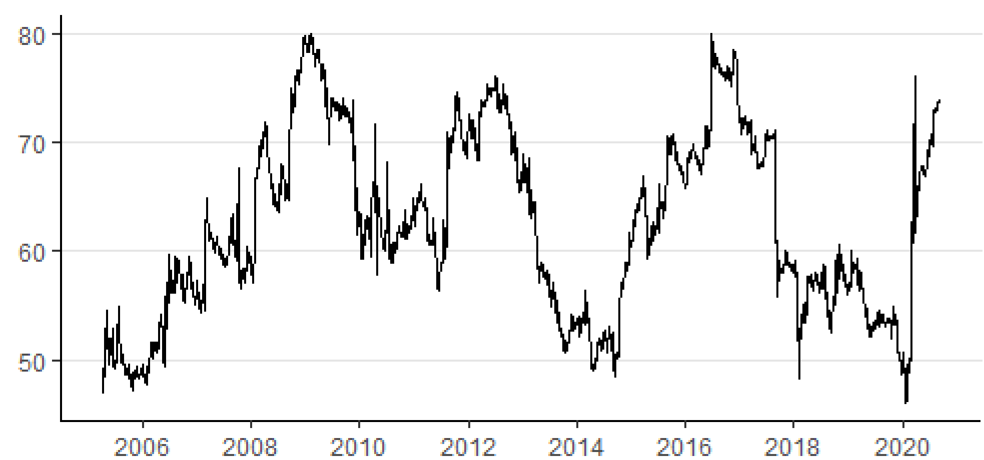
Appendix 5: Long-term within frequency connectedness, a year.

Weighting by the spectral density of the frequency band, the long-term total frequency connectedness is 47.29 %. The table presents within frequency band connectedness.

	from									
to	ALB	DANSKE	DNB	JYSK	NDA	SEB	SHB	SWED	SYDB	from others
ALB	51.65	2.55	2.50	1.56	0.79	2.52	2.86	1.31	0.70	14.79
DANSKE	1.59	26.77	4.17	7.64	4.54	8.22	4.95	9.24	9.60	49.96
DNB	2.01	3.98	24.31	7.53	6.03	11.40	8.68	8.64	4.18	52.43
JYSK	1.25	5.65	7.03	29.17	2.51	11.53	4.99	7.96	7.30	48.22
NDA	1.58	6.07	5.82	5.87	18.90	10.61	8.70	11.84	6.68	57.16
SEB	0.83	4.85	6.87	8.89	5.48	25.34	9.67	13.90	3.65	54.15
SHB	1.39	4.75	6.31	7.10	5.44	14.11	22.08	10.54	5.94	55.58
SWED	0.40	6.07	4.73	6.28	4.29	15.50	8.70	29.60	5.54	51.51
SYDB	0.52	8.44	4.15	8.42	3.85	3.93	4.72	7.84	37.94	41.86
to others	9.57	42.36	41.57	53.28	32.93	77.80	53.27	71.27	43.59	425.65
to others including own	61.22	69.13	65.88	82.45	51.83	103.15	75.35	100.87	81.53	Spillover index
net (to - from)	-5.22	-7.60	-10.86	5.07	-24.23	23.65	-2.31	19.76	1.73	= 61.56 %

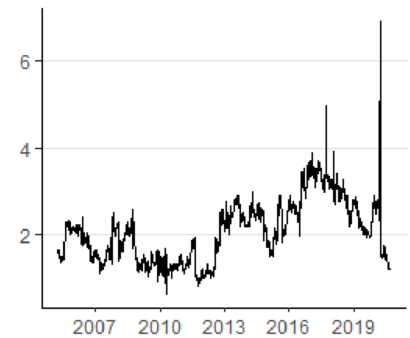
Appendix 6: Total connectedness summed from the frequency decomposition

The accompanying figure is the sum of the three different frequency band connectedness results. The three are separately presented in the next appendix

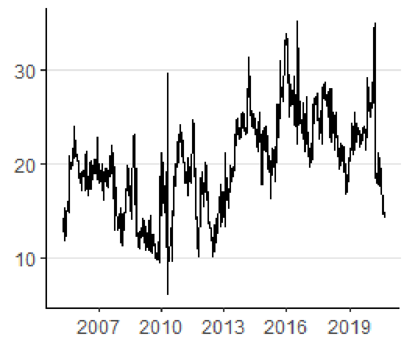


Appendix 6: Connectedness on separate frequency bands

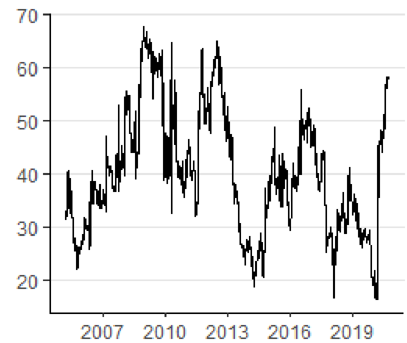
High frequencies = short-term connectedness, Medium frequencies = medium-term connectedness, Low frequencies = long-term connectedness



(a) high frequency connectedness



(b) medium frequency connectedness



(c) low frequency connectedness