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Volatility spillovers between meat markets, feed markets and energy markets

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List of acronyms

ADF	Augmented Dickey-Fuller
AIC	Akaike information criterion
CBOT	Chicago Board of Trade
CME	Chicago Mercantile Exchange
DF	Dickey-Fuller
FEV	Forecast error variance
FEVD	Forecast error variance decomposition
GARCH	Generalized autoregressive conditional heteroskedasticity
GFEVD	Generalized forecast error variance decomposition
GI	Generalized impulse response function
HQIC	Hannan-Quinn information criterion
MGARCH	Multivariate generalized autoregressive conditional heteroskedasticity
MMT	Million metric tons
MSE	Mean squared error
NYMEX	New York Mercantile Exchange
OLS	Ordinary least squares
SIC	Schwarz information criterion
SRW	Soft Red Winter
VAR	Vector autoregressive
VMA	Vector moving average

1 Introduction

The commodity price crisis in 2008, besides surging commodity prices also caused an unprecedented interest of the scientific community in price volatility and volatility linkages in commodity markets (Minot 2014). Price volatility is a concept that estimates the extent of price variability over time. This variability of a commodity price at a certain point in time can be spilled over into other commodity markets. News in one market can have implications for other markets and vice versa, which results in volatility relationships between markets that share information. Traders in commodity exchanges use these relationships between markets to continuously adjust their future expectation of a price to new market intelligence. Thus they can forward price variations in one market to another market based on their perception of market interconnectivity. The focus in research regarding commodity price volatility relationships in recent times has been on linkages between the energy and agricultural sector. An increasing demand for agricultural raw materials originated in the energy sector after policies have been introduced in several countries that stimulated the production of crude oil substitutes, based on agricultural inputs. This linkage of the agricultural market to the energy market provides many opportunities for traders to speculate or to hedge their market price risk since a price movement in one market can be answered by a corresponding price movements in the other market.

Another substantial shift in the demand for agricultural staples occurred due to developments in the livestock sector. The global per capita consumption of meat-based proteins almost doubled throughout the last four decades, while the overall share of proteins in the human diet remains constant. Thus, proteins originating in plants are increasingly replaced by proteins obtained from the livestock sector. A good example for this development is to be found in China where meat consumption per capita per day was surging from 4.2 grams in 1961 to 37.2 grams in 2011. Feed conversion ratios translate this into an increasing total calorie demand since producing one livestock calorie requires several feed calories. The vast increases in meat consumption concentrate on emerging economies such as China, Brazil or Mexico, but also high income countries like Japan or Spain significantly increased their consumption levels (Sans and Combris 2015). The increasing demand for meat in these nations also affects other economies. According to FAOSTAT the USA, which is the largest global pork exporter, experienced almost a 7000 percent increase in its pork meat exports since 1961 with Japan and Mexico depicting the largest importers (USDA 2017a).

The objective of this thesis is to determine the effect that increasing meat consumption has on the volatility relationship between livestock and crop futures prices. Furthermore, due to the competition between the livestock and energy sector for scarce agricultural resources, which increases the amount of information shared between the two sectors, the energy sector is also a part of the analysis. Ultimately, the thesis will answer the following four research questions:

Did the total volatility spillovers between the meat market, feed market and energy market increase over time?

Is the flow of volatility happening unidirectional from input into output markets?

Which commodities transmit and which commodities receive more volatility over time?

What is the influence of the energy sector on volatility spillovers?

Until recently the methodological focus in volatility related studies has been almost exclusively on GARCH-type models, which were introduced by Bollerslev (1986) as an extension to Engle (1982). Anyway, the methodology applied in this thesis is built upon an alternative estimation procedure, which was introduced by Diebold and Yilmaz (2012). This approach allows for an extended market network and can capture time-varying effects in the data sample. The thesis does not figure as an attempt to compare the two methodologies or to provide any form of statement regarding superiority of one to the other.

