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Abstract

In the 21st century, there has been an increase in the investments in commodity markets. More investors have started to include commodities in their portfolios. The research on how commodity markets interact with other markets, like stock indices or other commodity markets, is extensive. However, there exists little research on volatility spillover between commodities and company stocks.

In this thesis the volatility spillover between three commodities and company stocks that might be related to each commodity is investigated. The commodities are oil, steel, and cotton. Eleven companies have been selected to analyze with oil, six companies with steel, and five companies with cotton. Daily closing prices for each asset is collected from January 2002 to April 2020. The generalized spillover index developed by Diebold and Yilmaz (2009; 2012) is used to calculate the overall and net spillover as an average over the entire period. In addition, a rolling overall spillover analysis is performed to see how the volatility spillover varies over time.

The results suggest that the companies that are analyzed with oil have the highest volatility spillover followed by steel and lastly cotton. The companies that are related to oil have a moderate volatility spillover for the entire period, while the spillover for steel and cotton is low. Further, the results suggest that the volatility spillover between commodities and company stocks varies over time, with spikes caused by both highly volatile times in the financial markets, and by company specific events.

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Abbreviations		Meanings
ADF	-	Augmented Dickey-Fuller
AIC	-	Akaike Information Criterion
API	-	American Petroleum Institute
AR	-	Autoregression
BIC	-	Bayesian Information Criterion
CLT	-	Central Limit Theorem
CME	-	Chicago Mercantile Exchange
CNY	-	Chinese Yuan
DF	-	Dickey-Fuller
DY	-	Diebold and Yilmaz
E&P	-	Exploration & Production
FEVD	-	Forecast Error Variance Decomposition
FPE	-	Final Prediction Error
GDP	-	Gross Domestic Product
GLS	-	General Least Squares
GSE	-	Government Sponsored Enterprise
H&M	-	Hennes & Mauritz
HQ	-	Hannan-Quinn
i.i.d	-	Independently and identically distributed
ICE	-	Intercontinental Exchange
IEA	-	International Energy Agency
IOC	-	International Oil Company
IPO	-	Initial public offering
JB	-	Jarque-Bera
KPPS	-	Koop, Pesaran, Potter, and Shin
LLN	-	Law of Large Numbers
M&S	-	Marks & Spencer
MA	-	Moving Average

MFSE	-	Mean Squared Forecast Error
MLE	-	Maximum Likelihood Estimation
MSE	-	Mean Squared Error
Mt	-	Million tons
NOC	-	National Oil Company
NYMEX	-	New York Mercantile Exchange
OLS	-	Ordinary Least Squares
OPEC	-	Organization of the Petroleum Exporting Countries
OTC	-	Over the counter
PP	-	Phillips-Perron test
RMSFE	-	Root Mean Squared Forecast Error
S&P 500	-	Standard and Poor's 500
SC	-	Schwarz Criterion
SSR	-	Sum of Squared Residuals
VAR	-	Vector Autoregression
VIX	-	Volatility Index
WTI	-	West Texas Intermediate

1 Introduction

Over the last few years, the number of financial investors in commodity markets have grown rapidly (Domanski & Heath, 2007). The use of commodity derivatives have increased, and commodities have begun to be used more as financial assets in portfolio allocations (Alom, Ward, and Hu, 2011; Domanski and Heath , 2007; Mensi, Beljid, Boubaker, and Managi, 2013). Choi and Hammoudeh (2010) state that traders have started to concurrently examine the fluctuations of both stock and commodity markets, how they behave relative to each other, and if they find trends for both stocks and commodities. If there exists links between the volatility of commodities and equity prices, it might introduce new substitution strategies for stocks and commodities (Creti, Joëts, & Mignon, 2013).

Earlier analysis suggests that the returns on commodity futures have lower standard deviation than that of bond and stock returns (Delatte & Lopez, 2013). There have been found time-varying correlations among stock and commodity futures markets that increase in volatile markets (Silvennoinen & Thorp, 2013). Such changes in the market volatility might have major impacts on investments, consumptions, and other variables in the business cycle (Schwert, 1989).

Financial markets are sometimes exposed to large amounts of volatility. This if often due to its own serial correlation. However, there are times when a certain financial market might be affected by the volatility of another financial market. When a market is influenced by such a cross-market volatility, it is called a volatility spillover (Ke, Wang, & Murray, 2010). Such a volatility spillover may be measured by using the spillover index developed by Diebold and Yilmaz (2009; 2012). This is used to calculate the volatilities in returns across assets, markets, and portfolios to reveal spillover trends. It allows us to measure both total spillover and directional spillover. Such crucial information might help to prevent future crises (Diebold & Yilmaz, 2012).

Several markets and the spillover between them have been analyzed earlier. Such as: the spillover between different commodities, spillover between stock indices and commodities, and between different markets within the same commodity groups. One can find this research in for example: (Nazlioglu, Erdem, and Soytas ,2013; Baltagi , 2011; Mensi et al., 2013; Ji &

Fan, 2012; Lahiani, Nguyen, & Vo, 2013; Pindyck & Rotemberg, 1988; P. H. Dahl & El-Adawy, 2019; Du, Yu, & Hayes, 2011).

However, we have not found research on the spillover between company stocks and commodities, which will be the topic of this thesis.

1.1 Problem Statement

In this thesis we are interested to see if we can find volatility spillovers between three commodities and stock returns of companies that are exposed to the commodities' price. In addition, how the spillovers vary in changing market conditions. It would be interesting to see whether some of the companies are more robust against fluctuations in commodity prices than others. In addition, see if the commodities have different levels of spillovers with their respective company stocks. The objective of this thesis is to:

Explore the volatility spillover between commodities and equities that are linked to the commodity.

By using the spillover index established by Diebold and Yilmaz (2009; 2012), we will calculate both net and overall spillovers. This will be achieved by analyzing the volatility of company stocks and commodities. Finally, we will try to see how these spillovers vary during different market conditions by conducting a rolling spillover analysis.

We have chosen to look into three commodities: Crude oil, steel, and cotton. These have been chosen because they are all actively traded on today's market. In addition, these are commodities that are easy to link to companies and their uses. When analyzing oil, we will examine three types of companies: operators, oilfield service companies and airlines. Regarding steel: building and infrastructure contractors and car manufacturers. Finally, cotton includes retailers and clothing brands.

1.2 Structure of thesis

The structure of the thesis will be as follows. Chapter 2 will be about the commodity and equity markets, how assets are traded, a brief introduction to portfolio management, ending with the financialization of commodities. Chapter 3 goes into each commodity for this thesis, characteristics of the commodities, how they usually are traded, and finally the price history. Chapter 4 explains time series analysis and the basis for calculating the spillover index.

Concepts of volatility will be introduced. Then the generalized spillover method will be described. Lastly, the chapter goes into some descriptive statistical tests to apply on the data set. Chapter 5 will be about the data used for this thesis, descriptive statistics of the data, and the results from the statistical tests will be shown. Chapter 6 presents the empirical results and discussion of the findings. Chapter 7 concludes our work.

2 Markets and equities

This chapter starts with a brief description of commodities and storability. Further, an introduction on equities and factors affecting the stock market is given. Then, research on how commodities and equities are correlated is introduced. This leads into the concept of risk management through portfolio allocations and hedging. Some instruments that are used in the trading of assets are presented. Finally, the financialization of commodity markets is explained.

2.1 Commodities

A commodity can be seen as a good that has value, uniform quality, is produced in large quantities coming from many different producers, and seen as equal regardless of the producer (Warrier, 2011). Commodities are standardized goods that are traded across national borders and they are the lifeblood of the economic system (Knoepfel, 2012). Further, commodities are usually categorized into energy commodities (oil, natural gas, etc.), agricultural commodities (wheat, corn, cotton, etc.), industrial/base metals (steel, copper, aluminum etc.), and precious metals (gold, silver, palladium, platinum, etc.). They can also be categorized into investment commodities, like gold, and consumption commodities such as crude oil and wheat. Debreu (1959) states that a commodity is not only characterized by its physical properties, but also when and where it can be delivered. Most commodities cannot easily be stored without incurring large storage costs which leads to investors seeking exposure to commodities through derivatives (Knoepfel, 2012). Different derivatives with commodities as the underlying asset are discussed further down in chapter 2.5.

2.2 Storability

The ability of a commodity to be stored without losing its quality plays an important role in price formation as inventories can help producers act on demand changes using their inventories (Pindyck, 2001). The inventory can help a producer smooth out its production by selling out of the it in high demand periods and refilling it in low demand periods, which means production can be kept stable. This can be an advantage because changing production rates can be costly (Pindyck, 2001).

The theory of storage says that the difference between futures price and the spot price, F(t,T)-S(t) equals the foregone interest, S(t)*R(t,T), plus the storage cost, W(t,T), minus the marginal convenience yield, C(t,T) (Fama & French, 1987).

$$F(t,T) - S(t) = S(t) * R(t,T) + W(T) - C(t,T) \qquad [2.1]$$

The convenience yield arises from the value of having a commodity in inventory (Fama and French, 1987). This value can occur when the commodity goes into production. For example, a refinery uses crude oil in its production and having crude oil in inventory will therefore have a value for the refinery. Another example is that there can be a convenience yield in having inventories in instances of unexpected rise in demand. This means that a seller will store a commodity if the futures price compensates the costs incurred both in terms of storage and alternative costs minus the advantage of having the commodity (convenience yield). If not, the seller goes to the market straight away.

Fama and French (1987) also write about another theory for futures prices where the difference between futures and spot price, equals the sum of an expected premium and an expected rise in spot price, E[P(t,T)] + E[S(T) – S(t)].

$$F(t,T) - S(t) = E[P(t,T)] + E[S(T) - S(t)] \qquad [2.2]$$

In general, there is a difference between commodities that are storable and those that are not. If a commodity loses its quality when stored, the inventories does not play the same role as described above. A farmer of tomatoes cannot wait for a better price with his current ripe tomatoes if he does not like the current price. Instead, he can hedge his price risk, which is mentioned in subchapter 2.4.2.

2.3 Equities

Equity represents ownership in a company. When investing in equities, one buys a share of a company. This gives you rights to vote in decisions the company makes and a share of the profits. Equities can be both public and private, where public equities are sold on exchanges (Weisberger, 2017). The most common types of equities are:

- Common stock
- Preferred shares
- Depository receipts
- Investment companies (mutual funds)

People invest in equities hoping that they will profit in two ways, the first is from increased value of the equity, known as capital gains. The other is through dividends, which can be paid annually, quarterly, or at no set schedule. The payment from dividends depend on factors such as cash flow of the corporation, demand for further capital, industry practice, and the shareholders expectations (Bragg, 2012). Equities have become more attractive in recent years as it usually outperforms the inflation rate.

Equities are primarily used by corporations to gain more capital which may be used for research and development or funding an ongoing project. When issuing stocks for the first time it is called initial public offering (IPO) (Hobson, 2012). A corporation may also issue bonds or commercial loans. As opposed to stocks, bonds and commercial loans become a liability that must be repaid. When the corporation sells equity, the ownership interests are diluted and there are no liabilities. There are both advantages and disadvantages when choosing which method to raise capital. The method used will affect the corporations' balance sheet, tax liability, financially flexibility, and ownership structure (Hobson, 2012).

2.3.1 Stocks

Stocks can be found at either the primary or the secondary market. The primary market includes new stocks and bonds that are available for purchase. An IPO is an example of a primary market. When someone decides to sell their shares, these will be sold in the secondary market. The secondary market is where most shares are traded. Shares may be owned by people, but also large institution like pension funds. These are called institutional investors. When you buy shares on the secondary market, the money does not go to the company that initially issued the stock, but to the previous owner (Hobson, 2012).

When having stocks in a company, you own a certain share of that company. This means that if your shares make up 10% of a company, you have the right to 10% of the votes in a meeting between shareholders as well as 10% of any profit paid in dividends. It is important to note that larger shareholders do not gain an advantage information vice. Crucial information must be available for everyone through a stock exchange (Hobson, 2012).

2.3.1.1 Trading of stocks

The first shares were traded in coffee houses in London as early as the 17th century. The deals were made face to face. However, as companies grew, this became too impractical. Thus, exchanges for stock trading were established. At that time, investors would buy stocks through stockbrokers. The stockbrokers would pass the job to a jobber who would carry out the trade. Now in the 21st century, this process is electronic, and stocks may be traded through computers, phones, and tablets. As trading has become such an easy and quick process, it became hard to keep track of market developments. To get an estimate of how the market performs, indices were created. A market index consists of several stocks. As some shares fall and some rise, these indices average out the changes in the market (Hobson, 2012). Examples of well-known indices are Nasdaq, Dow Jones, and S&P 500.

2.3.1.2 What affects the stock market?

There are several theories on what drives the prices in the stock market. Many agree that the biggest price changer is the arrival of new information (Cutler, Poterba, and Summers, 1989; Roll, 1984; Shiller, 1981). A study by Kearney and Daly (1998) showed that the volatility of inflation and interest rate had significant impacts on the stock market in Australia. They also meant that money supply and industrial production had indirect effects. Schwert (1989) found that stock return volatility is correlated with interest rate. In addition, the volatility becomes larger in recessions. Other studies have shown that investments are much riskier at given times than others (Choudhry, Papadimitriou, & Shabi, 2016).

2.4 Portfolio management

A portfolio of investments can consist of several asset classes. As this thesis looks into the connectedness between commodities and equities it is useful to briefly go into some concepts of portfolio management.

The classic problem for a portfolio manager to solve is described in Alexander (2008) as:

- How to minimize the portfolio variance.

- Choose portfolio weights to achieve required expected return whilst minimizing the variance.
- Minimize portfolio variance subject to various constraints in the portfolio weights.

Alexander (2008) shows the concept of diversification with a portfolio with two risky assets, 1 and 2. The variance of the portfolio becomes:

$$V(R) = w^2\sigma_1^2 + (1-w)^2\sigma_2^2 + 2\rho w(1-w)\sigma_1\sigma_2 \qquad [2.3]$$

Where $V(R)$ is the variance of the portfolio, w is the weight of asset 1 in the portfolio, σ_1^2 and σ_2^2 are the variances of asset 1 and 2, and ρ is the correlation between asset 1 and 2. This shows that all else being equal, the variance of the portfolio as a whole becomes lower as the correlation between asset 1 and 2 is lower. The next challenge then becomes to find the weights between the assets to get the desired mix between expected return and variance.

2.4.1 Correlation between commodities and equities

Gorton and Rouwenhorst (2006) examined the correlation between commodities and equities from 1959 to 2004. Their results showed that investing in commodity futures had a negative correlation with the stock market while having as good returns as equities. They went on to conclude that investing in commodities would provide good diversification in a portfolio of stocks and bonds. Bhardwaj, Gorton, and Rouwenhorst (2015) took another look at the findings of Gorton and Rouwenhorst (2006). They concluded that much of the findings still held, but that there was a rise in correlation between commodities and stocks during the turmoil of the 2008 financial crisis. Another article states that the correlations between commodities and other asset classes dropped for a short while during the financial crisis before turning high in the aftermath of the crisis (Creti et al., 2013). Creti et al. (2013) go on to find that correlations between stocks and commodities are most volatile in crisis events. Further, they found that the financialization of the commodity market may have made the correlation rise in the times after the financial crisis. The financialization of commodities are further discussed in chapter 2.6. To look at commodities as a homogeneous asset class is not useful as different commodities behave differently, with for example oil being closely linked to the stock market (Creti et al., 2013).

2.4.2 Hedging

Hedging is a way to protect the price risk of an investment. Typically, one does this by taking a position in the financial market that is opposite of what one is invested in. The purpose is often to lock in a price so that the price risk is transferred to the party that handles the risk better (Edwards, 2014). The instruments mentioned in chapter 2.5 may be used to take hedging positions.

Sometimes, one does not have the opportunity to hedge in the same asset as the underlying one. Then hedges can be executed using similar assets, which is called a cross-hedge. An example of this is when airlines hedge jet fuel against crude oil. As the assets are not identical, the futures price and spot price might not converge. The difference between these are called basis risk (Tomek & Kaiser, 2014). Tomek and Kaiser (2014) explain that there are two types of traders of futures contracts. The types are hedgers and speculators, where hedgers try to use the financial products to offset their position in the cash market and speculators try to make money from the shifting prices.

2.5 Ways to trade financial assets

There are several ways to trade financial assets and in the following chapter some of the ways are introduced and briefly explained. In the trading of financial assets, prices of the financial assets are discovered. For commodities, Tomek and Kaiser (2014) introduce a three-way classification system. They suggest that the prices may be determined through negotiation, auctions, or administrative pricing. Another way to discover prices is by contracts. Hueth, Ligon, Wolf, and Wu (1999) suggest that the use of contracts has three effects: firstly, it introduces predictability for the participants. Secondly, it allows risk sharing. Finally, it helps to motivate performance.

2.5.1 Spot

The spot price of a financial asset refers to the present price. In a spot market the financial assets are traded for immediate delivery. A spot market does not exist for all types of assets, as some of them are only gathered seasonally, for example agricultural commodities (Rutherford, 2012).

2.5.2 Over the counter (OTC)

When securities are traded without being listed on a formal exchange, it is called over-the-counter (OTC) trading. Trading on an exchange brings some limitations. Those limitations can be that the trades must be between members of the exchange, the trades must be done within opening hours of the exchange, and the products that are traded on the exchange might be defined in a limiting way. If trades need to be executed outside these restrictions, the trades can be done directly between the counterparties. This gives increased flexibility, but also increased counterparty risk (Baker, 2015).

2.5.3 Futures and forwards

A futures contract is a legal instrument in which the participants is enforced to deliver or accept an amount of a given asset at a specified future date. The contract includes price, quantity, and quality specifications. These types of contracts are used to reduce risk in the economic commodity market (Tomek & Kaiser, 2014). In other words, one has locked in the price for a delivery in the future and hence eliminated price risk on that delivery. Most futures contracts are “closed out” or “rolled over” before the delivery date. This means that the underlying asset is not delivered. The reason for this is that the future contract is often used as a hedge and hence does not need delivering (Pindyck, 2001).

There are two different ways to trade in the futures market. The first is by buying or selling futures contracts that have specified terms in the contract on exchanges. The other way is by negotiating forward contracts directly with the counterparty. Forward contracts are OTC trades while the futures contracts are regulated and traded on exchanges. When the futures prices are higher than the spot prices, it is called contango, and when they are lower it is called backwardation (Marroni & Perdomo, 2013).

2.5.4 Options

Options and futures contracts are quite similar. The difference is that the options contract gives the buyer the right, but not the obligation to either sell or buy the commodity at a future date at a set price. The buyer of the contract does not have to exercise the right. In an options contract, one can have two different positions. A put option gives the buyer the right to sell the specified amount at a given date, while a call option gives the buyer the right to buy the specified amount of an asset (Tomek & Kaiser, 2014). An owner of an options contract is protected against the downside while still being able to take part in the upside. Options contracts are not free, as opposed to the futures contracts.

2.5.5 Collars

A collar is a combination of a put and a call option. Morrell and Swan (2006) go into how airlines use collars. They explain that airlines buy a call option which protects the airline from rising jet fuel prices above the strike price. At the same time, they sell put options, giving the buyers the right to sell them oil. The collar locks in the price between the put and the call strike price. The cost of the hedge is the premium paid for the calls minus the premium received for the puts sold.

2.5.6 Swaps

Swaps are an agreement of exchanging (swapping) cash flows or the exchange of cash for the pricing of an asset over a given period between two parties (Marroni & Perdomo, 2013). Commodity swaps is when two parties swap cash flows depending on how the price of the underlying commodity changes. There is typically a fixed leg and a floating leg in a commodity swap. The fixed leg is the agreed upon price at the beginning of the contract and the floating leg is the market price. If a party want to pay a fixed price for a commodity, they can go into a swap. They pay an agreed fixed price to a swap dealer and receives the market price in return at the same time as they pay the market price for the physical commodity. Here the market prices even out and the user of the commodity pay a fixed price every month (Corporate Finance Institute, n.d). The actual swap is settled for cash, evening out the price the user pays if the market price has changed.

2.6 Financialization

The rising participation of investors in commodity markets is referred to as the financialization of the commodity markets. From the early 2000s, commodities became a popular asset class for financial institutions which resulted in hundreds of billions of dollars flowing into the commodity markets (Tang & Xiong, 2012). The reason for the growing popularity was that commodity markets became recognized as giving potential diversification together with other assets in their portfolios.

When financial institutions have capital in different asset classes, they sell off their risk across asset classes in times of falling prices. This happens because their risk tolerance goes down across the portfolio (Danielsson, Shin, & Zigrand, 2013). The financialization of commodities make commodities more exposed to this effect. A finding of Tang and Xiong (2012) show that there is a difference between commodities in indices and those who are not. They found that financial institutions that want the diversification of having commodities in their portfolio often did so by investing in commodity indices like the S&P GSCI and the Dow Jones-UBS commodity index (Bloomberg Commodity index today). This can result in several commodities falling at the same time when investors sell off their commodity exposure by selling their index positions. They found that together with increased index investing in commodities, the non-energy commodities have become more correlated with oil prices, and especially so for commodities in indices. Tang and Xiong (2012) also state that the increased index investing in commodities increase the chance of volatility spilling over from other markets into the commodity markets.

3 Selected markets

In this chapter, the selected commodity markets and the related equities chosen will be introduced. The commodities to be discussed are oil, followed by steel, and finally cotton.

3.1 Crude oil

Crude oil is the unrefined mixture of hydrocarbons. The number of carbon atoms can vary with heavier crude oil having more carbon atoms per molecule than lighter crude oils. Crude oil is refined to many different products with different uses. Examples are diesel, jet fuel, gasoline, heating oil, heavy fuel oil etc. (Hilyard, 2012).

Oil is the world's most important source of energy because of its energy density, transportability, and availability (Hilyard, 2012). In 2017, the International Energy Agency (IEA) estimated that crude oil was responsible for approximately 32% of all energy production, which was the highest percentage of all energy sources. Coal and natural gas are the other big contributors to the world energy mix. Crude oil is such a big source of energy that price fluctuations have great influence on how societies develop (Speight, 2011).

Crude oil is refined before it is used, and according to Hilyard (2012), approximately 85% of crude oil is used to make liquid fuels. The rest is used to make a wide range of products like plastics, pesticides, pharmaceuticals, solvents, etc.

There are three main parameters to classify the quality of a crude oil:

1. Geographic location
2. API gravity
3. Sulfur content

The location determines the transportation costs to deliver the oil. The API gravity tells how light or heavy the crude oil is, where the lighter oil yield higher prices. More of the lighter crudes are refined into more desirable products such as gasoline. The sulfur content tells if the oil is sweet or sour, where sweet oils are worth more than the sour ones. This is because the sour ones have bigger environmental impact and requires more refining to obtain the end products (Hilyard, 2012; Speight, 2011).

Certain areas have oil with defined qualities and has thus become benchmarks to use as a reference for oil pricing (Hilyard, 2012). The two main benchmarks are WTI (or light sweet) traded on NYMEX(CME) in the US and Brent traded on ICE in the UK (Van Vactor, 2010).

Oil that is not specified as a benchmark is priced with a premium or a discount depending on the traits of the oil that is delivered (Hilyard, 2012; Van Vactor, 2010). According to Hilyard (2012), the benchmark oils are being depleted. Therefore, the crude oils that are delivered can be different from the benchmarks. The benchmarks will then act as a price reference. Oil tankers make it possible to transport oil relatively cheap to almost anywhere. The low transportation costs make the prices of the benchmarks move up and down together (Van Vactor, 2010).

3.1.1 Oil market

The price of crude oil is basically decided by supply and demand, however, there are other factors to consider. The prices in the spot market are affected by natural disasters, political developments, weather events, and changes in estimates in supply and demand (Hilyard, 2012). Van Vactor (2010) states that day to day prices are affected by political events, changing economic growth, OPEC meetings, revised resource assessments, and consumer reactions. Speight (2011) explains that the oil markets essentially are a global auction. The crude oil price is established by the global market's supply and demand conditions, where the main refining centers have a big influence.

The supply and demand of crude oil are inelastic in the short term. This leads to high volatility. Producers at near capacity have high marginal cost which require high prices to increase their production. Consumers have invested in equipment that need crude oil products to run and it takes time to adjust to new sources of energy (Van Vactor, 2010).

When it comes to the change in oil prices, they tend to be permanent, difficult to predict, and governed by different regimes at different points in time. Forecasting of oil prices is difficult and in principle one could just guess that the oil price at any given time from now is the same as today. Because of the volatility of oil prices, the 95% confidence interval for oil prices would have a huge specter of prices (Hamilton, 2009).