The thesis is divided into six distinct sections. After the introductory chapter the literature review begins, which familiarizes the reader with the markets included in the analysis and presents relevant results regarding volatility in the futures market and volatility spillovers between the commodity markets. In chapter three the methodology applied in the analysis is elaborated, introducing first a stationarity test for time series data and afterwards going into vector autoregressive models and their capabilities to analyze relationships between variables in a multivariate time series setup. The indices to measure the volatility spillovers are established at the end of chapter three. The subsequent chapter four contains the model specification and estimation plus an extended description of the data. In chapter five the empirical results of the volatility spillover indices are presented successively and discussed at the end of the chapter. The thesis ends with a brief summary and concluding remarks in chapter six.

2 Literature review

This chapter gives an overview about the most relevant aspects regarding the fundamental developments in the agricultural sector with respect to the increasing meat consumption and its evolving relationship to the energy sector. Furthermore, the commodity futures market itself is introduced. Literature is used to identify the patterns that these developments caused regarding commodity price volatility spillovers. Following this goal, the chapter first introduces the relevant markets and subsequently volatility in the futures market and volatility spillovers within the agricultural markets as well as between the agricultural and energy markets are discussed. Price developments of the individual commodities are presented with the data in chapter four.

2.1 Futures market

The first futures market was established 1848 in Chicago, namely the Chicago Board of Trade (CBOT). The purpose of this new institution was to provide a location for all grain suppliers and customers to conduct their business. In 2007 the CBOT merged with its greatest competitor, the Chicago Mercantile Exchange (CME), into the CME Group to form the world's largest market for derivatives. In 2008 the New York Mercantile Exchange (NYMEX) joined the CME Group. Within the CME Group, agricultural futures like soybeans or grains are traded in the CBOT division, while livestock and energy futures are traded in the CME and in the NYMEX division respectively (Garner 2010).

The commodity futures contracts traded in the exchange between the traders are expiring agreements to exchange a commodity with a predefined quantity and quality at a specific time and a specific location. The delivery date of the contract links the commodity price today to its future expectation. The contracts are standardized, thus all traders in one market are dealing with identical contracts. The only variable for futures contracts is the price, which speculators constantly try to predict accurately to earn a profit. The futures market knows two basic position, the short position and the long position. If a trader takes a short position on the futures market he is taking the position of selling the commodity, while a long position would be equivalent to buying the commodity. However, only a small minority of all contracts lead to a physical exchange of the commodity. The rest of the contracts is offset before the expiring date by traders taking the opposite position of their initial contract. The price variations are restricted for certain commodities to prevent a speculative excess to cause large movements of commodity prices (Hull 2012). In the futures market the price of a commodity is not only influenced by fundamental demand and supply factors but can also incorporate other futures market specific factors, like option expiration dates or margin calls (Garner 2010).

Three distinct types of traders are operating inside the futures market. Hedgers use futures contracts to reduce the risk from potential price movements in their specific market. The arbitrageurs are seeking risk-free profits in the markets, which is keeping the futures markets in balance and bound to spot market prices. The speculators, which depict the largest group, are using their market intelligence to bet on prices to go up or down in the future (Garner 2010). The speculators are competing in collecting and interpreting all kinds of market-related information, resulting in a competitive discovering of prices (Natarajan et al. 2014). Lehecka et al. (2014) provide some recent empirical evidence for this statement with respect to the corn market. The authors use per minute return volatility and trading volume from July 2009 until May 2012 to show that the publication of the USDA corn market report has significant positive effects on both these variables. Thus, a futures price contains the collective expectation for the future price of the commodity. The advances in information technology and global networking continuously improve the processing of incoming news, which allows domestic markets to quickly adjust to news from world markets. Today, this competitive price discovery process is one of the key economic functions of the futures market (Natarajan et al. 2014).