Oil is a political energy source. Most oil producing countries have more oil than they need and their governments tend to be frail. The income from oil have a large impact on the economy and it can potentially be destabilizing when oil prices go down for these producing countries. This can lead to a series of unstable and fickle governments which again can lead to upward spiraling prices (Speight, 2011).

Oil can be traded in both physical form for delivery and in different financial instruments. The most used financial instruments are futures, options, and swaps. Further, there are two largely discrete, but intersecting worlds of trading. The physical trade of volumes of oil, and more speculative trading using financial instruments (Hilyard, 2012). Oil is a storable commodity which gives advantages mentioned in chapter 2.2. It is possible to store crude oil without it degrading and one can even store it by leaving it in the ground.

The futures market for crude oil is roughly eight times bigger than the spot market. The purpose is to manage price risk and set the general trend. The changing prices in the futures market flashes to the physical markets by end of the trading days (Van Vactor, 2010). Speight (2011) says that both spot and futures markets provide important price information for contracts markets. Prices in the spot markets are seen to be a signal of the balance between supply and demand. Futures markets give information about supply and demand in addition to the market's expectations of the spot prices in the future. Finally, the demand for crude oil has a seasonality to it and the main determinant for petroleum product prices is the price of crude oil (Speight, 2011).

3.1.2 Equities within oil

This thesis looks into companies with different ties to the crude oil market. These are oil producing companies or commonly referred to as operators, oil service companies, and airlines. The first two are involved in the production side and airlines are consumers of petroleum products.

3.1.2.1 Oil operators

The oil operators considered are:

- BP
- Chevron
- Equinor
- ExxonMobil
- Shell

These are companies that operate oil fields and sell crude oil in the market, but also refine crude oil themselves. There are three classifications of oil producing companies (Hilyard, 2012; Van Vactor, 2010); NOCs are state owned oil companies, IOCs which are international oil companies, and Hybrids or GSEs where a government is part owner of the company. In this thesis all but Equinor are IOCs. Equinor is partly owned by the Norwegian state as well as being on a stock exchange.

3.1.2.2 Oil service companies

Oil operators use service companies to do hands on work in the building and operation of drilling rigs. These service companies deliver a wide variety of services and knowledge in operating and maintaining wells and equipment in the production of crude oil. When the price of oil goes up, the demand for oil field services goes up as well (Hilyard, 2012). In this thesis “the big three” companies in oilfield services are considered. These are:

- Baker Hughes
- Halliburton
- Schlumberger

These three make up 26% of the oilfield service market between them (French & Hampton, 2020).

3.1.2.3 Airlines

Airlines do not rely on crude oil directly in their operations, but on jet fuel which is a refined product from crude oil. Airlines’ fuel costs accounted for around 23.7% of their operational costs in 2019 (International Air Transport Association, 2019). There are several ways for airlines to hedge their fuel costs, alternatives are forwards, futures, swaps, options, and collars (Morrell & Swan, 2006). The market for hedging jet fuel is not liquid, therefore, it is normal to hedge in other oil products, where crude oil is a much-used alternative. (Morrell and Swan, 2006; Adams and Gerner, 2012).

One to two thirds of airlines’ fuel costs are typically hedged and airlines’ managers state that reasons for hedging is to stabilize costs and hence profit. Risk is seen as a cost to investors and the benefit of stabilizing the profits should then yield higher stock prices (Morrell & Swan, 2006). In classical investment theory, investors can hedge for the rise in oil prices themselves at their own discretion. However, Morrell and Swan (2006) say that investors can view the fact that an airline hedges their fuel costs as a signal of competent management. In this thesis the following airlines will be considered:

- Air France-KLM
- Lufthansa
- SAS

3.2 Steel

Steel is one of the most used metals in the industrial society. The steel products are made from raw materials retrieved from iron ore mines. The raw materials are gathered by collectors, brokers, and dealers in what is known as the ferrous scrap industry. Using steel mills and steel foundries, the iron ore is transformed to steel. Aluminum, glass, and high-performance plastic composites are the only viable substitutes as of today, however, none of them can compete against the low production cost of steel (Fenton, 2005).

The finished steel products are typically made from iron ore with up to 2% carbon. Steel is made into many different alloys with various elements, for example manganese, phosphorus, silicon, and sulfur. The different elements and the amount of them contribute to determine the characteristics of the steel. Some desired properties when designing steel alloys are high strength, high temperature resistance, corrosion resistance, or a combination of these (Fenton, 2005).

When referring to steel, one does not talk about a single product. In 2004, there were over 3500 products with distinct both chemical and physical attributes. At least 75% of these products have been invented throughout the last 20 years. Today, steel has become an important material due to its high strength combined with the vast possibilities of modifying its properties. It is used in applications such as bridges, houses, highways, machine tools, pipelines, trains, cars, and other vehicles (Fenton, 2005).

3.2.1 Steel market

Back in 1950, the world's steel production was 200 million tons (Mt). 51 years later, this increased to 847Mt, with an expectation for further growth (Hidalgo, Szabo, Carlos Ciscar, & Soria, 2005). There has been a large growth in the steel industry in China since the 1990s. In 2011, China produced nearly half of the world's steel production contributing with 680 Mt. The steel demand in 2025 in china alone is estimated to be 750 million tons (Yin & Chen, 2013).

The demand for steel products has increased in the last decades. (Hidalgo et al., 2005; McQuiston, 2004; Fenton, 2005). One of the reasons for the increase being that less developed countries have started to industrialize. However, in the beginning of the 21st century, there was an over-capacity of steel, causing the demand to grow at a much lower rate (Fenton, 2005; McQuiston, 2004).

The price of steel has seen both high and lows. During the over-capacity, the prices were low for a long time. Research on the price elasticity of steel demand ranges from an inelastic demand of 0.62 to an elastic demand of 2.0 (Demailly & Quirion, 2008). The steel market has over the last decades been subjected to large changes. The production and trading patterns of steel have changed, with countries such as China and India being a driving force in the increasing steel market. In addition, recessions and booms of the general economy have large impacts on the steel industry (Wårell, 2014). Also, the use of exchanges has decreased. Most steel transactions come from private bilateral negotiation between two parts (OTC), or by middlemen called steel service centers (Hall & Rust, 2002).

3.2.2 Equities within steel

To see how the volatility of steel prices affect equities of companies, two large categories of steel consumers will be analyzed. These are building and infrastructure contractors and car manufacturers (World Steel Association, n.d-c).

3.2.2.1 Building and infrastructure contractors

The building and infrastructure industry accounts for more than half of the worlds steel demand. As the population continues to increase, the demand in the sector is also expected to grow. In this industry, steel is used as reinforcing bars, sheets products, structural sections, equipment, transport networks, and other utilities (World Steel Association, n.d-b).

The following building and infrastructure companies will be considered:

- Fluor
- Skanska
- Vinci

3.2.2.2 *Car manufacturers*

International Organization of Motor Vehicle Manufacturers (2018) states that during the year of 2018, a total of 95.6 million vehicles were produced. The average vehicle uses 900kg of steel, meaning that the automotive industry is a large contributor to the world steel consumption (World Steel Association, n.d-a). The following car manufacturers are considered:

- Daimler
- Ford
- Toyota

3.3 Cotton

The cotton plant provides us with natural fibers which have been used by humans for thousands of years. While the plant is mostly cultivated due to its natural fibers, it does also provide cottonseed used for products such as oils and animal feed (Çalişkan, 2010). Cotton plants are subjected to pests and pathogens. Therefore, biotechnology has become increasingly used to protect them (Rathore, 2010). This technology has also helped increase the amount of cotton harvested per crop. Throughout many years, cotton has been an important commodity for the economy and social culture in many countries (Baffes, 2005). Cotton is a broadly traded commodity all over the world. In the past, cotton was only in specific parts of the world. Developments in technology and transportation during the last centuries has made sure that the commodity is widely used and has become a favorable fiber for many (Riello, 2013).

3.3.1 Cotton market

Today, cotton is produced all around the globe, however, the northern hemisphere accounts for over 90% of that production (Baffes, 2005). During the period 1960-2000, the volume of cotton traded doubled from 10 to 20 million tons. The three largest cotton producing countries today are China, India, and the United States. They contribute with more than half of the worlds cotton production. Other countries that are worth mentioning are Pakistan and Brazil (United States Department of Agriculture, 2019).

For numerous central Asian and African countries, cotton is an important commodity. In some of them, cotton makes up 40% of exports and between 5 to 10% of the total GDP. Therefore, changes in price and market share have large impacts on their economy. In the US and Europe, cotton is heavily subsidized, causing the prices producers receive to be between 80 and 160% higher than the world price (Baffes, 2005).

The use of cotton expanded tremendously after the industrial revolution took place, reducing its production cost, and increasing production volume significantly. It is still the most used natural fiber in the world. However, new competitors are emerging. Examples of large competitors are rayon, nylon, and polyester. The synthetic fibers nylon and polyester have been frequently traded since the 1970s at a comparable price to cotton (Baffes, 2005). By analyzing the cotton prices, it is noticeable that the general price level stays put with periods of price spikes, see figure 3. This can be related to improved technology resulting in decreasing production costs, a relatively low increase in demand, and the appearance of new substitutes such as other synthetic fibers. Innovations in the transportation industry reduces the amount of cotton that needs to be stored, which again cut costs (Baffes, 2005).

Reports suggest that the demand for cotton has increased, but at a slow rate. From 1960 to 2000, it increased annually by only 1.8%. One third of the produced cotton is exported internationally (Baffes, 2005; Çalişkan, 2010). As cotton is harvested in crops, the commodity is usually traded on futures contracts (Riello, 2013). Cotton is storable, hence current demand and supply does not have to be equal. The current supply is determined by the amount currently harvested plus the carryover from the previous period(s). This suggests that as the availability of cotton in storage decreases, cotton prices rise and become more volatile (Janzen, Smith, & Carter, 2018).

3.3.2 Equities within cotton

To determine which equities to analyze, a report by Holland et al. (2016) have been used. They have made a list of the largest cotton consuming companies. How this was estimated can be found in their report. Based on available data, the following companies are considered:

- Adidas
- Hennes & Mauritz (H&M)
- Inditex (Zara)
- Marks & Spencer (M&S)
- Nike

All companies above have reported that cotton is an important material in their production (Inditex, n.d; H&M group, n.d; Nike inc, 2018; Adidas group, n.d; Marks & Spencer, n.d).

3.4 The prices of crude oil, steel, and cotton

Below are the price developments of the chosen commodities from 2002 to 2020. The prices are daily closing prices. Keep in mind that the prices are in different currencies and that the quantities are specific for each commodity. Oil is priced in US dollars per barrel, the steel transactions are in Chinese yuan (CNY) per ton, and cotton is given in US cents per pound. The reason for the steel prices being in CNY is that we did not have access to steel data from exchanges using USD. From the figures below, one sees that the prices for the commodities have been quite volatile throughout the period with relatively big fluctuations. Another note is that the steel and oil prices seem to develop more closely to each other than the cotton price.

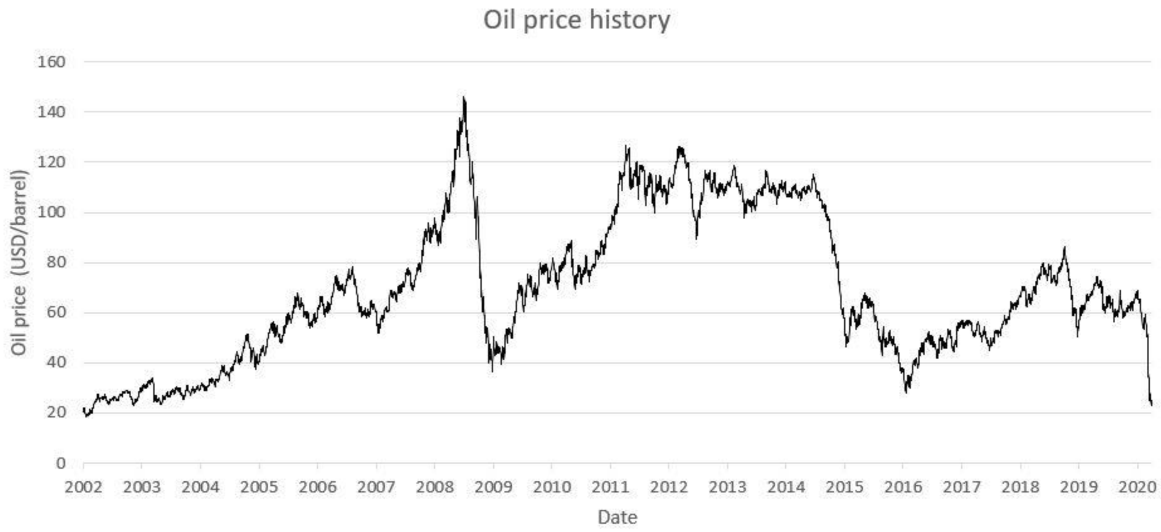

Figure 1: Oil price history over the analyzed period

Figure 2: Steel price history over the analyzed period

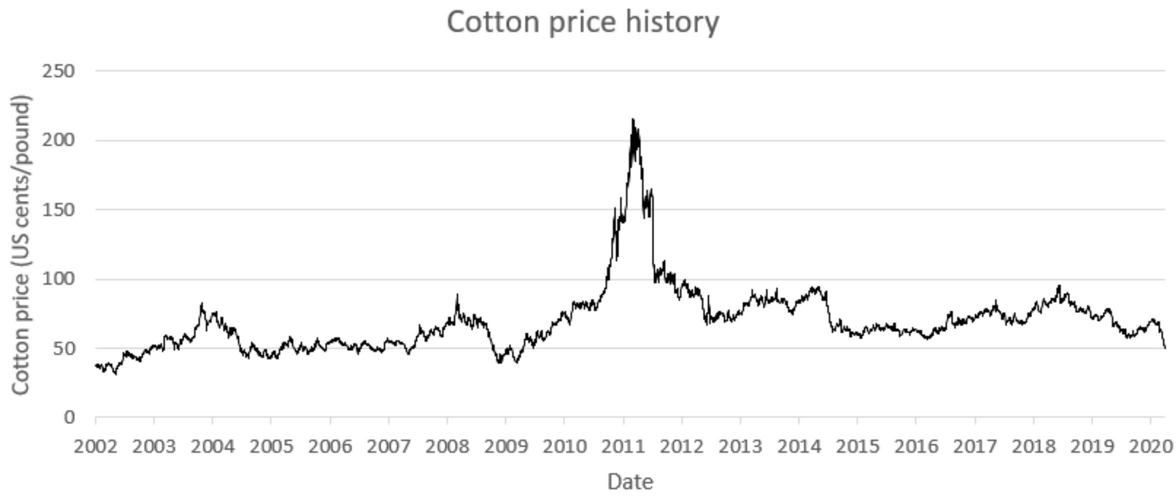

Figure 3: Cotton price history over the analyzed period

4 Methodology

To fully understand the spillover index developed by Diebold and Yilmaz (2009; 2012), some fundamental knowledge is required. First, theories of regression and time series analysis are introduced. This knowledge will then be extended into the concepts of autoregression and vector autoregression. Both are essential in understanding the spillover index. Further, concepts of volatility are explained. Then, the generalized spillover index is derived. Finally, some descriptive statistical tests are explained.

4.1 Fundamentals of time series analysis

The spillover index is based on regression models using time series data. Let us first look at the most basic regression model. This would be the simple regression model and is given in equation [4.1] below:

$$y = \beta_0 + \beta_1 x + u \qquad [4.1]$$

This model aims to find the relationship between two variables. In equation [4.1], y is called the explained variable while x is described as the explanatory variable (Wooldridge, 2014). Here, β_1 is called a slope parameter and explains the relationship between x and y. The last term, u, is the error term. u explains all other factors that affect the explained variable y which is not described by x. β_0 is referred to as the intercept parameter.

Equation [4.1] represents a simple linear regression model using cross-sectional data, meaning that the data is gathered at one point in time (Wooldridge, 2014). The spillover index, however, uses time series data. In time series, the observations are collected at different times (Lütkepohl, 2005). This data is collected over a specified time at equal spaced time intervals. This could be yearly, weekly, daily, hourly etc. Equation [4.1] can be re-written as:

$$y_t = \beta_0 + \beta_1 x_t + u_t \qquad [4.2]$$

Here, t represents the time at which the data is observed. As in equation [4.1], β_1 describes the relationship between y_t and x_t. However, this is only true if the ceteris paribus assumptions can be made about x_t on y_t. The ceteris paribus refers to keeping all other factors constant (Wooldridge, 2014). To draw the ceteris paribus conclusion, certain assumptions are made. The first assumption being that the average value of the error term u_t is zero.

$$E(u_t) = 0 \qquad [4.3]$$

Since u_t and x_t both contribute to explain y_t, it is interesting how u_t and x_t interact. This is where the crucial assumption comes into play. By assuming that the error term does not depend on the explanatory variable, one can derive the following:

$$E(u_t|x_t) = E(u_t) \qquad [4.4]$$

$$E(u_t|x_t) = 0 \qquad [4.5]$$

If these assumptions hold, one can confirm that the ceteris paribus effect is upheld and that β_1 explains the relationship between x_t and y_t. This can be seen by looking at the expected value of y_t on x_t.

$$E(y_t|x_t) = \beta_0 + \beta_1 x_t + E(u_t|x_t) \qquad [4.6]$$

By remembering that the last term $E(u_t|x_t) = 0$ from [4.5], equation [4.6] is simply:

$$E(y_t|x_t) = \beta_0 + \beta_1 x_t \qquad [4.7]$$

4.2 Obtaining the estimators

Now that the ceteris paribus assumption is obtained, the next step is to derive estimators for the parameters β_0 and β_1. An estimator is a function of the data collected (Stock & Watson, 2020). Two ways to obtain the estimators are through ordinary least squares (OLS) or maximum likelihood estimation (MLE) (Walpole, Myers, Myers, & Ye, 2016). This thesis will focus on OLS. By combining equations [4.3] and [4.4] the covariance of x_t and u_t are zero.

$$Cov(x_t, u_t) = E(x_t u_t) = 0 \tag{4.8}$$

Equations [4.9] and [4.10] are obtained by combining equations [4.2], [4.5] and [4.8]:

$$E(y_t - \beta_0 - \beta_1 x_t) = 0 \tag{4.9}$$

$$E[x_t(y_t - \beta_0 - \beta_1 x_t)] = 0 \tag{4.10}$$

Further, using the collected data, the estimators for β_0 and β_1 given as $\hat{\beta}_0$ and $\hat{\beta}_1$ are derived. Equation [4.9] and [4.10] become:

$$\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{\beta}_0 - \hat{\beta}_1 x_t) = 0 \tag{4.11}$$

$$\frac{1}{n}\sum_{t=1}^{n} x_t(y_t - \hat{\beta}_0 - \hat{\beta}_1 x_t) = 0 \tag{4.12}$$

By applying some fundamental properties about the summation operator on equation [4.11], an expression for $\hat{\beta}_0$ can be obtained:

$$\bar{y} = \hat{\beta}_0 + \hat{\beta}_1 \bar{x} \quad [4.13]$$

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x} \quad [4.14]$$

By substituting equation [4.14] in equation [4.12] the expression for estimator $\hat{\beta}_1$ is:

$$\hat{\beta}_1 = \frac{\sum_{t=1}^{n}(x_t - \bar{x})(y_t - \bar{y})}{\sum_{t=1}^{n}(x_t - \bar{x})^2} \quad [4.15]$$

The estimators obtained, $\hat{\beta}_0$ and $\hat{\beta}_1$, are what is known as the ordinary least squares or OLS for β_0 and β_1, respectively (Wooldridge, 2014). From the retrieved data, the OLS estimator will choose the coefficients so that the regression line will be as close to the obtained data as possible. The difference between the real value and the estimated value is called a residual and is usually denoted as $\hat{u}$ (Stock & Watson, 2020).

$$\hat{u}_t = y_t - \hat{y}_t = y_t - \hat{\beta}_0 - \hat{\beta}_1 x_t \quad [4.16]$$

The main goal of ordinary least squares (OLS) is to minimize the sum of squares between the observed and predicted values. As there are many such residuals, a summation operator is applied to equation [4.16], where the goal is to minimize it. The equation to be minimized is given below.

$$\sum_{t=1}^{n} \hat{u}_t^{\,2} = \sum_{t=1}^{n} \left(y_t - \hat{\beta}_0 - \hat{\beta}_1 x_t\right)^2 \quad [4.17]$$

4.3 Multiple regression analysis

Above, the simple linear regression model have been considered. In that case, it is assumed that the dependent variable is only relying on one explanatory variable. However, in many cases there might be several factors that affects y_t. For example, wage may be affected by education, years of experience, and performance. The value of a house might be explained by size (m^2), number of bedrooms, and location. One of the many advantages of multiple regression analysis is that it is easier to maintain the ceteris paribus effect as there are more variables to control for (Wooldridge, 2014).

When considering multiple regression in time series, equation [4.2] is extended to:

$$y_t = \beta_0 + \beta_1 x_{t1} + \beta_2 x_{t2} + \beta_3 x_{t3} + \cdots + \beta_k x_{tk} + u_t \qquad [4.18]$$

As in simple linear regression, the error term u_t explains all other factors affecting y_t which is not explained by $x_{t1},\ldots,x_{tk}$. The method of ordinary least squares is also valid for multiple regression and the method is the same. The residuals can be calculated as shown below:

$$\hat{u}_t = y_t - \hat{\beta}_0 - \hat{\beta}_1 x_{t1} - \hat{\beta}_2 x_{t2} - \cdots - \hat{\beta}_k x_{tk} \qquad [4.19]$$

To obtain the estimates using OLS, once again the goal is to minimize the sum of squared residuals:

$$\sum_{i=1}^{n} \left(y_t - \hat{\beta}_0 - \hat{\beta}_1 x_{t1} - \hat{\beta}_2 x_{t2} - \cdots - \hat{\beta}_k x_{kt}\right)^2 \qquad [4.20]$$

By applying multivariable calculus to the above equation, we obtain k+1 linear equations and unknowns which allows us to solve it and obtain estimates for $\beta_0,\beta_1,\ldots,\beta_k$.

4.4 Assumptions on time series

When using OLS estimation in time series analysis, there are six assumptions to be considered. However, for some time series data sets, the classical linear model assumptions are too restrictive. If the data sample is large, the asymptotic Gauss-Markov assumptions may be used to justify using OLS. These consists of five assumptions. All assumptions are retrieved from Wooldridge (2014).

The first assumption implies that all parameters in the time series analysis are linear, where the stochastic process is assumed to be stationary and weakly dependent. The weakly dependent assumption means that the central limit theorem (CLT) and law of large numbers (LLN) are usable. Finally, assumption [1] suggests that both the dependent and the independent variable may be lagged. The model is assumed to be described by the following equation:

$$y_t = \beta_0 + \beta_1 x_{t1} + \cdots + \beta_k x_{tk} + u_t \qquad \text{Assumption [1]}$$

Assumption [2] states that there is no perfect collinearity. This means no independent variable is constant nor a perfect linear combination of the others. Assumption [3] suggests zero conditional mean. i.e., the expected value of the error term u_t, given the other variables, are zero. However, the explanatory variable are contemporaneously exogeneous. This means that there is no restriction on the parameter u_t and its relation to other time periods in the time series.

$$E(u_t|x_t) = 0 \qquad \text{Assumption [3]}$$

If assumptions [1] to [3] are upheld, the OLS estimators are consistent (Wooldridge, 2014).

The fourth assumption implies that the errors are contemporaneously homoscedastic. Homoskedasticity means that the variance of the error term, u_t, is constant when conditional on the explanatory variables. If the variance of the error term does depend on x_t, there is heteroskedasticity. Assumption [4] written mathematically:

$$Var(u_t|x_t) = \sigma^2, t = 1,2,..,p \qquad \text{Assumption [4]}$$

Assumption [5] says that there is no serial correlation.

$$Corr(u_t, u_s|x_t, x_s) = 0, for\ all\ t \neq s \qquad \text{Assumption [5]}$$

If assumptions [1] to [5] are upheld, the OLS standard errors for F statistics and t statistics are valid. In addition, the OLS estimators are asymptotically normally distributed (Wooldridge, 2014).

4.5 Vector Auto Regression (VAR)

In the following section, autoregression will be introduced and how this can be used to forecast. This will further be extended to a vector autoregressive model and what criterions that may be used when determining the amount of lagged values to consider. Finally, the concept of forecast error variance decomposition will be explained.

4.5.1 Autoregression

What happens in the future often tends to be correlated with what has already happened in the past. An analysis that predicts the future based on the already occurred indices is known as an autoregression model. Said mathematically, the variable Y_t will depend on its past lagged values Y_{t-1}. This is shown in the following equation [4.21]:

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + u_t \qquad [4.21]$$

As earlier, u_t represents the error term and the equation has two coefficients, β_0 and β_1, which needs to be estimated. This estimation can be done using ordinary least squares (OLS).

Equation [4.21] represents the first order autoregression model [AR(1)]. This means that the value Y_t is estimated using one lagged value. Sometimes, it might be better to use even more information from the past. This can be achieved by including more lagged values. The p^{th} order autoregressive model [AR(p)] can be written as:

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \cdots + \beta_p Y_{t-p} + u_t \quad [4.22]$$

4.5.2 Forecasting

The use of time series data combined with autoregression models can be used to predict the period immediately following the current data available. This is denoted as Y_{T+1} and known as the one-step ahead forecast. When forecasting even further in the future, it is known as multi-step ahead forecast. The estimated forecast of Y_{T+1} is written as $\hat{Y}_{T+1|T}$. The subscript T+1|T means that the forecast is done at a time T+1 using data through time T (Stock & Watson, 2020).

As the predicted forecasted value is based on estimators, it will most likely be different from the real value at time T+1. The difference between the forecasted value and real value is known as the forecast error.

$$Forecast\ error = Y_{T+1} - \hat{Y}_{T+1|T} \quad [4.23]$$

Forecast errors are nearly impossible to avoid, therefore, the goal is to minimize them. A popular measurement of the forecast error is known as the mean squared forecast error (MSFE). When forecasting, it is the large errors that affect the outcome the most. By using this model, the large fluctuations are captured. The root mean squared forecast error (RMSFE) is often used as it is easy to interpret. By using unbiased estimators, the forecast error will have a zero mean and the RMSFE will represent the standard deviation (Stock & Watson, 2020). RMSFE is given as:

$$RMSFE = \sqrt{E\left[\left(Y_{T+1} - \hat{Y}_{T+1|T}\right)^2\right]} \quad [4.24]$$

4.5.3 Vector autoregression model

The autoregression model consists of a single equation to determine a variable. Sometimes, it is more interesting to model the relationship between several variables. This may be achieved by using a vector autoregression (VAR) model. The VAR model is a multivariate model used to measure several variables using lagged values (Davidson & MacKinnon, 2004).

Stock and Watson (2020) show that the VAR model is an extension of the univariate autoregressive model. To give an example, lets continue to show a VAR model for three time series variables, $Y_{1,t}$,$Y_{2,t}$ and $Y_{3,t}$ with 1-lag, making it a VAR(1) model.

$$
\begin{aligned}
Y_{1,t} &= \beta_{10} + \beta_{11}Y_{1,t-1} + \beta_{12}Y_{2,t-1} + \beta_{13}Y_{3,t-1} + u_{1,t} \\
Y_{2,t} &= \beta_{20} + \beta_{21}Y_{1,t-1} + \beta_{22}Y_{2,t-1} + \beta_{23}Y_{3,t-1} + u_{2,t} \\
Y_{3,t} &= \beta_{30} + \beta_{31}Y_{1,t-1} + \beta_{32}Y_{2,t-1} + \beta_{33}Y_{3,t-1} + u_{3,t}
\end{aligned}
\qquad [4.25]
$$

The equations above can more easily be expressed in matrix form.

$$Y_t = \alpha + Y_{t-1}\Phi_1 + U_t \qquad [4.26]$$

In this case $\alpha = \begin{bmatrix} \beta_{10} \\ \beta_{20} \\ \beta_{30} \end{bmatrix}$, $\Phi_1 = \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} \\ \beta_{21} & \beta_{22} & \beta_{23} \\ \beta_{31} & \beta_{32} & \beta_{33} \end{bmatrix}$, and $U_t = \begin{bmatrix} u_{1,t} \\ u_{2,t} \\ u_{3,t} \end{bmatrix}$.

α represents the intercepts, Φ_1 the coefficients, and U_t the error terms. From the equation above one can observe that each of the variables depend on its own lagged value as well as the lagged values of the other two variables. This can further be expanded to a VAR(p) model with K-variables (Davidson & MacKinnon, 2004):

$$Y_t = \alpha + \sum_{j=1}^{p} Y_{t-j}\Phi_j + U_t \qquad [4.27]$$

U_t is a 1 x K vector of error terms and are assumed to be independent and identically distributed (i.i.d) with zero expectation and the covariance matrix Σu. If not stated otherwise, the covariance matrix is nonsingular (Lütkepohl, 2005). α is a 1 x K vector of the intercepts and Φ_j is a K x K matrix of the coefficients for j = 1,…,p. All these terms need to be estimated (Davidson & MacKinnon, 2004).

4.5.3.1 Moving average representation

A moving average (MA) model is an often-used model in time series analysis. The output variables depend on past and current values linearly. One big advantage of the MA model, compared to an AR, is that it is always stationary if it is finite order (Reinsel, 1993). The VAR(p) model may be written as a MA model. Lütkepohl (2005) shows that equation [4.26] can be written as:

$$Y_t = \alpha\left(I_K + \Phi_1 + \cdots + \Phi_1^j\right) + \Phi_1^{j+1} Y_{t-j-1} + \sum_{i=0}^{j} \Phi_1^i u_{t-i} \qquad [4.28]$$

I_K represents the identity matrix with K x K dimensions. Lütkepohl (2005) continues to state that if the eigen values of Φ_1 is less than one and $j \to \infty$ the sequence $\Phi_1^i, i = 0,1, \dots, j$ becomes absolutely summable which gives the infinite sum:

$$\sum_{i=1}^{\infty} \Phi_1^i u_{t-i} \qquad [4.29]$$

The term $\Phi_1^{j+1} Y_{t-j-1}$converge to zero as $j \to \infty$ and the first term in [4.28] becomes

$$\alpha\left(I_K + \Phi_1 + \cdots + \Phi_1^j\right) \underset{j\to\infty}{\longrightarrow} \alpha(I_K - \Phi_1)^{-1} \qquad [4.30]$$

This gives the moving average representation shown in [4.31]:

$$Y_t = \mu + \sum_{i=0}^{\infty} \Phi_1^i u_{t-i} \qquad [4.31]$$

Where μ equals $\alpha(I_K - \Phi_1)^{-1}$.

4.5.4 Var model selection

When constructing VAR models, there may be several that are viable. Therefore, one needs to choose between competing models where there are different numbers of variables and lags. In this case, one should use a procedure explicitly designed for model selection, which typically involves calculating a criterion function and choosing the model that maximize or minimize the criterion (Davidson & MacKinnon, 2004).

When adding more variables to a VAR model, more coefficients must be estimated. This increases the estimation error in a forecast. The number of coefficients that needs to be estimated is K(Kp+1). Where K is the number of variables and p is the number of lags. (Stock & Watson, 2020). Davidson and MacKinnon (2004) say that between several correctly specified models one should choose the one with the fewest parameters. This is called the parsimonious principle.

There are several criterions that can be used to help choose the correct model. Lütkepohl (2005) suggests four methods: Schwarz (SC), Hannan-Quinn (HQ), Akaike (AIC), and Final Prediction Error (FPE) criterion. Box, Jenkins, Reinsel, and Ljung (2016) mention all but the final prediction error while Stock and Watson (2020) mention Akaike and Schwarz criterions. The Schwarz criterion is also known as the Bayesian information criterion (BIC).

4.5.4.1 Schwarz criterion

The formula for calculating the Schwarz criterion is given in Lütkepohl (2005) as:

$$SC(p) = \ln\left[\det(\tilde{\Sigma}_u)\right] + \frac{lnT}{T} * (number\ of\ freely\ estimated\ parameters)$$

Using the number of coefficients formula used in Stock and Watson (2020) and OLS instead of MLE SC(p) becomes:

$$SC(p) = \ln\left[\det\left(\hat{\Sigma}_u\right)\right] + \frac{lnT}{T} * K(Kp + 1) \tag{4.32}$$

Where $\det(\hat{\Sigma}_u)$ is the covariance matrix made from the residuals using OLS on $\hat{u}$, T is the sample size, K is the number of variables, and p is the number of lags. The estimated lag length, $\hat{p}$, is the lag length, p, that minimizes $SC(p)$ among a set of possible p's. In other words, the model that has the number of lags that minimizes $SC(p)$ is chosen as the appropriate model. Stock and Watson (2020) explain that the first term is an extension from the case of just one equation and not a VAR model. In that case, the first term would simplify to $\ln\left[\frac{SSR(p)}{T}\right]$, where adding more variables would never increase the $SC(p)$ if OLS is used to estimate the VAR model. The second term does penalize the addition of more variables.

4.5.4.2 Akaike criterion

The Akaike information criterion (AIC) follows much of the same logic as the Schwarz criterion, with the only difference being that the $\ln(T)$ in the second term is replaced by the number two, making the criterion:

$$AIC(p) = \ln\left[\det\left(\hat{\Sigma}_u\right)\right] + \frac{2}{T} * K(Kp + 1) \tag{4.33}$$

The same goal applies here as in SC(p). The estimated number of lags is the p value that minimizes AIC(p). Davidson and MacKinnon (2004) show that AIC penalizes models for adding parameters/variables, however, AIC does not penalize as hard as SC does. This can lead AIC to include more lags than SC. In other words, a less decrease in SSR is needed for the AIC criterion to justify another variable than in SC (Stock & Watson, 2020).

4.5.4.3 Hannan-Quinn criterion

The Hannan-Quinn (HQ) criterion is similar to the others explained above. Here, the p value, which gives the lowest HQ(p), is preferred. The criterion is calculated in the following way.

$$HQ(p) = \ln\left[\det\left(\tilde{\Sigma}_u\right)\right] + \frac{2\ln\,(lnT))}{T} * K(Kp+1) \qquad [4.34]$$

In this case the covariance matrix, $\tilde{\Sigma}_u$, is found using MLE instead of OLS.

4.5.4.4 Final prediction error

One way to choose the VAR order is to minimize the measured error. The final prediction error (FPE) is based upon minimizing the mean squared error (MSE). The VAR order choice is then based on the approximate 1-step ahead forecast mean squared error shown in the equation below:

$$\Sigma_{\hat{y}}(1) = \frac{T + Kp + 1}{T}\Sigma_u \qquad [4.35]$$

The covariance matrix Σ_u must be replaced by an estimate, which is the OLS estimator $\hat{\Sigma}_u$.

$$\hat{\Sigma}_u(p) = \frac{T}{T - Kp - 1}\tilde{\Sigma}_u(p) \qquad [4.36]$$

Here $\tilde{\Sigma}_u(p)$ is the maximum likelihood estimator of Σ_u obtained by fitting a VAR(p) model. The FPE criterion is thus:

$$FPE(p) = \left[\frac{T + Kp + 1}{T - Kp - 1}\right]^K \det\,(\tilde{\Sigma}_u(p)) \qquad [4.37]$$

Where the p that minimizes the FPE(p) is chosen as the appropriate model (Lütkepohl, 2005).

4.5.5 Forecast error variance decomposition (FEVD)

Forecasting is one of the main objectives for generating time series models. (Box et al., 2016; Lütkepohl, 2005). The use of past and present observations can be used to forecast future values, which can be used in a variety of ways (Box et al., 2016). Lütkepohl (2005) describes the situation where a forecaster at time t, the forecasting origin, has information set Ω_t, containing all available information with past and present variables of the system. Forecasting can be performed for one or H-periods-ahead in the future. This is called a H-step-predictor. The goal of the forecasting from then on is to minimize the error of the forecast since a perfect prediction is impossible. In a model with K-variables, the variables can influence each other. By considering two variables Y_i and Y_j, the FEVD gives information about how much of the error in Y_i is from the H-step forecast for Y_j (Lütkepohl, 2005). Diebold and Yilmaz (2009; 2012) use the variance decomposition in the error of a one-step ahead forecast. There one finds how much of the error variance in the forecast of Y_i comes from shocks to Y_i, and how much comes from shocks to Y_j, and vice versa.

4.6 Volatility

Volatility measures the fluctuations of a series of financial data, usually price. To have a precise definition of the term, one must decide on which method used to calculate the volatility. The method chosen makes a big difference on the calculated volatility. The appropriate method depends on the context and how the calculated parameter is thought to be used (Rakkestad, 2002). A volatility can be historical, based on a model, or a forecast (Rutherford, 2012). The risk of an asset is often measured by volatility and is therefore of importance in portfolio management.

4.6.1 Historical volatility

Historical volatility is an estimation of the volatility for a given period of the past. The historical volatility is calculated by taking the sample standard deviation over a period. The question then becomes; what is the correct period to include? A long period might make the model irrelevant today, and a short period can make the sample noisy (Engle, 2004). The historical volatility will have a smoother curve if calculated over a longer period. Another complication with the period length is that the past data is equally weighted in the calculation. Therefore, short term spikes in volatility will affect the calculation if they are in the period, regardless of when they happened.

4.6.2 Squared log returns

One can estimate a volatility proxy by using the squared log returns (Patton, 2011). Andersen, Bollerslev, Diebold, and Ebens (2001) state that squared log returns is a model free unbiased estimator of the volatility ex post. One negative characteristic is that squared log returns are a noisy indicator of volatility (Patton, 2011; Andersen et al., 2001). Therefore, it may not be reliable in inference regarding true latent volatility.

4.6.3 Intraday volatility

Intraday volatility refers to the volatility on a given day from when the markets opens and closes. There are two common ways to estimate intraday volatility. The first estimator uses the highest and lowest prices from the intraday data to compute volatility. The second estimator utilizes the open and closing prices when estimating the volatility (Garman & Klass, 1980). When computing volatility, Diebold and Yilmaz (2009) based their estimation on the work by Garman and Klass (1980) and Alizadeh, Brandt, and Diebold (2002). This allowed them to combine the high, low, open, and closing prices to estimate the stock return volatility.

4.6.4 Volatility spillover

As defined in the introduction: when a market is influenced by a cross-market volatility, it is called a volatility spillover (Ke et al., 2010). The method that was developed by Diebold and Yilmaz (2009) is based on a variance decomposition that allows for aggregate spillover effects across markets. The basic idea of the spillover index follows from the notion of variance decompositions with a K-variable VAR. They further describe the method as: "For each asset i we simply add the shares of its forecast error variance coming from shocks to asset j, for all $j \neq i$, and then we add across all i = 1,…,K." (Diebold & Yilmaz, 2009)

By considering a two variable VAR(1) model, the 1-step-ahead error vector can be shown as:

$$e_{T+1|T} = Y_{T+1} - \hat{Y}_{T+1|T} = \mathrm{A}_0 u_{T+1} = \begin{bmatrix} \alpha_{0,11} & \alpha_{0,12} \\ \alpha_{0,21} & \alpha_{0,22} \end{bmatrix} \begin{bmatrix} u_{1,T+1} \\ u_{2,T+2} \end{bmatrix} \qquad [4.38]$$

Where the covariance matrix is:

$$E\left(e_{T+1}, e'_{T+1|T}\right) = \mathrm{A}_0\mathrm{A}'_0 \quad [4.39]$$

This shows that the variance of the 1-step-ahead error for the forecasted variable $Y_{1,T}$ is $\alpha_{0,11}^2 + \alpha_{0,12}^2$ and for $Y_{2,T}$ it becomes $\alpha_{0,21}^2 + \alpha_{0,22}^2$. In this case, the variances are defined as own-variance and cross-variance. The own variances are $\alpha_{0,11}^2$ and $\alpha_{0,22}^2$ for $Y_{1,T}$ and $Y_{2,T}$, respectively, while the cross variances are $\alpha_{0,12}^2$ and $\alpha_{0,21}^2$. The $\alpha_{0,12}^2$ is the shock in $Y_{2,T}$ affecting $Y_{1,T}$ and $\alpha_{0,12}^2$ is the shock in $Y_{1,T}$ affecting $Y_{2,T}$. Thus, total spillover in this case is $\alpha_{0,12}^2 + \alpha_{0,21}^2$. The total forecast error variance is: $\alpha_{0,11}^2 + \alpha_{0,12}^2 + \alpha_{0,21}^2 + \alpha_{0,22}^2 = trace(\mathrm{A}_0\mathrm{A}'_0)$. Finally, the total spillover can then be represented relative to the total forecast error variance as a percentage.

$$S = \frac{\alpha_{0,12}^2 + \alpha_{0,21}^2}{trace(\mathrm{A}_0\mathrm{A}'_0)} * 100 \quad [4.40]$$

The equation above represents the spillover for a first order, two variable model. For a pth-order K-variable VAR, 1-step-ahead forecast, equation [4.40] becomes:

$$S = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \alpha_{0,ij}^2}{trace(\mathrm{A}_0\mathrm{A}'_0)} * 100 \quad [4.41]$$

For the fully general case, considering a H-step-ahead forecast, the spillover index becomes:

$$S = \frac{\sum_{h=0}^{H-1} \sum_{\substack{i,j=1 \\ i \neq j}}^{N} \alpha_{h,ij}^2}{\sum_{h=0}^{H-1} trace(\mathrm{A}_h\mathrm{A}'_h)} * 100 \quad [4.42]$$

4.7 Generalized spillover index

The generalized spillover index is an extension of the work established by Diebold and Yilmaz (2009), which is described in the subchapter above. That spillover index only allowed for total spillover estimation. The old spillover index from 2009 used Cholesky factorization to calculate variance decompositions and made it order dependent. The new generalized spillover index allows for measurement of directional spillovers and it excludes the problem of ordering (Diebold & Yilmaz, 2012). This problem was solved by using a generalized VAR framework established by Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998). This framework was given the name KPPS by Diebold and Yilmaz (2012), and we will continue to refer to it as that. Further, the generalized spillover index may be used to perform both full-sample and rolling-sample analysis. The full-sample look at the average connectedness, while a rolling-sample finds a connection over a certain time frame.

To obtain the generalized spillover index, remember the K-variable VAR(P) model:

$$Y_t = \alpha + \sum_{j=1}^{p} Y_{t-j}\Phi_j + U_t \qquad [4.27]$$

As mentioned in subchapter 4.5.3: U_t is a 1 x K vector of error terms and are assumed to be independent and identically distributed (i.i.d) with zero expectation and the covariance matrix Σu. α is a 1 x K vector of the intercepts and Φ_j is a K x K matrix of the coefficients for j = 1,…,p. To calculate the FEVD for each variable, equation [4.27] needs to be written as a moving average representation of the model. This operation was explained in 4.5.3.1 and gives equation [4.43].

$$y_t = \mu + \sum_{i=0}^{\infty} A_i u_{t-i} \qquad [4.43]$$

To fully understand the dynamics of the system, the moving average coefficients is important (Diebold & Yilmaz, 2012). With the moving average coefficients, one can identify each variable's forecast error variance (R. E. Dahl & Jonsson, 2018). By decomposing those variances, one can find how much of the forecast error variance of each variable are coming from different system shocks. The variance decompositions tell us what fraction of the H-step-ahead error in forecasting Y_i is due to shocks to Y_j, for all $j \neq i$, for each i.

4.7.1 FEVD

Remember that own variance and cross variance, or spillovers, were defined in subchapter 4.6.4. By utilizing the KPPS framework, the H-step-ahead forecast error variance decomposition can be calculated, denoted as $\theta_{ij}^{g}(H)$.

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e'_i A_h \sum e_j)^2}{\sum_{h=0}^{H-1} (e'_i A_h \sum A'_h e_i)} \qquad [4.44]$$

$\theta_{ij}^{g}(H)$ is a matrix where the elements display the spillover from market i to j. In equation [4.44], Σ represents the variance matrix for error vector U_t, σ_{jj} is the standard deviation for the error term for the j^th equation. e_i is the selection vector, with one as the i^th element and zeros otherwise. Using this method, the sum of the elements in each row of the FEVD matrix, will not necessarily be equal to one. Therefore, each entry in the matrix must be normalized by the row sum (Diebold & Yilmaz, 2012):

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \qquad [4.45]$$

The FEVD matrix may be represented as below:

Table 1: Example of a FEVD matrix

	From			
To	**1**	**2**	**...**	**K**
1	θ_{11}^{g}	θ_{12}^{g}	...	θ_{1K}^{g}
2	θ_{21}^{g}	θ_{22}^{g}	...	θ_{2K}^{g}
⋮	⋮	⋮	⋱	⋮
K	θ_{K1}^{g}	θ_{K2}^{g}	...	θ_{KK}^{g}

4.7.2 Generalized total spillover index

The total spillover, by using the KPPS framework, can be described as:

$$S^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{K} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{K} \tilde{\theta}_{ij}^{g}(H)} * 100 = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{K} \tilde{\theta}_{ij}^{g}(H)}{K} * 100 \qquad [4.46]$$

The numerator represents all cross-variances while the denominator is the sum of all variances or observations. In practice, this means to sum all the off-diagonal elements in the spillover matrix $\tilde{\theta}_{ij}^{g}(H)$ and divide by the sum of all elements in the table. This formula is analogous to the spillover index developed in subchapter 4.6.4 (Diebold & Yilmaz, 2012).

4.7.3 Generalized directional spillovers

The generalized spillover index makes it possible to determine the direction of the spillover. The spillover received by market i from other markets j is measured as:

$$S_{i.}^{g}(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{K} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{K} \tilde{\theta}_{ij}^{g}(H)} * 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{K} \tilde{\theta}_{ij}^{g}(H)}{K} * 100 \qquad [4.47]$$

Thus, the directional spillover from i to all other markets j are:

$$S_{.i}^{g}(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{K} \tilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{K} \tilde{\theta}_{ji}^{g}(H)} * 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{K} \tilde{\theta}_{ji}^{g}(H)}{K} * 100 \quad [4.48]$$

In other words, directional spillovers offer a decomposition of the total spillovers. This makes it possible to track where the spillovers are coming from.

Finally, the net spillover from market i to other markets j, is the difference between transmitted and received volatility.

$$S_{i}^{g}(H) = S_{.i}^{g}(H) - S_{i.}^{g}(H) \quad [4.49]$$

4.7.4 Generalized net pairwise spillovers

While equation [4.49] brings information about how each market provides volatility to others, it is also useful to get information about the volatility spillover between market i and j. This is referred to as net pairwise spillover. More general, the difference between volatility from market i to market j, and vice versa. The formula for net pairwise spillover is:

$$S_{ij}^{g}(H) = \left(\frac{\tilde{\theta}_{ji}^{g}(H)}{\sum_{i,n=1}^{K} \tilde{\theta}_{in}^{g}(H)} - \frac{\tilde{\theta}_{ij}^{g}(H)}{\sum_{j,n=1}^{K} \tilde{\theta}_{in}^{g}(H)} \right) * 100 \quad [4.50]$$

4.8 Descriptive Statistical Tests

There will be conducted some statistical tests on the data used in this thesis. Those tests will be for autocorrelation, normality, and stationarity. Three tests will be considered for stationarity, while only one for normality and autocorrelation. When using the spillover index by Diebold and Yilmaz (2009; 2012), the data set needs to be stationary.

4.8.1 Autocorrelation

One of the time series assumptions mentioned earlier is the assumption of no autocorrelation between the error terms (Assumption [5]). A popular test for autocorrelation between the residuals in a VAR model with lags up to h is the portmanteau test (Lütkepohl, 2005). Portmanteau tests the null hypothesis:

$$H_0: \boldsymbol{R_h} = \left(R_{1,} \ldots, R_h\right) = 0 \text{ against } H_1: R_h \neq 0$$

Where the **R_h** is the autocorrelation matrix for the VAR model. The test statistic in the portmanteau test is Q_h and has an approximate χ^2-distribution. In practice one finds a modified Q_h value, $\bar{Q}_h$, and for large samples and large h, $\bar{Q}_h$ becomes:

$$\bar{Q}_h \approx \chi^2(K^2(h-p))$$

Then the test statistic above is compared with the appropriate χ^2 critical value to see if it rejects the null or not. If the null is rejected, there is statistically significant autocorrelation at the selected confidence level.

4.8.2 Normality

Several economic tests are built on the assumption that the error terms are normally distributed. This includes both the F-test and t-test. In addition, OLS and the maximum likelihood estimators are equal if this is true. This further suggests that the best estimation method is OLS as it is asymptotically efficient and consistent (Heij, de Boer, Franses, Kloek, & Dijk, 2004). Because of the arguments just listed, it is important to test for normality before continuing with the analysis. One way to test this is using a Jarque-Bera (JB) test. In the given test, kurtosis and skewness are used jointly to test for normality. To be normally distributed, the skewness must be zero and the kurtosis equal to 3 (Thadewald & Büning, 2007). The JB test is as follows:

$$JB = \frac{n}{6}\left(Skewness^2 + \frac{(Kurtosis-3)^2}{4}\right) \qquad [4.51]$$

When the amount of observations, n, becomes large, the JB test can be modelled as a chi-squared distribution with 2 degrees of freedom. The null hypothesis is rejected if JB > $\chi^2_{(\alpha,2)}$. If the null hypothesis is rejected, the data is not normally distributed (Heij et al., 2004).