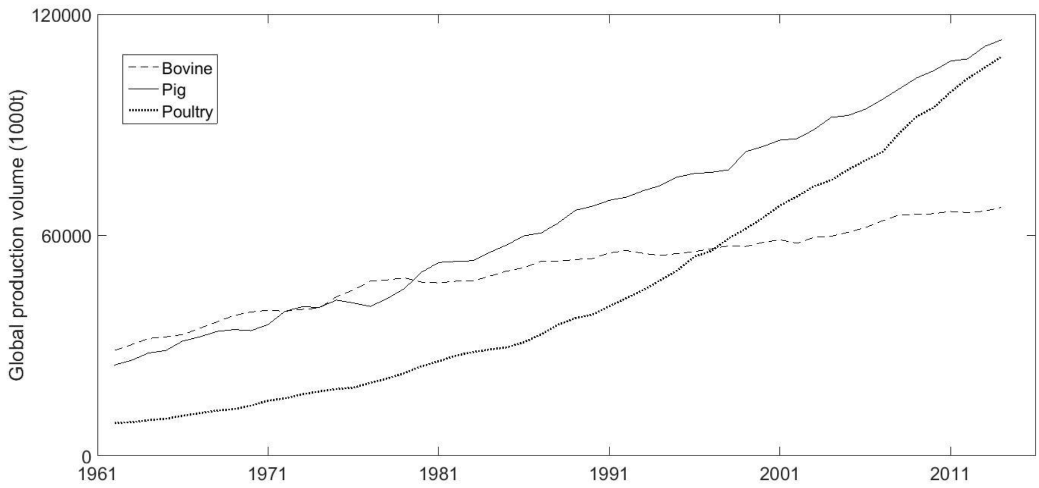
The liquidity of a market measures the ability of the market to transform assets into cash money, i.e. how quickly a contract can be sold. To form a liquid market there must be enough traders with opposing interests, i.e. buyers and sellers. Suitable proxies for market liquidity are the open interest and the contract trade volume of a specific market. Throughout this thesis the focus lies on the contract trade volume as a liquidity proxy since it has widely been recognized as the appropriate measure for information flows (Floros and Salvador 2016).

The structure of the futures market remained rather constant from its beginnings in the mid-19th century until the beginning of the 21st century. But since the new millennium started important changes happened. The trading changed from an open outcry and telephone based platform into an electronic system, which caused a significant market access expansion of the commodity futures markets. The markets saw many new participants entering, for example pension funds, which increased market liquidity. This development has been named the financialization of commodity markets (Irwin and Sanders 2012). The financialization of the futures market was followed by the commodity price crisis in 2008, which saw vast increases in commodity prices. However, Irwin et al. (2009) cannot find statistical evidence for a causal connection between the two events. The authors conclude that economic fundamentals changed, i.e. changes in supply and demand, and subsequently caused the boom and bust in the futures market. The largest increases of the total trading volume happened after 2006, which coincides with the time when trading in the pit had been mostly replaced by electronic ordering (Irwin and Sander 2012).

2.2 Meat market

The global livestock production increased significantly throughout the past 50 years. According to FAOSTAT, starting from approximately 70 million metric tons (MMT) in 1961, the production volume of meat reached nearly 310 MMT in 2013. The three largest single meat markets are the beef meat, pig meat and the poultry market. Beef production currently accounts for more than 20 per cent of the total meat production. Pig meat and poultry meat production both account for around 35 per cent each. Thus, together these three varieties cover more than 90 percent of the total production volume. Figure 1 shows their development over the time period from 1961 to 2013.

Figure 1: Global meat production



Source: Own illustration based on FAOSTAT

The largest meat producing countries currently are China, USA and Brazil, together accounting for almost 45 per cent of global meat production. The production volume of China increased most significantly, coming from a mere three percent of global production in 1961 up to almost one quarter of total production in 2013, supported by China’s WTO accession in 2001, allowing for surging imports of livestock feeds from the world market.