4.8.3 Stationarity

An important condition for time series analysis as well as the spillover index, is stationarity. By upholding this criterion, regression models may be used to forecast values. Stationarity means that the probability distribution does not alter over time when considering the variable in the time series (Stock & Watson, 2020). Davidson and MacKinnon (2004) define the model as stationary if the expectation E(u_t) and variance Var(u_t) is independent of t. In addition, if the covariance Cov(u_t, u_{t-j}), given any value for j, is independent of t. They refer to this as covariance stationarity or wide sense stationarity.

If the above criteria are not upheld, the time series are said to be nonstationary. This is often the case when the time series fluctuates around a trend. A trend can be either deterministic or stochastic. Nonstationarity may also be caused by breaks. A break is a sudden price movement. When analyzing data, it is important that the data is adjusted for breaks (Stock & Watson, 2020).

As stationarity is an important criterion for the spillover index, it is essential to test for stationarity when using time series. When checking for stationarity, many use the principle of unit roots. A time series are nonstationary if it has unit roots. The easiest way to test for unit roots is by considering the difference in an [AR(1)] model. Remember the [AR(1)] model in subchapter 4.5.1:

$$\Delta Y_t = \beta_0 + \rho Y_{t-1} + u_t \qquad [4.21]$$

In equation [4.21] $\rho = \beta_1 - 1$ and ΔY_t resembles the first difference of Y_t. thus, the null and alternative hypotheses are:

$$H_0: \rho = 0$$

$$H_1: \rho < 0$$

If the null hypothesis is rejected, the time series are said to be stationary. One problem is that regular t-statistics are not valid as the central limit theorem is not applicable in this case. However, by utilizing a Dickey-Fuller (DF) test which uses asymptotic distribution with critical values, t-statistics may be used. This means that t-statistics is usable for $\hat{\rho}$, if $t_{\hat{\rho}} < c$, where c is a critical negative asymptotic value. These critical values are much larger in magnitude than regular critical values and they depend the on the significance level (Wooldridge, 2014).

Three tests that utilizes and extends the theory of the DF test that are often used when analyzing time series data are: the augmented DF test, DF generals least squares (DF-GLS), and Phillips-Perron (PP) test.

4.8.3.1 The augmented Dickey-Fuller test

The augmented Dickey-Fuller test extends the work of the regular DF test as it uses lagged differences, known as Δy_{t-h}. These lagged differences are independent variables and are meant to improve the regression by mitigating the risk of serial correlation in Δy_t. Fortunately, the lagged differences are just about t distributed. Therefore, the augmented DF test is asymptotically distributed, meaning that they have the same critical values as the normal DF test (Baltagi, 2011; Wooldridge, 2014).

4.8.3.2 Dickey-Fuller general least squares

The Dickey-Fuller general least squares is yet another extension of the regular DF test. The time series is transformed by utilizing a generalized least squares estimation. GLS give better results for errors considering heteroskedasticity or correlation between observations than OLS. This makes the DF-GLS test more robust than the DF test (Stock & Watson, 2020).

4.8.3.3 Phillips-Perron test

The Phillips-Perron test is another extension of the regular DF test. This test uses a different standard error for ρ. PP use Newey-West standard error to handle serial correlation in residuals. This allows it to tackle both heteroskedasticity and autocorrelation in the error terms (Heij et al., 2004).

5 Data

The data for this thesis are daily closing prices of the commodities oil, cotton, and steel, as well as daily closing prices of the selected equities. All data are extracted from Thomson Reuters Eikon. For oil and cotton, the prices extracted are 1-month future contracts, while for steel the selected prices are OTC-transactions. The data sets have observations from the first available trading day in 2002 until April 2020. This gives over 4000 observations per asset for the analysis. In addition, the S&P 500 index is included to be used as a reference when measuring the spillover between the commodities and the equities. The assets chosen for the thesis are in the tables below where some descriptive statistics are shown and statistical tests are performed. When one or more asset lacks price information for a date, all the data for that date is excluded.

5.1 Daily returns

Table (2) shows descriptive statistics for the daily returns of the assets given in percentages. For all assets, the mean and median returns are close to zero. The minimum and maximum returns in a day vary more, with the minimum returns varying between -13.55% for Skanska and -47.23% for Halliburton. The maximum returns vary between +12.32% for Inditex and +56.63% for Fluor. The cotton related companies have a smaller range from minimum to maximum returns than the other groups.

The companies that are analyzed together with oil have a higher correlation with oil than the companies in the other two commodity groups. The three oil service companies, Baker Hughes, Halliburton, and Schlumberger have the highest correlation with their commodity. The S&P 500 index returns are most correlated to oil and least to steel.

Oil is the commodity with the highest standard deviation in this analysis. The oil operators have lower standard deviation than the service companies, while the airlines have quite similar standard deviation as the service companies. Higher standard deviation indicates more volatility. In the steel and cotton group the companies seem to have similar standard deviations. In the data set, S&P 500 has the lowest standard deviation out of all assets.

Table 2: Data for daily returns given in percentages (%)

	Mean	Median	Min	Max	Std.dev	Skewness	Kurtosis	Corr.
Oil	0.00	0.07	-27.58	15.56	2.24	-0.50	11.69	1.00
BP	-0.01	0.00	-21.67	19.54	1.76	-0.41	16.69	0.37
Chevron	0.01	0.07	-25.00	20.49	1.75	-0.75	29.16	0.46
Equinor	0.02	0.00	-19.50	12.74	1.94	-0.42	8.85	0.41
ExxonMobil	0.00	0.03	-15.03	15.86	1.58	-0.28	15.62	0.41
Shell	-0.01	0.02	-19.22	20.26	1.66	-0.41	20.37	0.39
Baker Hughes	-0.02	0.02	-25.18	23.89	2.50	-0.48	13.89	0.47
Halliburton	0.00	0.03	-47.23	23.53	2.73	-1.43	32.60	0.48
Schlumberger	-0.01	0.00	-32.05	14.07	2.28	-1.08	18.92	0.49
Air France-KLM	-0.03	0.01	-22.59	17.03	2.68	-0.24	6.90	0.09
Lufthansa	-0.01	0.00	-18.23	15.71	2.15	-0.28	7.94	0.13
SAS	-0.06	0.00	-32.91	28.21	3.21	0.15	12.88	0.08
S&P 500	0.02	0.07	-13.78	10.96	1.27	-0.62	14.87	0.30
Steel	0.02	0.00	-31.41	22.31	1.36	-4.00	161.77	1.00
Fluor	-0.02	0.03	-31.00	56.63	2.99	0.19	49.34	0.00
Skanska	0.02	0.00	-13.55	15.60	1.92	-0.18	9.35	0.00
Vinci	0.04	0.06	-18.72	16.66	1.89	-0.27	14.13	0.01
Daimler	-0.02	0.04	-34.90	24.12	2.29	-0.62	24.38	-0.03
Ford	-0.03	0.00	-28.77	25.87	2.73	-0.30	20.80	-0.02
Toyota	0.02	0.00	-21.26	13.25	1.68	-0.60	16.32	-0.02
S&P 500	0.02	0.07	-13.78	10.96	1.27	-0.62	14.87	-0.03
Cotton	0.01	0.00	-15.55	13.62	1.92	-0.06	7.54	1.00
Adidas	0.05	0.00	-16.69	12.80	1.84	-0.06	9.76	0.13
H&M	0.00	0.00	-13.90	15.38	1.78	0.05	11.06	0.09
Inditex	0.04	0.00	-21.88	12.32	1.81	-0.36	12.54	0.11
Marks & Spencer	-0.03	0.00	-28.14	21.31	2.06	-1.21	26.10	0.10
Nike	0.06	0.07	-12.60	14.13	1.75	0.21	11.11	0.09
S&P 500	0.02	0.07	-13.78	10.96	1.27	-0.62	14.87	0.17

5.2 Daily volatility

Table (3) shows the descriptive statistics for the volatilities of the assets given in percentages. The volatilities are measured using squared log returns. Squared log returns were used due to lack of intraday data. The ranges are generally from 0% to around 10%, with some outliers having a higher maximum volatility.

The companies in the oil group are most correlated to their commodity. SAS has a correlation to oil of 0.09, which is the lowest in the oil group. None of the companies in the steel or cotton group have higher correlation to their commodity than SAS has to oil. S&P 500 has higher correlation to oil compared to the other two commodities.

The standard deviations of the volatilities are lowest for the cotton group. In the oil group, the oil operators and airlines have lower standard deviations than the service companies. In the steel group, there are varying standard deviations within the builders and car manufacturers. When considering cotton, the related equities seem to have similar standard deviations. The only one that stands out is Marks & Spencer with twice as high standard deviation than the others. The S&P 500 has the lowest standard deviation in the data set.

5.3 Statistical tests

As described earlier, statistical tests are conducted to give information about the sample data. These were presented in chapter 4.8. Three of the tests check for stationarity, one for normality, and the last one for autocorrelation. The statistical tests are conducted in the program R and the results are found in table (4). All tests are statistically significant at 0.01%. The results show that the data are stationary, experience non-normal distribution and are serially correlated.

Table 3: Data of the daily volatility in given in percentages (%)

	Mean	Median	Min	Max	Std.dev	Skewness	Kurtosis	Corr.
Oil	0.05	0.01	0.00	7.60	0.16	24.94	1036.04	1.00
BP	0.03	0.01	0.00	4.70	0.12	22.29	710.16	0.55
Chevron	0.03	0.01	0.00	6.25	0.16	23.35	705.49	0.43
Equinor	0.04	0.01	0.00	3.80	0.11	15.02	415.87	0.59
ExxonMobil	0.03	0.01	0.00	2.52	0.10	14.35	273.84	0.37
Shell	0.03	0.01	0.00	4.10	0.12	20.80	589.98	0.53
Baker Hughes	0.06	0.02	0.00	6.34	0.23	16.92	395.19	0.50
Halliburton	0.08	0.02	0.00	22.31	0.42	36.24	1774.61	0.71
Schlumberger	0.05	0.01	0.00	10.27	0.22	27.12	1091.92	0.67
Air France-KLM	0.07	0.02	0.00	5.10	0.18	10.41	206.69	0.14
Lufthansa	0.05	0.01	0.00	3.32	0.12	11.58	222.44	0.19
SAS	0.10	0.02	0.00	10.83	0.35	14.83	334.93	0.09
S&P 500	0.02	0.00	0.00	1.90	0.07	15.06	315.99	0.44
Steel	0.02	0.00	0.00	9.87	0.24	32.89	1239.13	1.00
Fluor	0.09	0.02	0.00	32.07	0.62	35.91	1701.86	0.02
Skanska	0.04	0.01	0.00	2.43	0.11	9.55	139.34	0.03
Vinci	0.04	0.01	0.00	3.51	0.13	14.20	283.07	0.07
Daimler	0.05	0.01	0.00	12.18	0.26	30.94	1307.12	0.04
Ford	0.08	0.01	0.00	8.28	0.33	14.47	265.44	0.03
Toyota	0.03	0.01	0.00	4.52	0.11	24.65	857.65	0.02
S&P 500	0.02	0.00	0.00	1.90	0.07	15.06	315.99	0.03
Cotton	0.04	0.01	0.00	2.42	0.09	10.30	180.23	1.00
Adidas	0.03	0.01	0.00	2.79	0.10	11.49	217.11	0.07
H&M	0.03	0.01	0.00	2.37	0.10	11.29	179.91	0.04
Inditex	0.03	0.01	0.00	4.79	0.11	22.08	807.03	0.03
Marks & Spencer	0.04	0.01	0.00	7.92	0.21	23.50	703.61	0.02
Nike	0.03	0.01	0.00	2.00	0.10	9.63	127.31	0.07
S&P 500	0.02	0.00	0.00	1.90	0.07	15.06	315.99	0.14

Table 4: Statistical test for daily volatilities in the data set

	Stationarity			Normality	Autocorrelation
	ADF	**DF-GLS**	**PP**	**Jarque-Bera (JB)**	**Portmanteau (PM)**
Oil	-39.08	-38.22	-58.89	×	179.03
BP	-38.24	-36.58	-63.58	×	112.95
Chevron	-29.08	-28.09	-66.59	×	141.84
Equinor	-38.95	-38.51	-61.34	×	137.45
ExxonMobil	-25.99	-24.59	-60.36	×	385.85
Shell	-36.50	-35.62	-65.29	×	121.46
Baker Hughes	-34.77	-34.54	-63.93	×	184.60
Halliburton	-39.03	-8.01	-66.27	×	61.04
Schlumberger	-39.12	-36.90	-64.80	×	126.88
Air France-KLM	-39.90	-38.78	-64.14	×	74.33
Lufthansa	-40.80	-40.80	-64.10	×	55.02
SAS	-42.52	-39.60	-62.03	×	69.08
Steel	-43.31	-42.90	-58.21	×	52.78
Fluor	-33.06	-32.51	-54.72	×	223.70
Skanska	-39.54	-35.62	-61.28	×	67.96
Vinci	-29.53	-29.19	-62.07	×	193.50
Daimler	-40.12	-35.19	-66.08	×	9.57
Ford	-34.41	-34.23	-55.88	×	284.04
Toyota	-38.66	-37.57	-64.59	×	44.00
Cotton	-40.11	-35.95	-56.88	×	162.97
Adidas	-38.49	-38.49	-60.55	×	103.86
HM	-40.04	-40.02	-63.19	×	44.92
Inditex	-44.16	-25.07	-63.82	×	15.77
M&S	-41.72	-38.85	-64.52	×	23.45
Nike	-34.96	-32.75	-61.04	×	150.07
S&P 500	-49.43	-35.21	-73.50	×	52.11

6 Empirical results

In the following chapter the results from the analysis will be presented. First, a general explanation of the interpretation of volatility spillover results will be given. Further, oil, steel, and cotton results will be analyzed and discussed separately. Finally, the three commodities will be compared.

6.1 Interpretation of volatility spillover results

In the following two chapters, the output from R will be described. How the results are obtained in R is provided in Appendix A. Further, an explanation of how the output is treated, interpreted, and then presented will be given below.

6.1.1 Overall and net spillover output

When calculating the spillover index between a commodity and an equity, R returns a 3x3 matrix. This information includes own and cross variance shares, “contribution from others”, “contribution to others”, and overall spillover. “Contribution from others” is calculated by summing all cross spillovers and indicates how much the equity or commodity are affected by the other. “Contribution to others” is the same as previously, only vice versa. From this information, it is possible to calculate the assets’ “contribution including own” and net spillover. A sample of this output considering oil and BP is presented in the table below:

Table 5: Spillover table for BP

	Oil	**BP**	**Contribution from others**
Oil	76.46	23.54	23.54
BP	24.93	75.07	24.83
Contribution to others	24.93	23.54	
Contribution incl. own	101.39	98.61	**Overall spillover:**
Net spillover	1.39	-1.39	**24.23**

“Contribution including own” consists of its own variance share plus the spillover given to the other part. In the case above, 76.46% of oils volatility comes from oil itself, and 24.93% of BPs volatility originates from oil. This sums up oil’s total volatility contribution between oil and BP to 101.39%. The net spillover between oil and BP is thus 1.39%. For the example above, this means that oil is a net giver of volatility to BP of 1.39%. The minus sign on BPs net spillover indicates that BP is a net receiver of volatility from the other part.

As the objective of this thesis is to analyze an equity and a commodity, only the spillover between two and two assets will be considered at the same time. This simplifies the calculation of net spillover. Therefore, only the overall spillover and net spillover will be provided further on. A list of all output tables for all companies and its commodity is given in Appendix B.

6.1.2 Rolling spillover output

The overall spillover calculated in the table above shows the average spillover for the whole sample period. To see how the spillover between assets have varied over time, a rolling spillover analysis is conducted. In this thesis, the rolling window is 250 days, meaning that the spillover between assets are calculated for a 250-day period at a time. A business year is approximately 250 days. Again, oil and BP are shown as an example of a rolling spillover plot in figure 4. There, one can follow how the volatility spillover between oil and BP has varied at different times in the sample period ranging from 2003 to April 2020. The rolling spillover plot starts in 2003 because of the rolling window of 250 days. This means that the first calculated spillover is after 250 days.

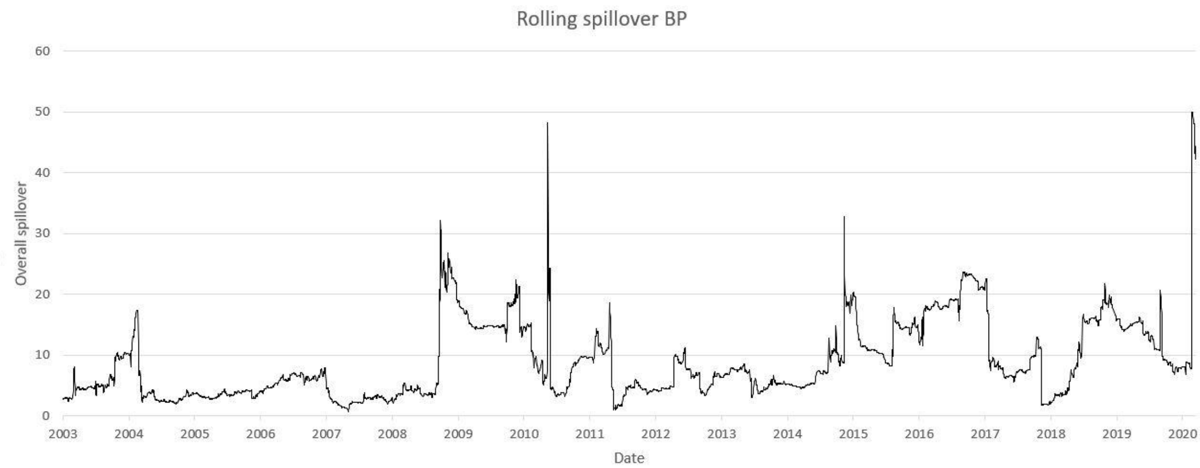

Figure 4: Rolling overall spillover for BP

The rolling spillover analysis have been conducted for each equity and their related commodity. To prevent too many figures, each group of company types will be plotted into the same figure and then discussed focusing on spikes and trends. Each individual rolling spillover plot will be available in Appendix C.

6.2 Oil results

The following chapter contains the results for all oil related equities. The net and overall spillover will be analyzed first and compared to the S&P 500 index. The oil companies are sorted into operators, service companies, and airlines, and will be discussed in that order. Then a rolling spillover analysis will be conducted group by group with a comparison with the S&P 500 index just after. Finally, a summary of the oil findings is given.

6.2.1 Oil net and overall spillover

Table 6 contains the net and overall spillover between oil and all equities within the oil group.

Table 6: Net and overall spillover for oil group

Oil group	Companies	Net Spillover	Overall Spillover
Operators	BP	-1.39	24.23
	Chevron	-17.31	22.01
	Equinor	0.46	25.44
	ExxonMobil	-2.25	12.47
	Shell	-3.25	24.16
Service	Baker Hughes	-2.87	20.89
	Halliburton	-0.17	34.23
	Schlumberger	-0.47	31.76
Airlines	Air France-KLM	-1.14	3.29
	Lufthansa	-3.14	5.93
	SAS	0.15	1.24
Index for reference	S&P 500	-11.40	21.55

6.2.1.1 Operators

For the operator group the results are generally quite similar, with overall spillovers above 20%. However, ExxonMobil stands out with about half the overall spillover compared to the rest of the group. The overall spillover is well under 50% for all the companies, indicating that most of the volatility for each company comes from itself or something other than the oil price. When compared to the spillover between the oil price and S&P 500, all but ExxonMobil have higher overall spillover than the index. Generally, the oil operators have similar overall spillover with the oil price compared to the S&P 500 index.

For the net spillovers, all but Equinor seem to be net receivers of volatility. In general, this indicates that Equinor is a net giver of volatility to oil. However, the value is only 0.46%, making it negligible. What really stands out is the net spillover of Chevron, indicating that Chevron receives a substantial amount of spillover from the oil price compared to the other operators.

Low net spillover at the same time as there is a relatively large overall spillover indicates that a company both give and receive similar amounts of volatility. Also, the spillover tables shown in Appendix B become quite symmetrical in these cases.

In the cases with low net spillover and high overall spillover, the spillovers are highly correlated, and the movement of the prices are usually on the same day. Another take from the net spillovers is that only Chevron have higher net receiving volatility from oil than the S&P 500 index. All the other operators receive much less net volatility than the S&P 500 index even though the index contains many companies that have nothing to do with the oil industry.

6.2.1.2 Service

Own-variance share explains most of the volatility for the overall spillover for the service companies. Halliburton and Schlumberger both have higher overall spillover than S&P 500 with an overall spillover above 30%. Baker Hughes have the lowest overall spillover of the group with 20.9%, which is lower than the reference.

The net spillovers are all negative in the group, meaning they all are net receivers of volatility from the oil price. Halliburton has the highest overall spillover, but the lowest net spillover in the group. This indicates that the stock price and the oil price move correlated on the same days, and that Halliburton both gives and receives volatility. Baker Hughes have the highest net spillover and lowest overall spillover among the service companies, but the net receiving of 2.87% from the oil price is still much lower than what the S&P 500 index receives.

6.2.1.3 Airlines

The airlines have, as the other groups, most of the volatility stemming from their own-variance shares. The overall spillovers in the group are very low compared to the overall spillover of the index with oil. Lufthansa has the highest overall spillover of 5.9%.

The net spillovers are also low, with SAS even being a net giver of volatility. As the net spillover is only 0.15%, it is most likely just noise. Air France-KLM and Lufthansa also have low net spillovers, both being on the receiving end. However, Lufthansa has high net spillover compared to its overall spillover.

6.2.2 Oil rolling spillover

The following chapters include the rolling spillovers for operators, service companies, airlines, and a comparison with the S&P 500.

6.2.2.1 Operators

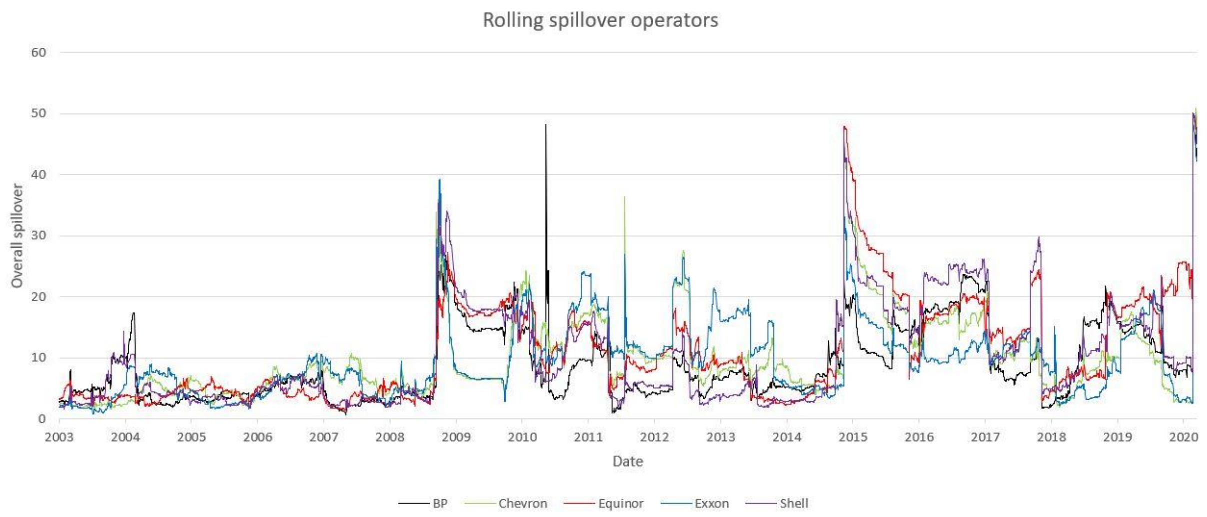

Figure 5: Rolling overall spillover for operators

The rolling overall spillover of the oil operators with crude oil is shown in figure 5. All the operators are plotted in the same graph to show when they move similarly and when single companies spike. One can see from the plot that the operators' overall spillover with oil have changed over the sample period. Except for a small spike from Shell and BP in 2003/2004, the overall volatility spillover generally lies below 10% up until the financial crisis. After the financial crisis, the overall spillovers range from about 7% to 20% with more spread between the companies until the oil price plummeted in 2014-2016. After the spike in 2014, the overall spillover ranges from about 10% to 25% with a big spread between the companies. Then in 2020, all spike up due to the impacts from the covid-19 pandemic. It seems from looking at the figure above that ExxonMobil and Chevron follow each other more closely than the rest of the operators.