The first futures contract for a living animal was introduced by the CME in 1964 for live cattle, followed by lean hog futures in 1966. (Clark 2014). Today the livestock futures traded within the CME Group are live cattle futures, feeder cattle futures and lean hog futures. The live cattle futures contract has a volume of 18 metric tons and results in physical delivery of the product if not offset by the trader beforehand. The contracts are always listed for the upcoming nine month with expiration dates in February, April, June, August, October and December. Feeder cattle futures have a volume of 23 metric tons and do not end in physically delivery of the product, but are financially settled. The contracts are listed for the upcoming eight month with expiration dates in January, March, April, May, August, September, October and November (CME 2017a). Feeder cattle futures are dealing with cattle that have reached around 300 kg and subsequently are sold to feedlots. In the feedlots, feeder cattle are fattened up to their slaughter weight of around 550 kg and afterwards are traded as live cattle towards the slaughterhouses (Ryan 2012). Lean hog futures contain a volume of 18 metric tons and are also finically settled after their expiration (CME 2017a). The trading volumes of livestock futures have experienced among the most drastic increases of all agricultural futures markets since the beginning of the new millennium (Irwin and Sanders 2012).

The lack of a futures market for poultry at the CME Group is due to the level of vertical integration of the chicken industry in the USA. Giant producers integrated all steps of the production process and possess long-term contracts with large customers, which ends in a very narrow price range for this commodity. Furthermore, the production cycles of poultry are relatively short if compared to other livestock production systems and thus supply can react to changes in demand rather quickly. These reasons add up to low demand for hedging or speculation in the poultry futures market and attempts to introduce a vital futures market repeatedly ended up with trading volumes going down to zero (DePillis 2014).

The meat market exercises a fundamental relationship with feed crop markets and changes in these input market can have long-term effects on price levels or price variations in the meat markets and vice versa. The meat markets themselves are related to each other since a lot of market information is shared between them as they compete for similar natural resources. The meat market has a direct and an indirect fundamental relationship with energy markets. Directly it uses energy as a production input. The indirect relationship is via biofuels. Biofuel production uses agricultural products and thus figures as an additional competitor for limited natural resources (Gardebroek and Hernandez 2013).

2.3 **Feed market**

The focus of this sub-chapter is on feed components used in intensive indoor livestock production systems for beef and pig meat. The most important feed crops for livestock production in this context are grains and oilseeds that have high natural protein content, especially soybeans. First, the grain markets are introduced, concentrating on corn and wheat. Afterwards, the soybean market is discussed, figuring as the representative for oilseed markets.

2.3.1 **Grain market**

Grains depict the key staple food for human consumption and a major input for livestock diets throughout the globe. The direct human consumption of grains is decreasing with increasing wealth, whilst indirect consumption of grains, for example as an input to livestock production, is increasing (Gilbert and Morgan 2010). Wheat occupies the largest share of global crop land and it can easily be stored or transported. Most of the wheat is consumed by humans, although it is also very suitable for animal feeding (Sariannidis 2011). The plantation of winter wheat in the USA, a major producer of wheat, happens mostly around October, while the harvesting takes place mostly in June and July. Despite wheat, corn is another major grain. In the USA, the largest producer of corn, planting of the crop usually takes place in late April and early June, while the harvest comes in between October and November (USDA 2010). The demand for corn in recent decades changed, as more and more of the corn production got allocated into the livestock sector where corn is a key feed compound. Additionally, the developments in the energy sector are fueling the demand for corn throughout the last decade (Shiferaw et al. 2011). One externality of the increasing demand for corn in biofuel production so far has been that wheat is becoming more relevant as a feed crop in the livestock sector (Gilbert and Mugera 2014). The introduction of genetically modified corn varieties started in 1996 and nowadays accounts for around 80 per cent of the corn production in the USA (USDA 2017b). For the upcoming years, strong increases in demand for grains are expected, which needs to be met with further intensification (Neumann et al. 2010). A third major grain is rice, which is mostly consumed within Asia and western Africa. It is however not closely linked to other grains with respect to production or consumption and it does not play a mentionable role in the feed market (Gilbert and Morgan 2010).

Following FAOSTAT data, the global production volume of grains in MMT from 1961 until 2013 more than quadrupled. The main driver behind this increase used to be the intensification of production (Neumann et al. 2010). The period of the slowest increases in the total production volume of wheat took place between 1990 and 2007. This contributed to the minimum grain stocks that were available in 2007, which also played a role in the subsequent financial crisis (Wright 2011). Even though the growth rates of the corn production volume were increasing during the last decade, its production volume is still not sufficient to provide enough of the product to satisfy total demand (Vohra et al. 2014).