The first major spike that is observed in the figure is in the end of 2008, when the financial crisis hit the markets. The volatility spillover of all the operators with oil increase reaching nearly 40%. The financial crisis was a time with much uncertainty and high volatility in the financial markets. The VIX index, which is a measure of the volatility on wall street, reached its all-time high. During the financial crisis, the oil prices fell over $100 per barrel resulting in tough times for oil related companies. The oil price collapse can be seen in figure 1.

The next major spike can be found in 2010 where BP reached a volatility spillover of nearly 50% with oil. The spike can most likely be linked to the Deepwater Horizon accident in the Gulf of Mexico. This was the largest marine oil spill in history and was caused by an explosion on the drilling rig which was leased by BP (Pallardy, 2010). The event occurred on the 20th of April 2010. The leak of oil continued for 87 days until it was finally stopped, reaching a total leak equivalent to over 4 900 000 barrels of oil. The accident caused a total of eleven deaths. Several companies, including BP, were held responsible for this accident (Pallardy, 2010).

In August 2011, the stock markets had high volatility as several reports on the economic outlook of the United States were released. The VIX index rose 35% in one day after the reports were released and the three major indices in the US plummeted. That coupled with Standard and Poor's downgrading of the US credit rating led to high volatility during that period (Pepitone, 2011). From the results one can clearly see that the volatility spillover of ExxonMobil and Chevron spike especially high. The fact that both ExxonMobil and Chevron are American may be the reason those two rose more than the other operators. Even though the higher volatility also included European stock markets, it was the US who got their credit rating lowered. In the same period, the oil price did not have any dramatic movements indicating that the spillover in this period stemmed from the movements in the stock markets.

The next clear spike in the operators plot, happens as the oil price plummeted in 2014. From 2014 to 2016 the oil price faced a drop from over $100 down to about $30 per barrel. The downturn of the oil price lasted over a long period, being the longest lasting decline since 1986 (Stocker, Baffes, & Vorisek, 2018). Stocker et al. (2018) state that the coinciding of increased supply from especially oil shale in the US, plus the decline in demand from big oil importers made the price drop. The spike in 2014 in the operators plot clearly shows this event.

The final spike observed is seen in 2020. This spike in volatility spillover is due to the outbreak of the covid-19 pandemic. Covid-19 has caused a high unemployment rate and an enormous economic pressure on companies worldwide. This has led to many countries shutting down their economies which have major economic implications for many companies. At the same time the oil price has fallen to a price last seen in 2002. It is difficult to go further into this topic as there is still a lot of uncertainty at this stage and the pandemic is still ongoing at the time of writing this thesis.

6.2.2.2 Service companies

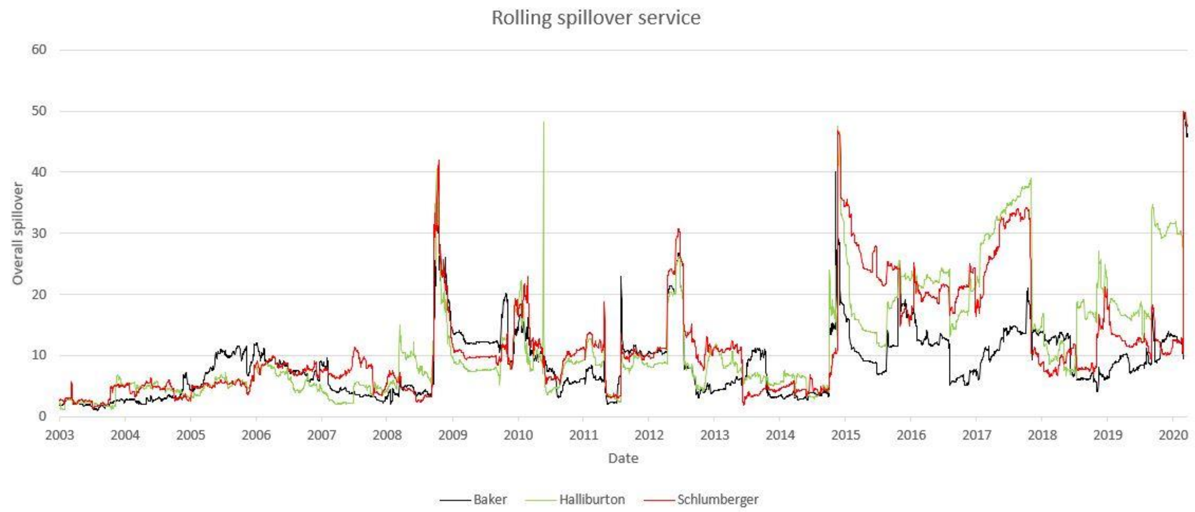

Figure 6: Rolling overall spillover for service companies

Figure 6 shows the rolling overall spillover for the service companies with oil. Until the financial crisis in 2008, the volatility spillover ranges from 3% to 15% with no spikes. After the financial crisis, the general volatility spillover seems to be higher than the previous period, containing spikes and having an overall higher average spillover. Baker Hughes has a lower overall rolling spillover than both Schlumberger and Halliburton towards the end of the data set. Finally, it is noticeable that the curves of the separate firms are similar, where the difference being the value of the volatility spillover.

The periods of high volatility spillover seen in 2008, 2014-2018 and 2020 can be related the financial crisis, oil crisis and aftermaths for the industry, and the covid-19 pandemic as described in the subchapter above. It is assumed that the service companies' spikes are because of the same reasons as for the operators. Service companies are hired by the operators and are therefore affected by the same events. When the oil operators foresee low oil prices, they generally lower their investments.

The first company to spike alone among the service group is Halliburton in 2010. This may again be related to the explosion on Deepwater Horizon in the Gulf of Mexico. During the accident, Halliburton were responsible for the cementing job in the well (Pallardy, 2010). The explosion was caused by a crack in the cementing. Even though BP had the responsibility, Halliburton was connected to the accident.

In 2012, all service companies spike reaching a volatility spillover above 25%. On the 30th of May 2012, the oil price fell below $88 per barrel after being worth more than $110 the previous month. At that time, countries such as Spain, Portugal, Greece, and Italy were fearing economic troubles. People thought that this could lead to an economic recession in Europe or even worldwide. Therefore, the demand for oil where expected to decrease and so the oil price dropped along with this fear (Hargreaves, 2012).

6.2.2.3 Airlines

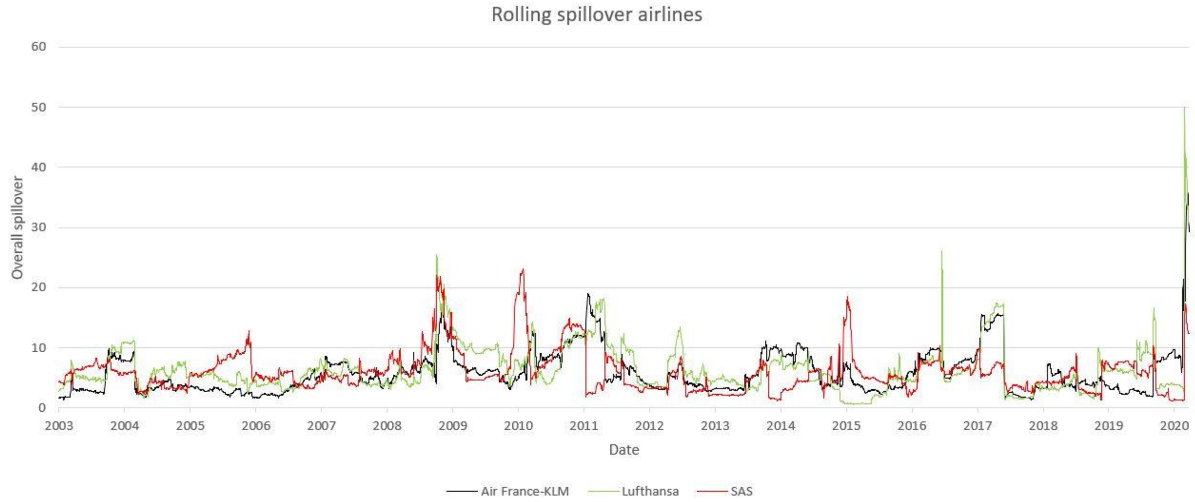

Figure 7: Rolling overall spillover for airlines

The figure above shows the rolling overall spillover for airlines with oil. The overall spillover stays within the range of about 2% to 10% until the financial crisis. The coming years after that, the volatility is higher than it was in the previous period before returning to the same level in 2012. From 2012 until 2020, it seems that only company related events make the volatility spillover spike and these spikes are all relatively low. In 2020, the airlines reach the highest volatility spillover due to the covid-19 pandemic which stopped airline traffic.

The first spike seen for all airlines, is the financial crisis where the overall spillover with oil spiked up to above 20%. In general, the connectedness between airlines and oil is not remarkable. The airlines spike under extraordinary volatile times in the financial markets, or when there are company related events that cause volatility in the stock prices. For example, the oil crisis in 2014-2016 does not show any rise in the volatility spillover.

A company specific spike visible in the figure is the one for SAS in 2010. The company delivered poor results during the last quarter of 2009, with a loss of about 1.5 billion SEK. The company was in crisis and was saved by issuing new shares to raise 5 billion SEK, hence diluting existing owners (E24, 2010). During this period, one can see that SAS has a higher connectedness to the oil price than the other airlines. Most likely, the increase can be explained by a highly volatile SAS stock causing high spillover.

The other noteworthy company specific spike in the figure is Lufthansa in 2016. Lufthansa struggled with conflicts with their employees throughout the year. In April, the ground personnel went on strike (Lufthansa Group, 2017). Coinciding with this event there is a spike in the connectedness between oil and Lufthansa in the figure. Again, there seem to be events within the company that causes this spike, and not the oil price or global economic events.

6.2.2.4 Comparison with S&P 500

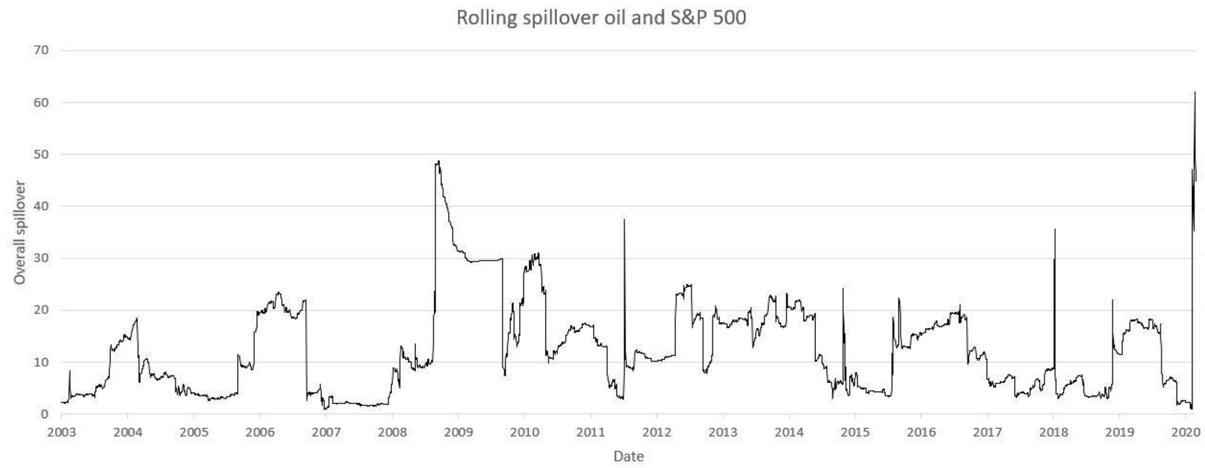

Figure 8: Rolling overall spillover between oil and S&P 500

When looking at the rolling overall spillover between oil and the S&P 500 index, one notices that there is more volatility spillover in the period before the financial crisis than in the plots for the companies. After the financial crisis, there are several periods were the overall spillover between the S&P 500 index and oil is higher than that of the oil operators and service companies. Between the financial crisis and the oil crisis is an example of a period where the connectedness between the index and oil is higher than between oil and single companies. The connectedness between oil and the index is higher than that of airlines throughout the period. The reason why the index has a higher connectedness with oil than the companies in the oil group at certain times, can stem from that oil prices have a big impact on the global economy. There is also a spike in February 2018. At that time, the VIX more than doubled in a day (DeCambre, 2018), and may be the reason for the increased connectedness spike one sees in the plot. This spike is not seen in the plots for the companies in the oil group.

As the oil crisis hit in 2014, the connectedness between S&P 500 and oil is less affected than for single companies. The volatility spillover in 2016 is almost as high and lasts over a longer period than the spike in 2014. The reason why the oil price shock in 2014 is not as evident in figure 8, can be that lower oil prices for most industries is good. The overall effect of an oil price drop of the magnitude that was seen in 2014-2016 resulted in a world net positive GDP effect of 0.5%, which was lower than expected (Rogoff, 2016). Rogoff (2016) writes that the reasons for the low positive effect was; 1) The lower prices did not reach consumers in developing economies like India and China because the governments there instead lowered state subsidies for oil, 2) Oil consuming countries used lower prices to repair their balance sheets after the financial crisis instead of increasing spending, and 3) the dropping oil prices led to less investment in the oil industry. Rogoff (2016) states that the price drop has been a contributor to the financial markets' high volatility of the time.

6.2.3 Summary oil

From figures 5-7, it is evident that the oil operators and service companies have a higher connectedness with oil than the airlines do. This is consistent with the results from the overall spillovers for the entire period. The increase in connectedness between oil and the companies after the financial crisis is seen in the operators and the service companies, but that same trend is not seen for the airlines. That can imply that there is low connectedness between the airlines and the oil prices outside extraordinary events which causes higher volatility in the financial markets in general. The operators and service companies have higher spillover when there is higher volatility in the oil price as well, which is not seen for the airlines. Finally, when looking at the overall plot, the American companies seem to follow each other more closely than the rest. The spike seen in 2012 is an example of this where all service companies as well as ExxonMobil and Chevron spiked.

6.3 Steel results

The following chapter contains the results for all steel related equities. The net and overall spillover will be analyzed first and compared to the S&P 500 index. The steel companies are sorted into building contractors and car manufacturers and will be discussed in that order. Then a rolling spillover analysis will be conducted group by group with a comparison with the S&P 500 index just after. Finally, a summary of the steel findings is given.

6.3.1 Steel net and overall spillover

Table 7 contains the net and overall spillover between steel and all equities.

Table 7: Net and overall spillover for steel group

Steel group	Companies	Net Spillover	Overall Spillover
Building contractors	Fluor	2.63	1.34
	Skanska	1.01	1.66
	Vinci	4.67	5.36
Car manufacturers	Daimler	22.42	12.53
	Ford	9.1	4.74
	Toyota	12.58	8.19
Index for reference	S&P 500	7.18	5.6

6.3.1.1 Building contractors

The building contractor companies have most of the volatility stemming from their own-variance share. All the contractors have lower overall spillover with steel than the S&P 500 index does. Vinci has a low overall spillover of 5.4%, but still has way higher spillover than the other contractors.

The contractors are all net givers of volatility to the steel price. Vinci has the highest net giving spillover in the group of 4.7%. For Fluor, the net spillover is higher than the overall spillover which shows that steel prices have close to no effect on the volatility of the stock price. Looking in Appendix B, one can see that Fluor receives 0.03% of its volatility from the steel price, while steel receives 2.66% of its volatility from Fluor. Overall, it seems that the building contractors are not very affected by the steel price and vice versa.

6.3.1.2 Car manufacturers

Among the car manufacturers, most of the volatility comes from the own-variance shares. The group has quite varying overall spillover. Daimler has the highest overall spillover of 12.5% and Ford the lowest one with 4.7%. Daimler and Toyota both have higher overall spillover with steel than the index has.

All the car manufacturers have higher net spillover than overall spillover with steel. All car manufacturers are net givers of volatility towards steel. Daimler again stands out with net giving volatility of 22.4%. All the car manufacturers have higher net spillover with the steel price than the S&P 500 index. The index is also a net giver of volatility to the steel market.

6.3.2 Steel rolling spillover

The following chapters include the rolling spillovers for building contractors, car manufacturers and a comparison with the S&P 500.

6.3.2.1 Building contractors

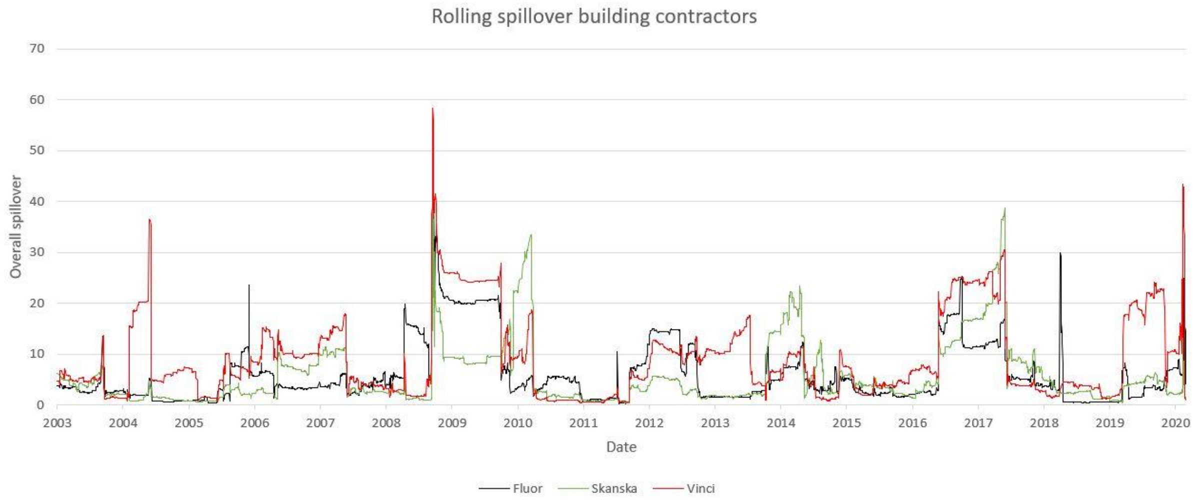

Figure 9: Rolling overall spillover for building contractors

The figure above shows the rolling overall spillover between steel and building contractors. From 2003 until the financial crisis, the volatility spillover is low ranging from about 1% to 15% with some spikes exceeding that range. Just before the financial crisis, the volatility spillover is very low. After the financial crisis, there is again a period of relatively low spillover. Mid-2016 to mid-2017 is the period containing the most volatility spillover except for the financial crisis. Finally, the overall spillover stays low until the eruption of the covid-19 pandemic.

The first period of higher spillover is observed in 2004 by Vinci. The higher spillover lasted for nearly six months. One reason might be that Vinci performed exceptionally well during 2004 which caused their stock price to increase over 50% (Vinci, 2005). At the same time, the steel price fell as seen in figure 2. Thus, the combination of a higher stock price and a decreasing steel price might have made the volatility spillover between Vinci and steel spike.

During the financial crisis, the steel price plummeted. In addition, the stock price of the companies decreased. Therefore, there is a large spike in connectedness between the building contractors and steel in the period 2008-2009. One notices that all building contractors are affected, however, Skanska declines much quicker to a lower level of volatility spillover than the others.

In the period of mid-2016 to mid-2017, all the building contractors have a higher volatility spillover than usual. Their respective stock prices fluctuated during that period, while the steel price had a steady increase. A report from Deloitte on the growth of the building industry in Europe suggested that Brexit negotiations and the US election, leading to the presidency of Trump, caused uncertainty in the building industry (Veldhuizen & Dijkstra, 2017). The report suggested that these two events caused both positive and negative effects for the construction industry. This might explain the fluctuation of stock prices and higher volatility spillover during the period.

On the 3rd of May 2018, Fluor released their first quarter report for 2018. This showed that Fluor had poor results in the beginning of the year and did not meet the expectations of shareholders. The year before, Fluor had a net positive result of $61 million, while in 2018 there was a loss of $18 million (Fluor Corporation, 2018). Thus, their stock fell nearly 23% in a day. The results of the stock price decrease may be the reason for the spike seen in 2018 in figure 9.

In the beginning of 2019, Vinci's stock price was £70. During that year, their stock price increased by 45% and went higher than £100 per share. During the same period, the were no significant changes to the steel price. As a result, Vinci's increasing stock price may have caused increased volatility spillover. This period is noticeable in the figure above.

6.3.2.2 Car manufacturers

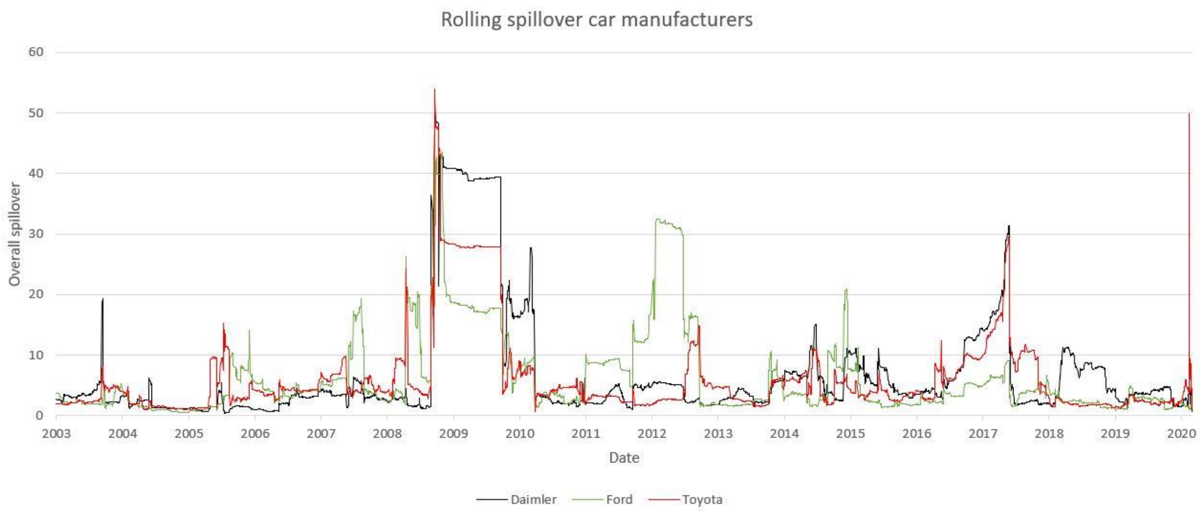

Figure 10: Rolling overall spillover for car manufacturers

By looking at the figure of the rolling spillover between car manufacturers and steel, the volatility spillover is low and stays mostly below 10% before the financial crisis. After the financial crisis, the volatility spillover goes down again and only spike up during short periods of time. It seems that the spikes are company related as they only spike alone, except in the period of mid-2016 to mid-2017. The volatility spillover stays low until the end of the dataset when all companies except Ford spike because of the covid-19 pandemic.

The largest spike found in the figure is the financial crisis in the end of 2008. The steel price was hit hard, dropping 60% and the volatility in the stock markets was high at the same time. All car manufacturers spiked during this event. In the period right after the financial crisis, Ford's overall spillover declines to below 20%, Toyota stays just below 30%, while Daimler is nearly 40% during the same period.

After the steel price had plummeted in 2008, it had a steady increase up to 2011. In mid-2011, the steel price had a noticeable fall. In 2012, the steel price had two major drops again. These movements can be seen in figure 2. In the same period as the steel price had these movements, Ford delivered positive net incomes several years in a row (Ford, 2013). This may be the reason for the high volatility spillover between Ford and steel in the same period. The other two companies did not have any significant spillover during this period.

In June 2017, the president of the United States, Donald Trump, announced that USA might place a tariff on foreign steel (Fitzsimmons, 2017). As a result, the global steel price had an increase in price. From figure 10, the volatility spillover of both Daimler and Toyota spiked while Ford only rose a little. This might be because Ford is an American company with most of its activity within America. Both Daimler and Toyota are not American, but still have high activity in the US. Therefore, this might have caused uncertainty among shareholders, which may be the reason for the increased spillover visible in the figure.

6.3.2.3 Comparison with S&P 500

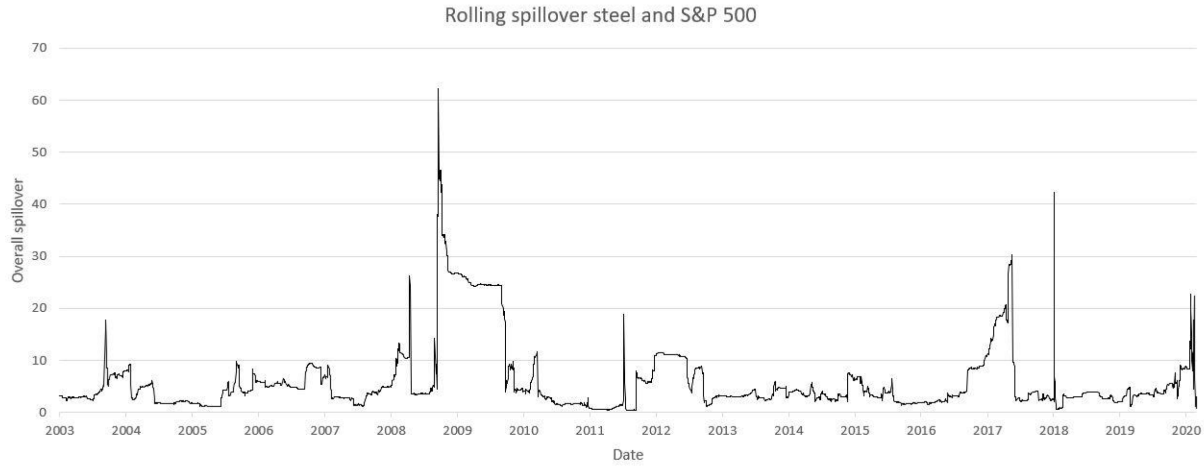

Figure 11: Rolling overall spillover between steel and S&P 500

When analyzing the volatility spillover between the steel price and the S&P 500 index, it seems that the spikes occur mostly because of shocks in the stock markets. The largest spike is during the financial crisis when the steel price decreased by nearly 60% at the same time as the stock markets crashed. In the timeframe of 2011 to 2012, the steel price rose once, followed by two large drops, which may be why there is increased volatility spillover in the plot at that period. The period from mid-2016 to mid-2017 is known as a volatile time due to the US president election and Brexit speculations. In addition, the speculation around a new and higher steel tariff might have caused uncertainty. In 2018, the S&P 500 index causes the high volatility spillover. As explained in the oil chapter above, in February 2018, the VIX index doubled in a single day causing the value of S&P 500 to decrease. These results imply that the steel market is more driven by the activity in the global economy than the global economy is affected by the steel prices.

By comparing the rolling overall spillover plots of building contractors and car manufactures with the S&P 500 index, there are several similarities. The financial crisis in 2008 are found in all figures as well as the timeframe of high volatility spillover in mid-2016 to mid-2017. The large volatility spillover found in 2018 are only visible for S&P 500 and for Fluor among the building contractors. Finally, the covid-19 pandemic is small in the S&P 500 figure compared to both building contractors and car manufacturers.

6.3.3 Summary Steel

The period between mid-2016 to mid-2017, both building contractors and car manufacturers have a higher volatility spillover than normal. Whether it is related to Brexit and presidential election as explained in 6.3.2.1 or the chance of a steel tariff explained in 6.3.2.2 is hard to say. What is certain is that this was a time with several events that can cause volatility spillover between the markets.

From the figures 9-10, regarding volatility spillover between steel related companies and the steel price, it is evident that there is a connection within each company group. The pattern of building contractors suggest that they follow each other quite closely. Vinci has the highest overall spillover which can be seen from both the spillover table and the rolling spillover figure. As with the building contractors, the same can be said about car manufacturers. They seem correlated and several company related events appear to be the reason to the increases in the amount of volatility spillover. Generally, the average overall spillovers of the car manufactures are higher than that of the building contractors.

Keep in mind that the steel price used in the analysis are from OTC transactions. This can be a factor causing less spillover as there will be days in the data set without any price change. The OTC transactions are used for the analysis due to lack of available data, as mentioned in chapter 3.4.

6.4 Cotton results

The following chapter contains the results for all cotton related equities. The net and overall spillover will be analyzed first and compared to the S&P 500 index. Then a rolling spillover analysis will be conducted with a comparison with the S&P 500 index just after. Finally, a summary of the cotton findings is given.

6.4.1 Cotton net and overall spillover

Table 8 contains the net and overall spillover between cotton and all equities.

Table 8: Net and overall spillover for cotton group

Cotton group	Companies	Net Spillover	Overall Spillover
Clothing manufacturers and retailers	Adidas	0.23	0.73
	H&M	0.08	0.16
	Inditex	-4.83	2.62
	Marks & Spencer	0.14	0.18
	Nike	0.82	1.21
Index for reference	S&P 500	0.21	1.83

The volatility for the cotton group is more from their own variance share than from spillovers. The group has low spillovers with cotton and the S&P 500 index has low volatility spillover too. The only company with excess spillover relative to the reference index is Inditex with an overall spillover of 2.62%. The stock prices of the group seem to be detached from the cotton price even though they use a lot of cotton in the manufacturing of their products.

The net spillover is very low for all the companies. All but Inditex are net givers even though the general level is very low. Inditex has the most net spillover with cotton of -4.8% and is the only company that is noticeably different from the reference index. In other words, only Inditex have more connectedness with cotton than the S&P 500 index, and still the connectedness is very low. Such small values as we see for the cotton group can mean that the spillovers observed are only noise.

6.4.2 Cotton rolling spillover

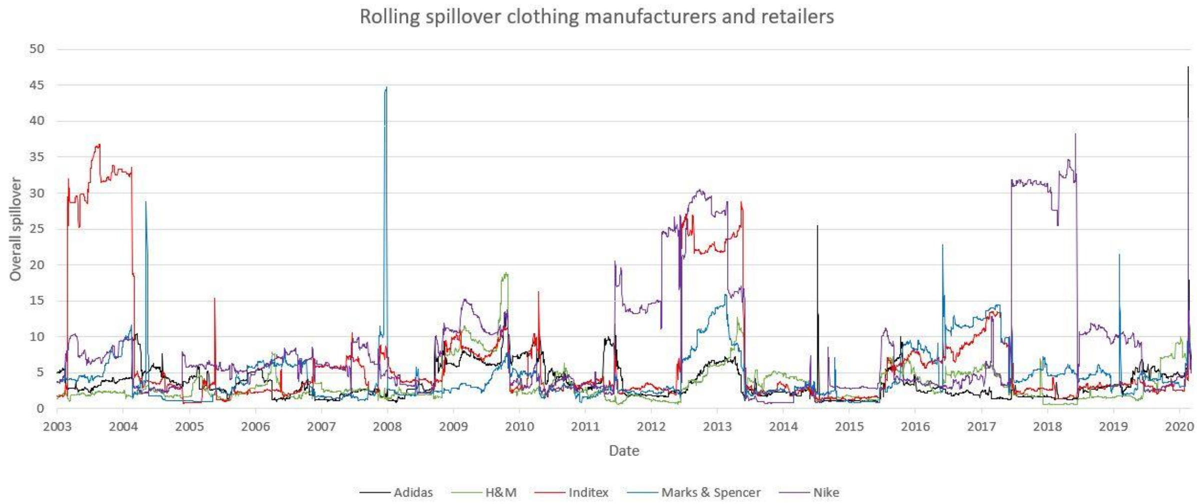

Figure 12: Rolling overall spillover for clothing manufacturers and retailers

Figure 12 shows that the general overall spillover between cotton and the companies is very low. Most of the time the companies have a volatility spillover ranging between about 1% and 10%. At different times throughout the period, single companies either spike or have longer periods with higher spillover, but they return to the other companies in all cases. These are discussed below.

Inditex stands out with high volatility spillover in 2003. During that period, the cotton price increased about 50% during the year before dropping. This can be seen in figure 3. At the same time, Inditex expanded rapidly (Tagliabue, 2003). The 4th quarter report for 2002 made the stock price fall considerably in March 2003 (Vincent, Kantor, and Geller, 2013). The connectedness between Inditex and cotton during the period can stem from a combination of the rising cotton prices, high volatility in a rapidly expanding company, and news that the stock market reacted heavily on.

Marks & Spencer spikes several times alone in the sample period. The first in May 2004, when the company was almost acquired, and the company appointed a new CEO just days afterwards (Wallop, 2006). This caused the company's stock price to increase by almost 30%, which may be the reason for the increased connectedness between M&S and cotton. M&S also spike with cotton reaching a volatility spillover of 45% around new year 2008. From an article in the financial times, the M&S stock price fell 18% in a day (Braithwaite & Rigby, 2008).

The article states that bad news from the company intensified investors' fear over a slowing economy and a falling housing market.

When the financial crisis hit in the end of 2008, all the companies in the group spiked, except for Marks & Spencer. As mentioned earlier, M&S had a big drop in its stock price earlier in the year and did not experience a big drop in September 2008. All the other companies in the sample increase their connectedness, but the level they reach is not particularly high compared to the other spikes visible in the figure. The connectedness is higher during the financial crisis than the general level in the sample, before returning to its low level. Looking at the price of cotton during that period, one sees that the price was not especially affected by the financial crisis compared to the other commodities in the thesis.

The cotton price surged and crashed in the beginning of 2011, which is not easy to find in figure 12 (except for Nike). This indicates that the real spillover effect between the cotton price and these companies is quite low, or that the companies drive the volatility spillover and not vice versa. The surge in price through 2010 and into 2011 does not seem to increase the connectedness of the companies in the group and the cotton price. The price surged as the demand in countries such as India and China increased drastically after the financial crisis (Braithwaite & Rigby, 2008; Cummans, 2011). At the time, India implemented an export ban which was a contributor to rising prices. During the surge in price, Cummans (2011) reported that clothing brands raised prices and then moved the higher costs of cotton to the consumers. As cotton reached a high price, the demand started to slow down at the same time as the supply was getting higher. Many farmers increased their cotton production to respond to the high prices, which led to the supply catching up to the demand and in the end exceeding it (Cummans, 2011).

The cotton price crash mentioned in the paragraph above, coincide with a spike in connectedness between Nike and cotton that lasts until mid-2013. Nike was quite public about sustainable cotton at the time. The company announced a goal of using 100% sustainable cotton by 2020 (Nike inc, n.d). Adidas released just about the same goal as Nike did in 2011 (Adidas group, 2011), but did not have a rise in connectedness during the cotton price drop. Nike's high spillover during the period might then just be a coincidence. Adidas is seen with an increase in connectedness with cotton during the price surge of cotton in 2010, but the spillover was not as high as that for Nike in the subsequent period. In august 2012, Inditex and

Nike have a high spillover with cotton. There are no big movements in the Inditex stock at the time and the cotton price is not especially volatile during the period either, so the reason for the higher connectedness might be a coincidence.

Adidas has a spike in connectedness with cotton in mid-2014. At the same time, the stock fell 13% in a day as Adidas announced that their net income forecast was lowered substantially after struggles in Russia (Kharpal, 2014). The article also states that the company slashed its targets for 2015. The next spike comes in May 2016 for M&S as the stock plummeted after a message from the CEO that their efforts to turnaround their business would hurt the profits of the company in the short term (Wood, 2016).

Nike has period from mid-2017 to mid-2018 with a high connectedness with cotton. The spike coincides with an almost 10% increase in the stock price after Nike released good 4th quarter results and a partnership with Amazon (Thomas, 2017). After that, there are no big volatility movements in either cotton or Nike that would suggest such a high spillover as seen in the figure during the period. The reason might be a coincidence or some reason we cannot find.

The last big spike is in 2020, when the Covid-19 pandemic led to extreme volatility in the financial markets. At the time of writing this thesis the pandemic is still ongoing and the effects of the pandemic is yet to be seen.

6.4.2.1 Comparison with S&P 500

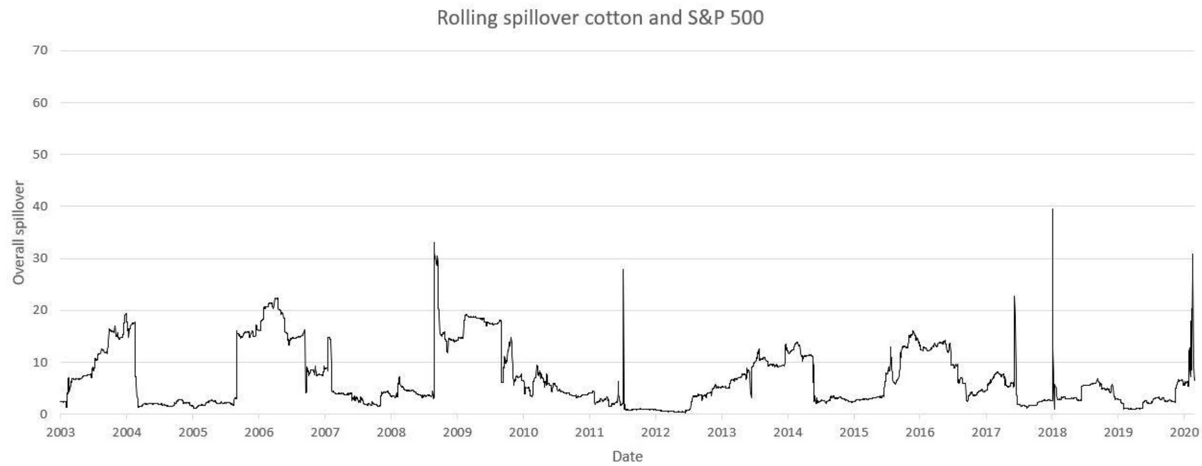

Figure 13: Rolling overall spillover between cotton and S&P 500

The rolling overall spillover between S&P 500 and cotton is shown in figure 13. During 2003, the cotton price increased about 50% during the year before dropping, and one sees an increase in spillover throughout 2003. The Financial crisis hitting in September 2008 is more visible in figure 13 where the spillover reaches around 30% while for the individual companies the spillover peaked at around 10% at the same time. The global economy seems to be relatively disconnected to the cotton price. While under extraordinary movements, the connectedness with financial markets increase. These are most likely due to large movements in all markets in those periods.

When the cotton price collapsed in June 2011 the only company that rise in connectedness is Nike. The S&P 500 rise in connectedness with cotton in August 2011, when the volatility in the American markets rose in august as mentioned earlier. If one looks at the figure that tracks the spillover between the S&P 500 and cotton, there is a tiny spike before the big spike in 2011. That tiny spike coincides with the cotton price drop. This implies that events in the stock markets play a bigger role in the spillover between cotton and S&P 500 than volatility in the cotton price.

The largest spike found in the S&P 500 figure is seen in 2018. At that time, there were no significant changes in the cotton price. As mentioned before, the VIX index doubled in a day. Thus, that spike is caused by high volatility in the financial markets rather than changes in the cotton price.

6.4.3 Summary cotton

A Master's thesis from UiS 2017 shows that the gross margins of H&M, Inditex and Uniqlo is not dependent of the cotton price. All three companies showed stable gross margins. They also state that there is a strategic difference between H&M and Inditex (Øgreid & Iversen, 2017). Inditex is fully integrated, making its own merchandise while H&M outsources its manufacturing. The gross margins staying stable through different cotton prices may explain the disconnectedness of the companies to the cotton price. Even though their findings only mention Inditex, H&M, and Uniqlo, there is no reason to believe that the other companies in the group should have a gross margin more dependent on the cotton price.

Overall, when interpreting the rolling spillover plot for the cotton companies, there seem to be company specific events that drive the overall spillover with cotton. When a stock has an extraordinary movement, there tends to be a spike in the spillover with cotton at the same time. However, when there are extraordinary movements in the cotton price, there is no clear trend that the connectedness with the companies increase. All in all, the cotton price and the stock prices tend to be quite disconnected.

6.5 Comparison between the commodity groups

From the results above it is evident that oil is the commodity that has the most spillover. Within the entire oil group, the average overall spillover equals 18.7%. For steel and cotton it equals 5.6% and 1.0%, respectively. By excluding the airlines in the oil group, the average overall spillover becomes 24.4%. This shows that the selected oil related companies for this thesis are significantly more connected to their commodity compared to both steel and cotton equities. Overall, most of the oil companies are net receivers of volatility, while the opposite is true for steel and cotton. However, in most cases, the net spillovers are so low that they are negligible.

Compared to the S&P 500 index, the average overall spillover of operators and service companies in the oil group have excess spillover, while the airlines are way below. In the steel group, building contractors are below while the car manufacturers have higher volatility spillover. Finally, all but Inditex in the cotton group have lower overall spillover than the reference index. The respective spillovers between S&P 500 and the commodities are 21.6%, 5.6% and 1.8% for oil, steel, and cotton. Keep in mind that for an oil company to have excess spillover relative to the index, it needs to have a higher overall spillover than the index. For example, oil companies need at least an overall spillover of 21.6% to have excess spillover. All but one operator and service company have this level of connectedness, while only one company within cotton have a higher level of connectedness than the reference of 1.8%. This indicates that oil is the commodity with the greatest connectedness with its respective equities as well as to the stock market. Looking at the net spillover for the S&P 500, oil is the only commodity that is a net giver to the index, while steel and cotton both receive volatility from the reference index. This is in line with what we see from the companies within the groups.

Before the financial crisis, as seen in the rolling spillover plots, the overall spillover is low with exceptions of some single companies spiking. As we reach the financial crisis, there is a distinct difference between the groups. Operators, service companies, building contractors and, car manufacturers exceed a volatility spillover of 40%. Airlines and clothing brands barely exceed

20% and 10%, respectively. The financial crisis is also seen in the S&P 500 plots. One interesting note is that for the cotton group, the S&P 500 spikes way higher than the single companies.

Across the groups, the overall spillover level seems to return after the financial crisis with exceptions of single companies spiking. This is true for all but the operators and service companies which have had prolonged periods of higher volatility spillovers.

Another difference between the commodity groups is the assumed cause of higher volatility spillovers. In both operators and service companies, several of the periods with high volatility are due to changes in the oil price. The fact that all companies move simultaneously proves this point. Compared to cotton, as the price of cotton change, only single companies have increased volatility spillover. Generally, oil related companies are more affected by changes in the oil price than what steel and cotton related companies are. An example is the oil-crisis in 2014 causing all the companies in the operator and service groups to spike. As opposed to the cotton prices collapsing in 2011 when only Nike had a visible change in the volatility spillover.

Looking at the rolling overall spillover between the S&P 500 index and the different commodities there are events that are seen in all the figures: the financial crisis, the volatility spikes in 2011 and 2018, and the covid-19 pandemic in 2020. These events caused high uncertainty in the financial markets. The fact that commodities have become more financialized as described in chapter 2.6 may be a contributing factor to why the volatility spillover increased in these periods. The spikes do reach different heights for the different commodities. For example, the financial crisis comes with a higher spike in connectedness for steel and oil with the S&P 500 index. That may be because the oil and steel prices also experienced a big drop at the same time, but it may also reflect the importance of oil and steel on the global stock markets compared to cotton.

When comparing across the commodity groups, the companies related to oil are most affected. Keep in mind that the two groups with the largest overall spillover, operators and service companies, are the only two on the production side of their related commodity. However, when compared to the S&P 500, the average excess spillover relative to the index for operators are lower than for car manufacturers, while service companies have higher excess spillover. There are only companies on the production side of the commodity in the oil group in this thesis. To further investigate this subject, it would be beneficial to find more production companies of oil as well as companies on the production side of steel and cotton that is listed on an exchange.

7 Conclusion

For this thesis, we have gathered daily closing prices of oil, steel, and cotton. In addition, a total of 22 companies' stock prices have been gathered from January 2002 to April 2020. Eleven of these are related to oil, while six and five are related to steel and cotton, respectively. The oil companies are sorted into operators, service companies, and airlines. The steel companies are sorted into building contractors and car manufacturers, while cotton has clothing manufacturers and retailers. The closing prices are used to calculate the volatility spillovers between each company and its related commodity. These spillovers are calculated using the generalized spillover index developed by Diebold and Yilmaz (2009; 2012). Our results suggest that there are big differences between the commodity groups and their related equities. However, we find similarities within each of the company groups. Further, the spillover levels are time varying consisting of several periods with high spillover.

Within the oil group, operators and service companies have a larger connectedness to the oil price than airlines do. Operators and service companies have the highest overall spillover out of all the company groups. Both groups have higher spillover than the S&P 500 index. These spillovers are only moderate with the highest spillover value of 34% seen for Halliburton. Overall, the airlines do not seem to be connected to the oil price to the same degree as the other two. In general, all company groups are net receivers of volatility spillover. The spillovers are time varying, where the time after the financial crisis have a higher level of volatility spillover than before. Other periods with high spillover are related to the oil crisis, the outbreak of the covid-19 pandemic as well as company related events such as the Deepwater Horizon accident.

In the steel group, car manufacturers have a higher overall volatility spillover than the building contractors. Compared to the S&P 500 index, the building contractors have lower overall spillover while the car manufacturers have higher. However, these spillovers are relatively low with the highest value of 13% seen in Daimler. Both company groups and the S&P 500 index are net givers of volatility to the steel price. One thing to note is that the car manufacturers have particularly high net spillover compared to the rest, and the net spillover is higher than the overall spillover. The spillover varies over time with spikes during the financial crisis, the uncertainty surrounding Brexit, the presidential election, steel tariffs, and the covid-19 pandemic. High volatility spillover does also originate from company related events.

The cotton group has very low volatility spillover, where Inditex has the largest spillover of 3%. All but Inditex have lower overall spillover compared to the S&P 500 index. In addition, Inditex is the only company that are a net receiver of volatility from cotton. The rest of the companies have close to 0% net spillover. The general spillover level is low throughout the period and there is not a single event that cause every company to spike simultaneously to a volatility spillover above 10%. The spikes that do exceed such a level of volatility spillover are company specific events like M&S in 2004, Nike in 2011, and Adidas 2018. The spillovers found in cotton seems to be connected to company related events and not changes in the price of cotton.

A comparison of the commodity groups shows that the oil group has by far the largest volatility spillover and cotton the lowest. In the oil group, several cases of high volatility are due to changes in the oil price. In the steel group, some events are due to steel prices and some due to company related events. Companies in the cotton group does not seem to be subjected to high volatility due to changes in the cotton price. Finally, it seems that all commodities experience a higher volatility spillover than normal during macroeconomic events and periods of uncertainty.

The results from this thesis show that single companies have relatively low spillover with their related commodities in steady market conditions. However, they have increased spillover with the commodity during highly volatile times and company specific events. The rolling spillover plots show that there are spikes in all the assets during some events in the data set, like the financial crisis and the covid-19 pandemic. This is in line with the theory from chapter 2.6 about the financialization of the commodity markets and that investors sell off their positions across asset classes during times of falling prices. This information can be of good use for investors when constructing portfolios.

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9 Appendix

9.1 Appendix A: Spillover analysis in R

To obtain our results, all analysis is executed using a program called R. R is a program used for graphical and statistical purposes and is also known as a very extensible program. Two of its great advantages is its simplicity and the ability to download and install packages (The R foundation). To fully utilize the spillover index developed by Diebold and Yilmaz (2012), it is required to download a package called "frequencyConnectedness" using the comprehensive R Archive Network (CRAN). The "frequencyConnectedness" package is developed by Krehlik (2020) and will be further described below.

The downloaded data from Thomson Reuters Eikon needs to be prepared before they are used in the formulas found in the "frequencyConnectedness" package. Firstly, the assets analyzed is not necessarily traded on the same dates. Therefore, we need to match the trading dates. To do that, a *match* function is used. If there is a date where not all assets are traded, R will return NA's in the dataset. Those dates are removed from our dataset using a *na.omit* function. Then the data set contains closing prices from only the dates where all assets are traded. The final step is to create squared log returns from the closing prices. Once these steps are executed, the data is ready to be used in the "frequencyConnectedness" package.

To utilize the "frequencyConnectedness" package, another package is required. That package is known as "vars" (Pfaff & Stigler, 2018). When downloading "frequencyConnectedness", this package is automatically downloaded. The "vars" package makes it easier to create a VAR-model which is used when calculating spillover. To create a VAR-model, the first step is to determine how many lags to use. In R, this function looks like this:

VARselect(y, lag.max = 10, type = c("const", "trend", "both", "none")

This function gives a recommended number of lags using the four criteria explained in subchapter 4.5.4 (AIC, SC, FPE and HQ). The *y* input is a matrix containing the squared log returns from the commodity and an asset. *lag.max* is the maximum number of lags to test for and is by default set to 10. *type* says something about which deterministic regressors to include in the calculation (Pfaff & Stigler, 2018).

Once the number of lags to include is determined, the next step would be to create a VAR-model. This is achieved using the following function:

VAR(y, p = 1, type = c("const", "trend", "both", "none")

For this function, the *y* and *type* arguments are the same as described above. The *p*, however, represents the number of lags. The number of lags used in the VAR function depends on the output from VARselect (Pfaff & Stigler, 2018).

Once the VAR-model is defined, one can continue to calculate spillovers using the "frequencyConnectedness" package. The average spillover of the data sets can be calculated by using this function:

spilloverDY12(est, n.ahead = 100, no.corr)

The argument *est* refers to the VAR-model calculated using the VAR function above. The *n.ahead* refers to how many periods should be calculated ahead. It is important that this number is set high enough so that the results does not change by adding an additional period. The final argument *no.corr*, determines whether the off-diagonal elements of the covariance matrix should be set to zero (Krehlik, 2020).

The function above captures the average spillover over the entire sample period. However, it might be more interesting to see how the spillover changes over time during different market conditions. This can be achieved by calculating rolling spillover. The function is as follows:

spilloverRollingDY12(data, n.ahead = 100, no.corr, func_est, params_est, window)

The arguments *n.ahead* and *no.corr* are the same as above. *data* is a variable that includes the dataset. In our case, this is the volatility matrix containing a commodity and a related equity. *func_est* describes the estimation function. This is typically a VAR-model. *params_est* is a list of parameters to be used in the estimation function. Finally, the *window* argument is the length of the window to be rolled (Krehlik, 2020). *spilloverRollingDY12* returns a list of spillover models in the same form such as *spilloverDY12* does. By using the function *overall(),* we can extract a list of all overall spillovers over the sample period. These overall spillovers can then be plotted against the trading dates to make a plot of the spillover.

9.2 Appendix B: Overall and net spillover

	Oil	BP	Contribution from others
Oil	76.46	23.54	23.54
BP	24.93	75.07	24.83
Contribution to others	24.93	23.54	
Contribution incl. own	101.39	98.61	**Overall spillover:**
Net spillover	1.39	-1.39	**24.23**

	Oil	Chevron	Contribution from others
Oil	86.65	13.35	13.35
Chevron	30.66	69.34	30.66
Contribution to others	30.66	13.35	
Contribution incl. own	117.31	82.69	**Overall spillover:**
Net spillover	17.31	-17.31	**22.01**

	Oil	Equinor	Contribution from others
Oil	74.33	25.67	25.67
Equinor	25.21	74.79	25.21
Contribution to others	25.21	25.67	
Contribution incl. own	99.54	100.46	**Overall spillover:**
Net spillover	-0.46	0.46	**25.44**

	Oil	ExxonMobil	Contribution from others
Oil	88.65	11.35	11.35
ExxonMobil	13.60	86.40	13.60
Contribution to others	13.60	11.35	
Contribution incl. own	102.25	97.75	**Overall spillover:**
Net spillover	2.25	-2.25	**12.47**

	Oil	Shell	Contribution from others
Oil	77.47	22.53	22.53
Shell	25.78	74.22	25.78
Contribution to others	25.78	22.53	
Contribution incl. own	103.25	96.75	**Overall spillover:**
Net spillover	3.25	-3.25	**24.16**

	Oil	Baker Hughes	Contribution from others
Oil	80.61	19.39	19.39
Baker Hughes	22.26	77.74	22.26
Contribution to others	22.26	19.39	
Contribution incl. own	102.87	98,61	**Overall spillover:**
Net spillover	2.87	-2.87	**20.83**

	Oil	Halliburton	Contribution from others
Oil	65.85	34.15	34.15
Halliburton	34.32	65.68	34.32
Contribution to others	34.32	34.15	
Contribution incl. own	100.17	99.83	**Overall spillover:**
Net spillover	0.17	-0.17	**34.23**

	Oil	Schlumberger	Contribution from others
Oil	68.48	31.52	31.32
Schlumberger	31.99	68.01	31.99
Contribution to others	31.99	31.32	
Contribution incl. own	100.47	99.53	**Overall spillover:**
Net spillover	0.47	-0.47	**31.76**

	Oil	Air France-KLM	Contribution from others
Oil	97.28	2.72	2.72
Air France-KLM	3.86	96.14	3.86
Contribution to others	3.86	2.72	
Contribution incl. own	101.14	98.86	**Overall spillover:**
Net spillover	1.14	-1.14	**3.29**

	Oil	Lufthansa	Contribution from others
Oil	95.64	4.36	4.36
Lufthansa	7.50	92.50	7.50
Contribution to others	7.50	4.36	
Contribution incl. own	103.14	96.86	**Overall spillover:**
Net spillover	3.14	-3.14	**5.93**

	Oil	SAS	Contribution from others
Oil	98.68	1.32	1.32
SAS	1.17	98.83	1.17
Contribution to others	1.17	1.32	
Contribution incl. own	99.85	100.15	**Overall spillover:**
Net spillover	-0.15	0.15	**1.24**

	Oil	S&P 500	Contribution from others
Oil	84.15	15.85	15.85
S&P 500	27.25	72.75	27.25
Contribution to others	27.25	15.85	
Contribution incl. own	111.40	88.60	**Overall spillover:**
Net spillover	11.40	-11.40	**21.55**

	Steel	Fluor	Contribution from others
Steel	97.34	2.66	2.66
Fluor	0.03	99.97	0.03
Contribution to others	0.03	2.66	
Contribution incl. own	97.37	102.63	**Overall spillover:**
Net spillover	-2.63	2.63	**1.34**

	Steel	Skanska	Contribution from others
Steel	97.84	2.16	2.16
Skanska	1.15	98.85	1.15
Contribution to others	1.15	2.16	
Contribution incl. own	98.99	101.01	**Overall spillover:**
Net spillover	-1.01	1.01	**1.66**

	Steel	Vinci	Contribution from others
Steel	92.31	7.69	7.69
Vinci	3.02	96.98	3.02
Contribution to others	3.02	7.69	
Contribution incl. own	95.33	104.67	**Overall spillover:**
Net spillover	-4.67	4.67	**5.36**

	Steel	Daimler	Contribution from others
Steel	76.26	23.74	23.74
Daimler	1.32	98.68	1.32
Contribution to others	1.32	23.74	
Contribution incl. own	77.58	122.42	**Overall spillover:**
Net spillover	-22.42	22.42	**12.53**

	Steel	Ford	Contribution from others
Steel	90.71	9.29	9.29
Ford	0.19	99.81	0.19
Contribution to others	0.19	9.29	
Contribution incl. own	90.9	109.1	**Overall spillover:**
Net spillover	-9.1	9.1	**4.74**

	Steel	Toyota	Contribution from others
Steel	85.52	14.48	14.48
Toyota	1.90	98.1	1.90
Contribution to others	1.90	14.48	
Contribution incl. own	87.42	112.58	**Overall spillover:**
Net spillover	-12.58	12.58	**8.19**

	Steel	S&P 500	Contribution from others
Steel	90.81	9.19	9.19
S&P 500	2.01	97.99	2.01
Contribution to others	2.01	9.19	
Contribution incl. own	92.82	107.18	**Overall spillover:**
Net spillover	-7.18	7.18	**5.6**

	Cotton	Adidas	Contribution from others
Cotton	99.16	0.84	0.84
Adidas	0.61	99.39	0.61
Contribution to others	0.61	0.84	
Contribution incl. own	99.77	100.23	**Overall spillover:**
Net spillover	-0.23	0.23	**0.73**

	Cotton	H&M	Contribution from others
Cotton	99.80	0.20	0.20
H&M	0.12	99.88	0.12
Contribution to others	0.12	0.20	
Contribution incl. own	99.92	100.08	**Overall spillover:**
Net spillover	-0.08	0.08	**0.16**

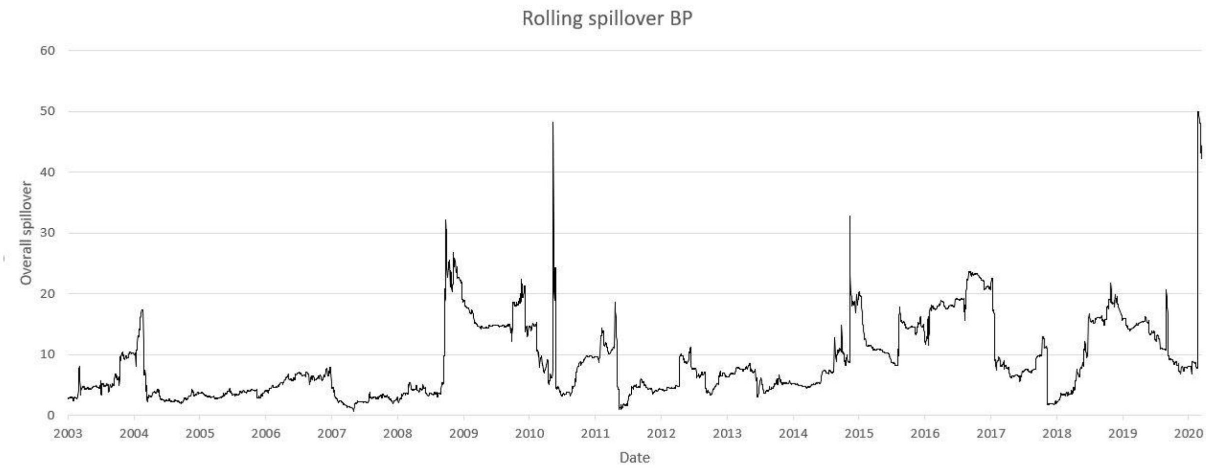
	Cotton	Inditex	Contribution from others
Cotton	99.79	0.21	0.21
Inditex	5.04	94.96	5.04
Contribution to others	5.04	0.21	
Contribution incl. own	104.83	95.17	**Overall spillover:**
Net spillover	4.83	-4.83	**2.62**

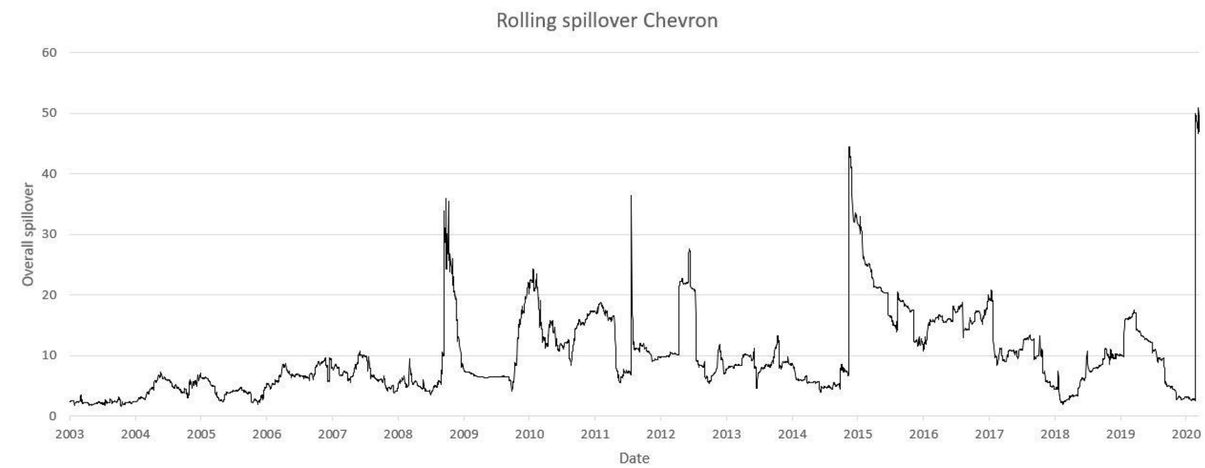
	Cotton	Marks & Spencer	Contribution from others
Cotton	99.75	0.25	0.25
Marks & Spencer	0.11	99.89	0.11
Contribution to others	0.11	0.25	
Contribution incl. own	99.86	100.14	**Overall spillover:**
Net spillover	-0.14	0.14	**0.18**

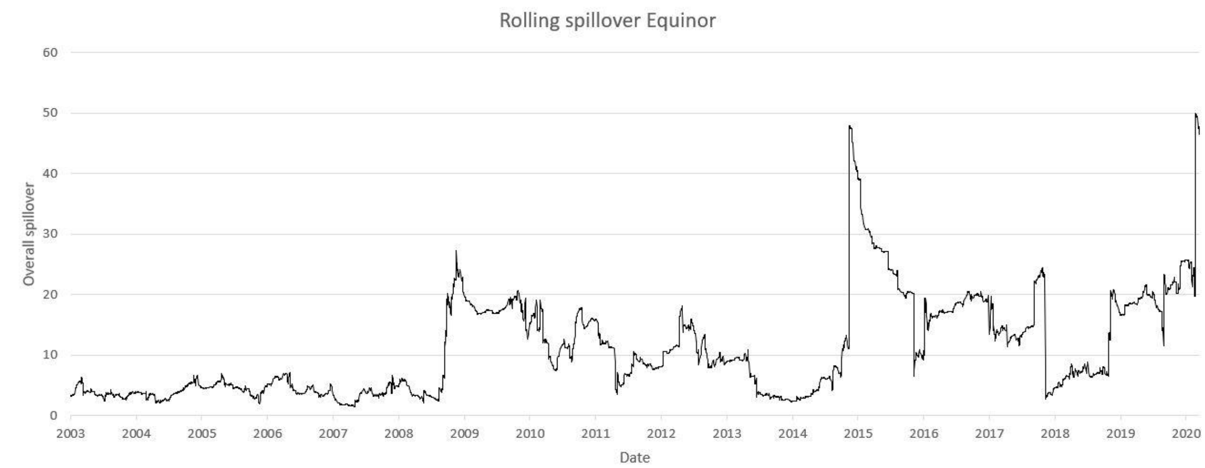
	Cotton	Nike inc.	Contribution from others
Cotton	98.38	1.62	1.62
Nike inc.	0.80	99.20	0.80
Contribution to others	0.80	1.62	
Contribution incl. own	99.18	100.82	**Overall spillover:**
Net spillover	-0.82	0.82	**1.21**

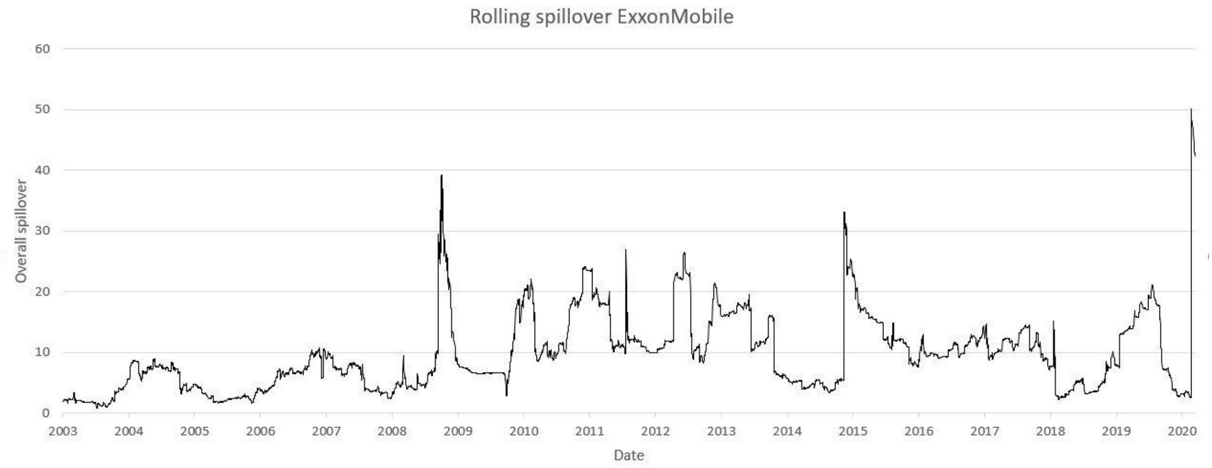
	Cotton	S&P 500	Contribution from others
Cotton	98.06	1.94	1.94
S&P 500	1.73	98.27	1.73
Contribution to others	1.73	1.94	
Contribution incl. own	99.79	100.21	**Overall spillover:**
Net spillover	-0.21	0.21	**1.83**

9.3 Appendix C: Rolling spillover figures








Rolling spillover ExxonMobile
Overall spillover
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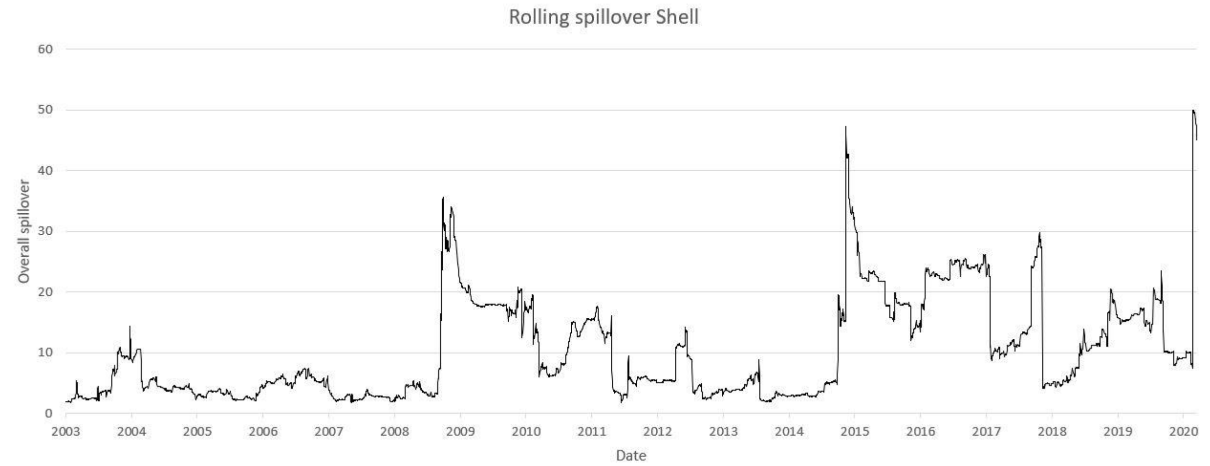
Rolling spillover Shell
Overall spillover
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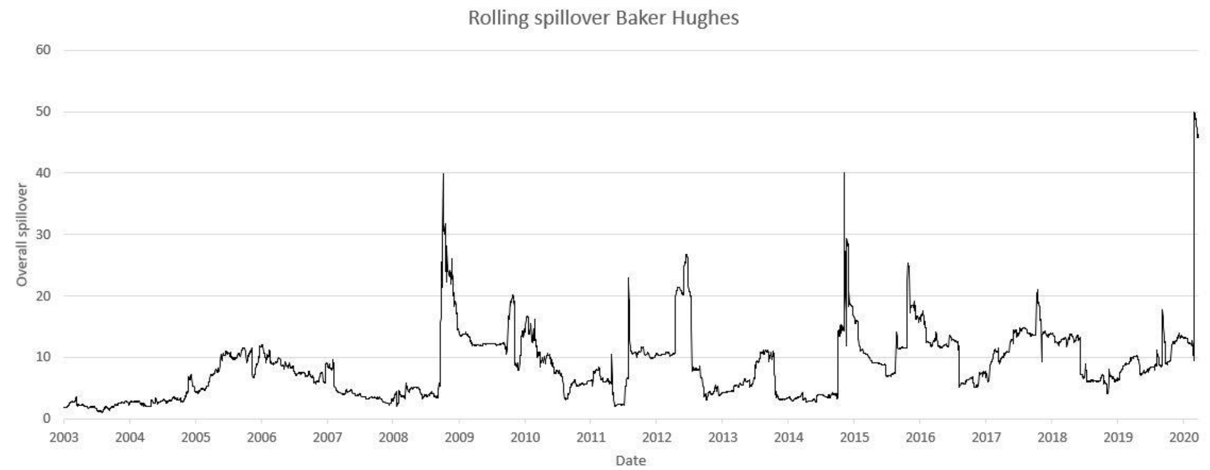
Rolling spillover Baker Hughes
Overall spillover
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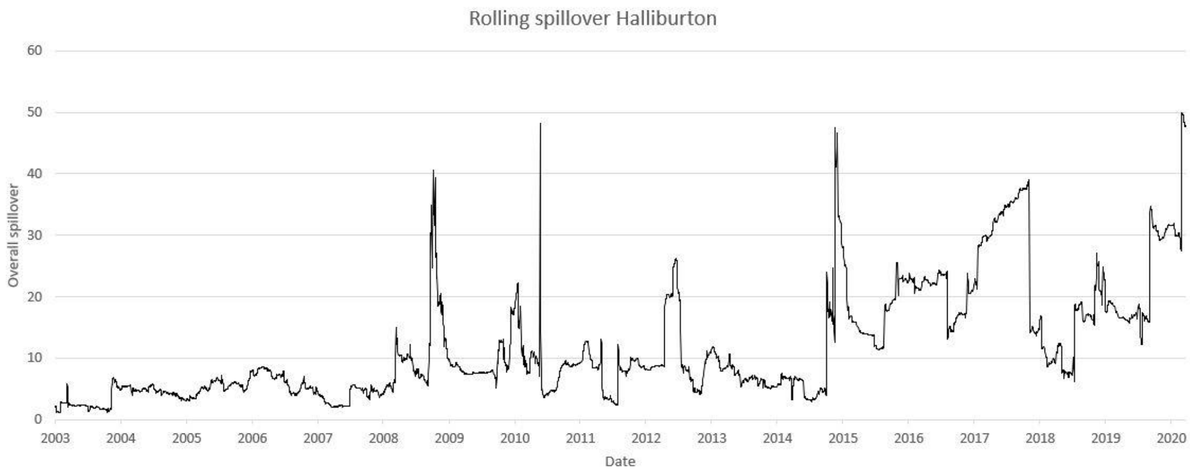

Rolling spillover Halliburton
Overall spillover
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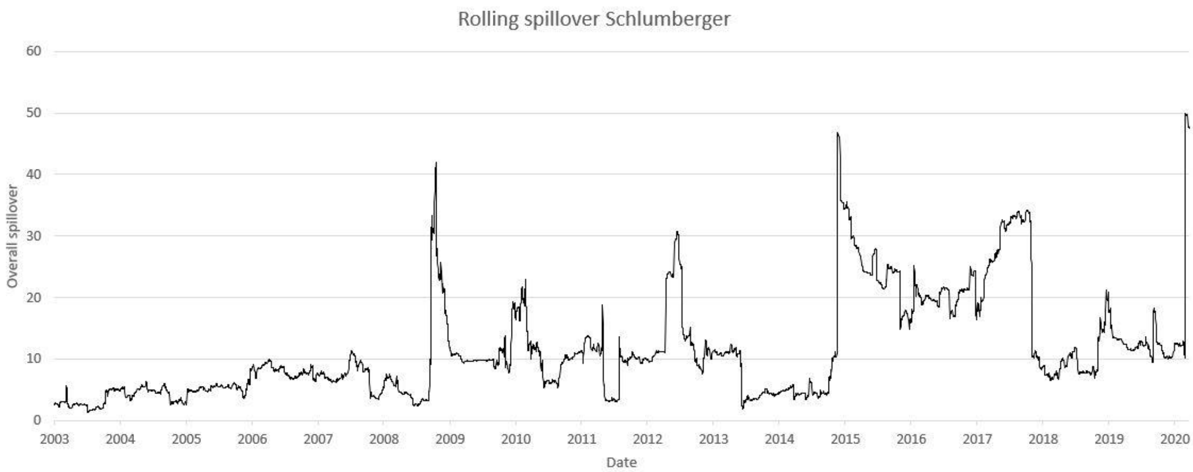

Rolling spillover Schlumberger
Overall spillover
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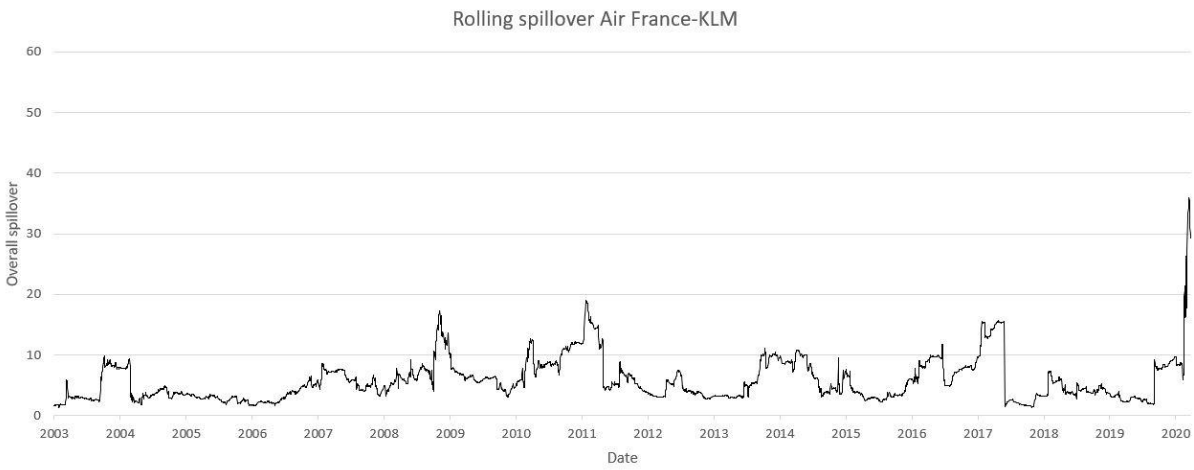

Rolling spillover Air France-KLM
Overall spillover
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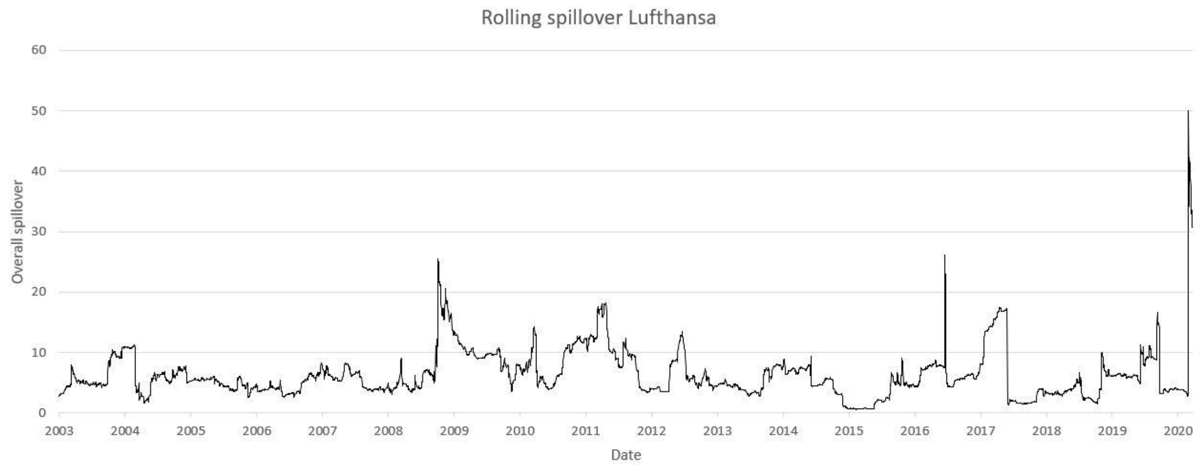
Rolling spillover Lufthansa
Overall spillover
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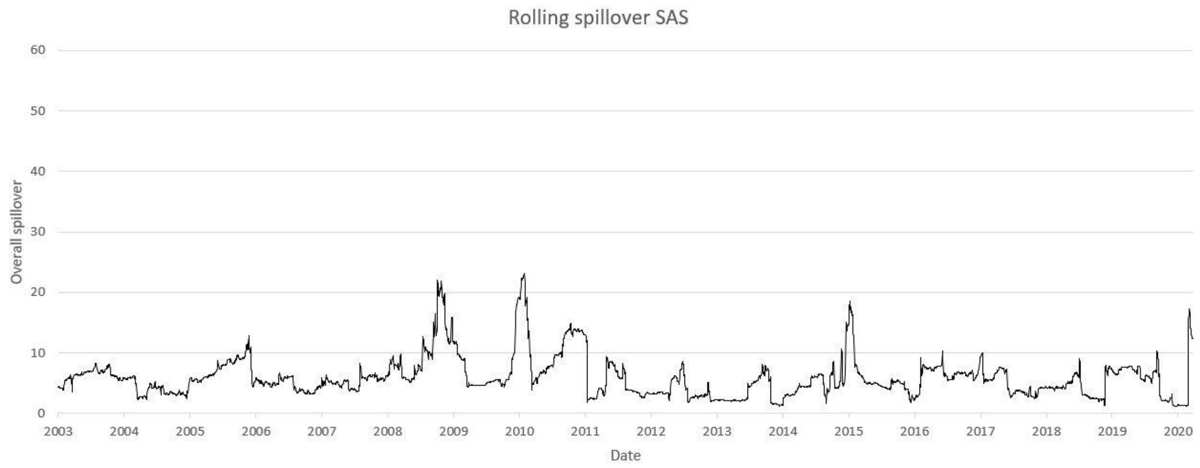
Rolling spillover SAS
Overall spillover
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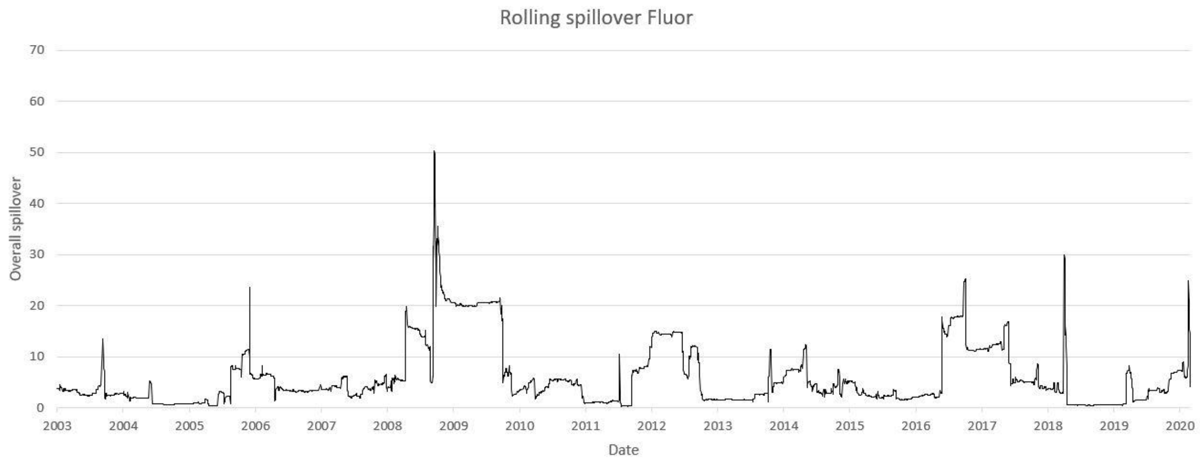
Rolling spillover Fluor
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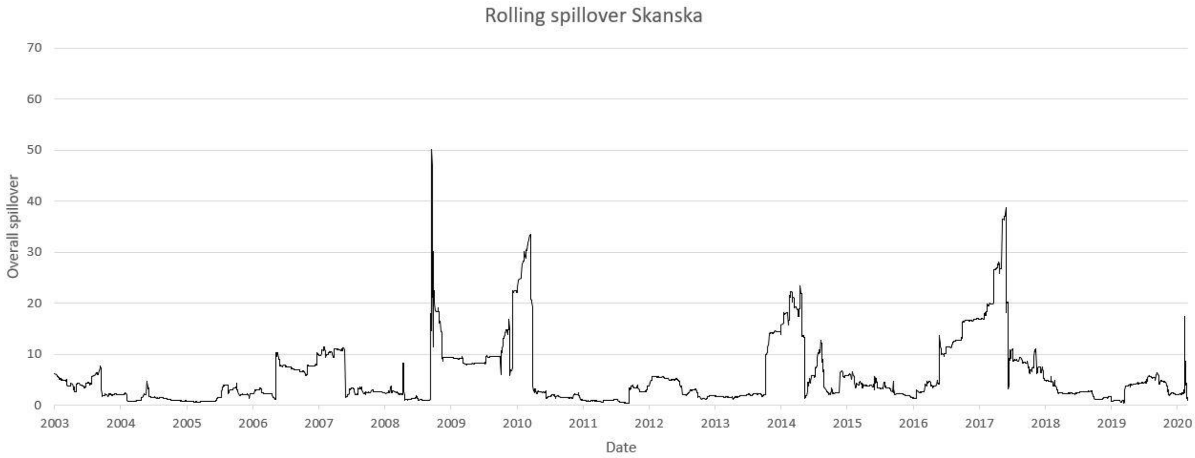
Rolling spillover Skanska
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Overall spillover
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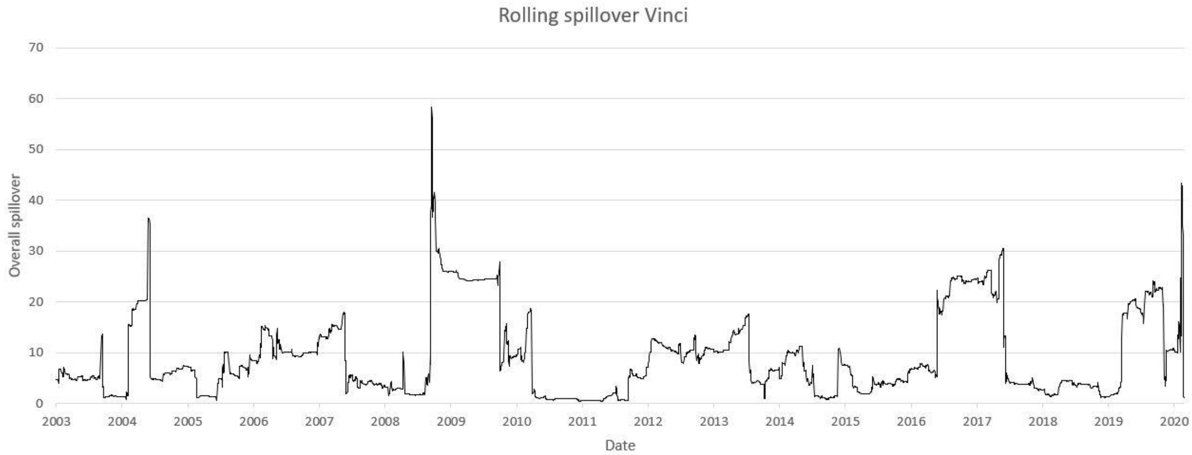
Rolling spillover Vinci
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Overall spillover
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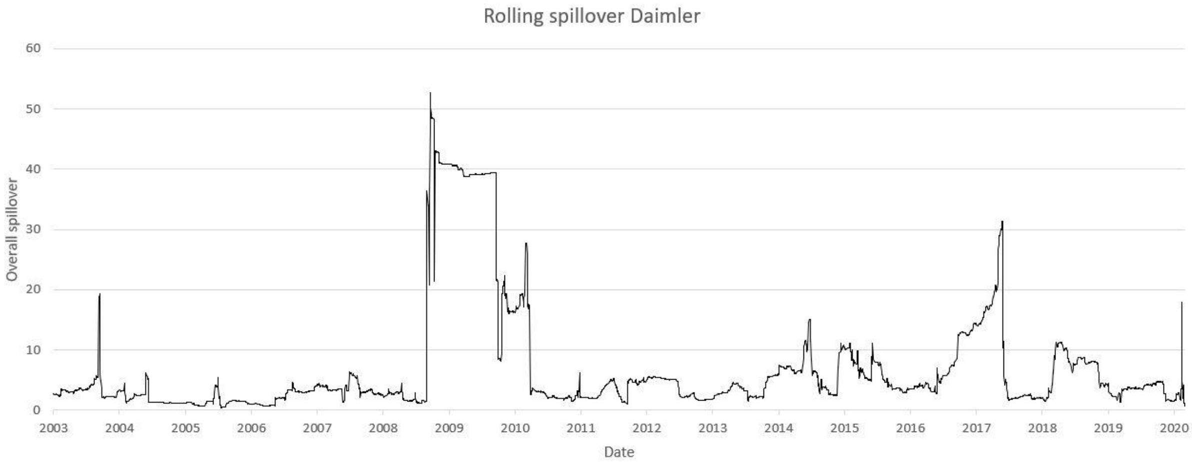
Rolling spillover Daimler
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Overall spillover
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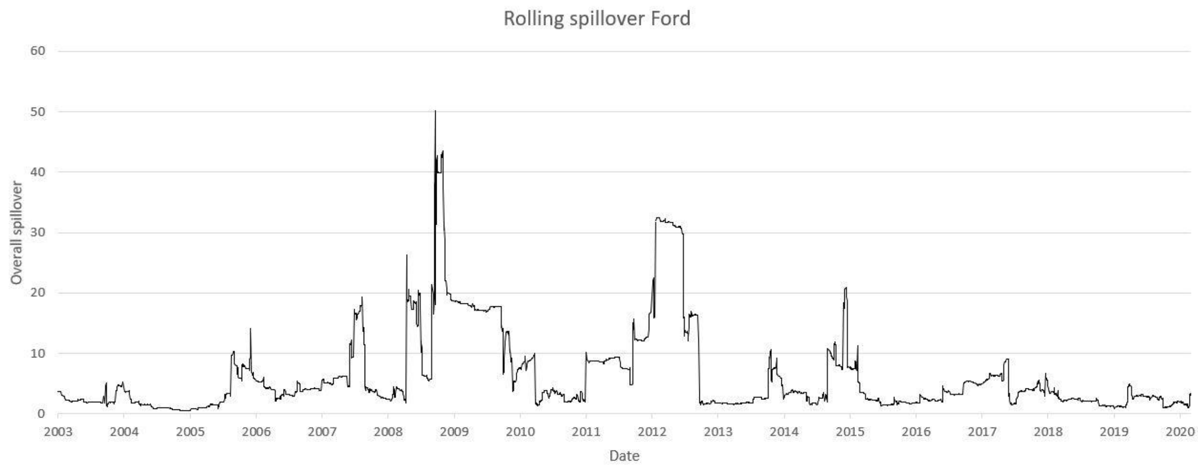
Rolling spillover Ford
Overall spillover
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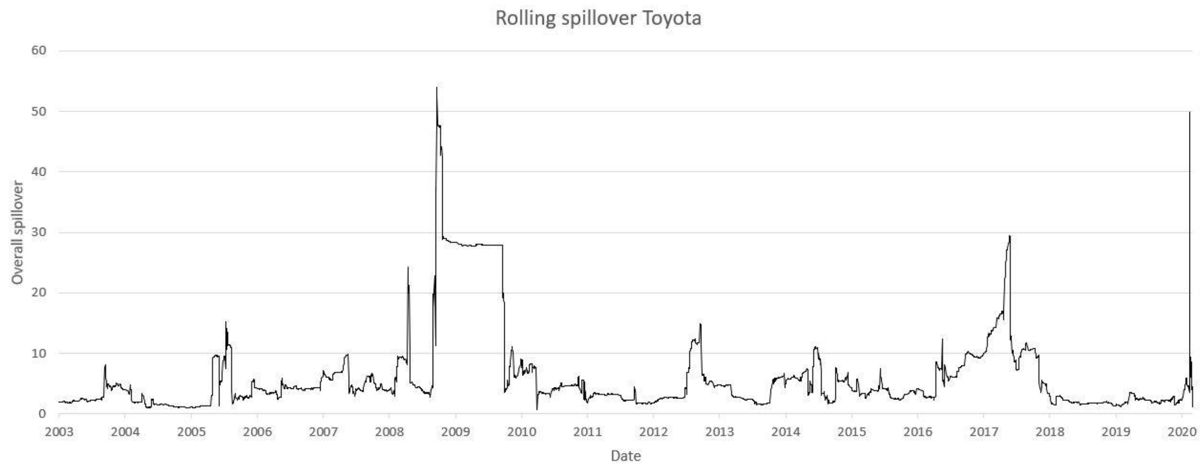
Rolling spillover Toyota
Overall spillover
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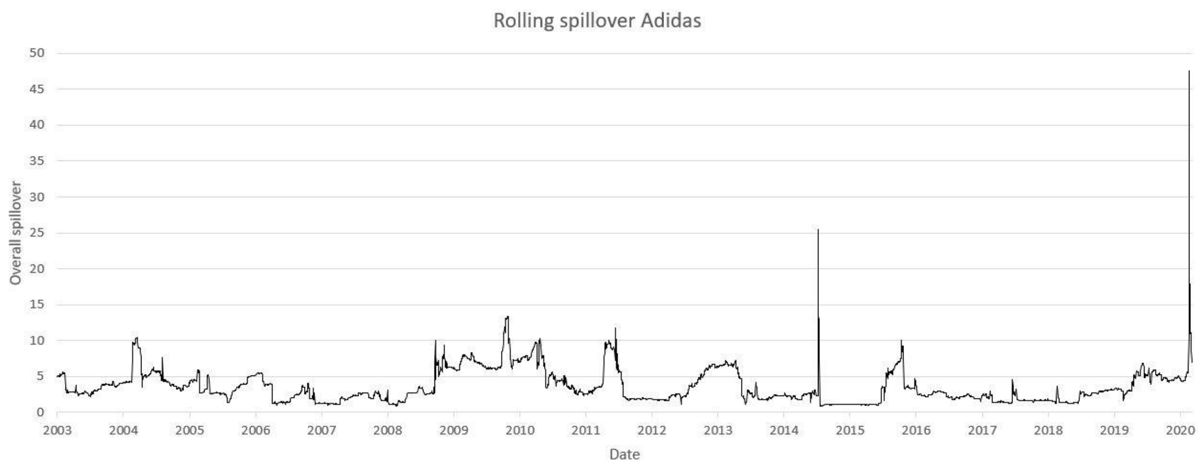
Rolling spillover Adidas
Overall spillover
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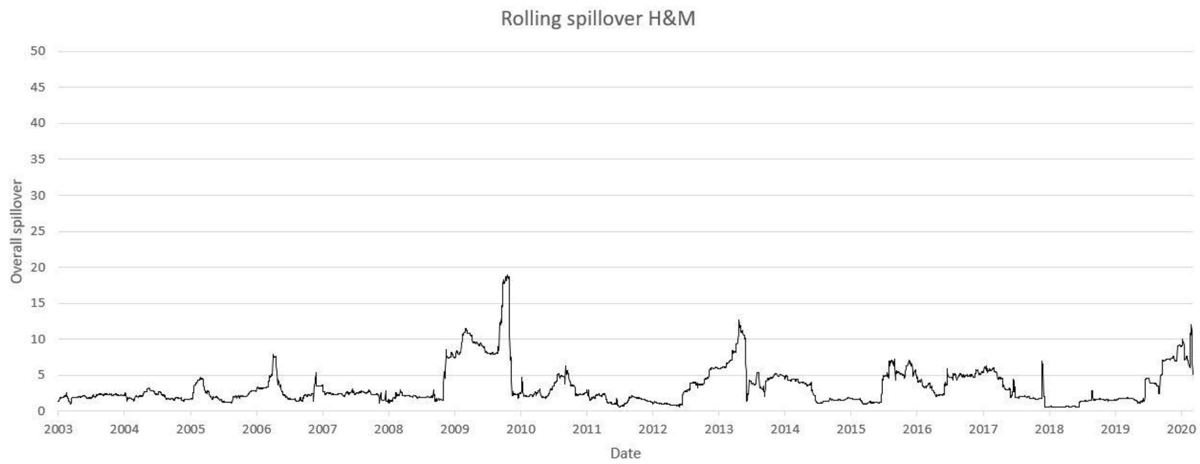
Rolling spillover H&M
Overall spillover
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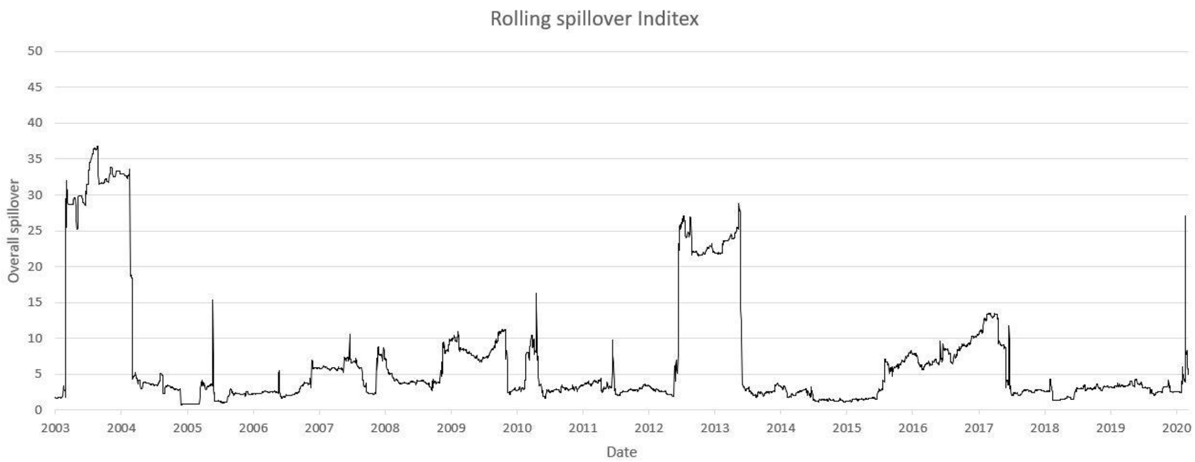
Rolling spillover Inditex
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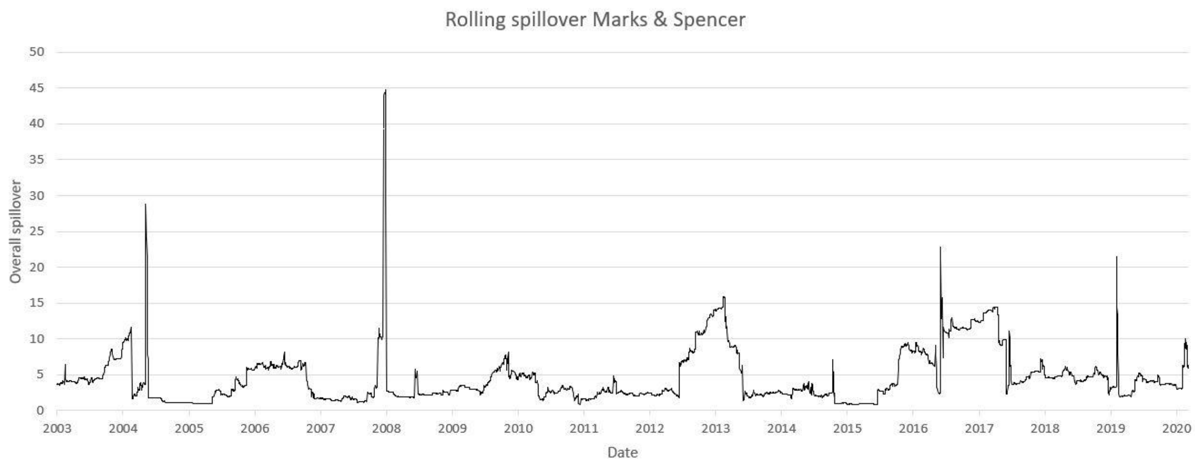
Rolling spillover Marks & Spencer
Overall spillover
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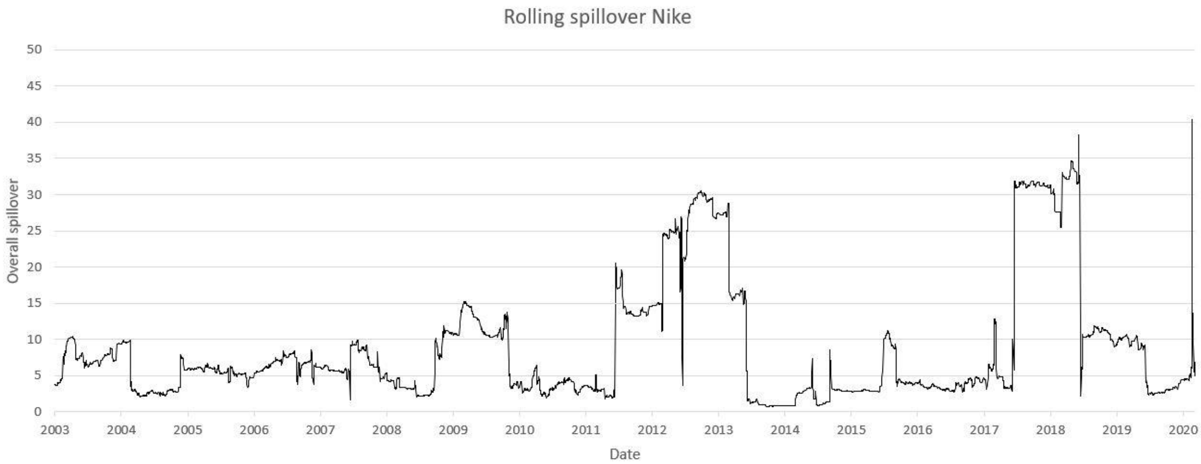
Rolling spillover Nike
Overall spillover
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