The first standardized wheat and corn futures contracts have officially been introduced to the CBOT in 1865 for farmers to hedge their price risks (Sariannidis 2011) and since 2003 these contracts have experienced dramatic increases in their trading volumes (Irwin and Sanders 2012). In recent times, corn has had the highest trading volumes of all agricultural commodities within the CME Group, with Chicago Soft Red Winter (SRW) wheat futures following on third position (CME 2017b). The corn futures contract consists of 127 metric tons and results in physical delivery in case the trader does not offset his position before the expiration date. The CME lists five corn contracts with expiration dates in the upcoming months of March, May, July, September and December. For wheat, the contract contains a volume of 136 metric tons and the same conditions for contract settlement as for corn futures regarding delivery and contract expiration dates (CME 2017c).

2.3.2 **Soybean market**

Soybeans are experiencing the highest increases in cultivated lands in percentage terms of all crops since the 1970s (Hartman et al. 2011). In MMT, the production volume of soybeans increased from roughly 27000 in 1961 up to almost 280000 in 2013, based on FAOSTAT. The production concentrates on the USA, Brazil and Argentina, who combined are responsible for more than 80 per cent of global soybean production. Soybeans depict a vital input to the livestock sector and China currently imports more than 60 MMT of soybeans per year to allow for the fast increases in its meat production volumes (Song et al. 2009). Most of the soybean production nowadays relies on genetically modified varieties, which were introduced to the USA in 1994. Since the soybean seeds are very rich in protein and fat, their main purpose is in livestock feeding and edible oil production. The increasing demand for soybeans is likely to be met by area expansions, which is mainly taking place in South America (Hartman et al. 2011). The plantation dates for soybeans in the USA, the largest producer of soybeans, are mostly in May and harvesting takes place in September and October (USDA 2010).

The futures contract for soybeans at the CBOT was launched in 1936 and since then developed to the agricultural commodity with the second highest trading volume (CME 2017b). The contract contains 136 metric tons and results in physical delivery of the commodity. The contracts listed at the CME Group are expiring in January, March, May, July, August, September and November (CME 2017c). Despite the vast growth in livestock futures trading volume, the growth in trading volumes of soybean futures also soared since 2003. Between the years 2000 and 2003 about 1.2 million contracts have been traded per month. This number more than tripled over the course of the subsequent years (Irwin and Sanders 2012). The fundamental relationship between corn and soybeans in the US market, i.e. both are summer crops competing for land resources, results in highly correlated futures prices between the two commodities (Goodwin and Zhao 2011).

2.4 Energy market

The attention energy markets receive from researchers experienced a vast increase after the food price crisis of 2008 (Irwin et al. 2009). The academic community widely agrees that biofuel policies contributed to the circumstances that led to the crisis. Several countries, like the USA, Brazil or the European Union, introduced certain biofuel policies, which substantially stimulated the production. Between 2005 and 2014 the volume of bioethanol production increased from 46 billion liters to 114 billion liters and the biodiesel production volume increased from 3.7 billion liters up to around 30 billion liters over the same time. These developments are suspected to have caused increases in price variations and price levels in the agricultural market (Enrisco et al. 2016).

The production of bioethanol, which is the most relevant biofuel, mostly depends on agricultural feedstocks, for example corn in the USA or sugarcane in Brazil (Gardebroek and Hernandez 2013). Biodiesel production is mainly based on vegetable oils, such as rapeseed and soybean oil (Chuah et al. 2017). Since biofuels depict a direct substitute for crude oil, the vast increase in biofuel production creates an intensified linkage for the agricultural market to the energy sector. Changes in the oil price will directly alter the demand for biofuels and subsequently influence the demand for certain agricultural crops that figure as feedstock for biofuel production. The manifold linkages within the agricultural market like competition for land resources or substitution in demand provide the possibility that a change in oil prices might influence many other agricultural markets (Gardebroek and Hernandez 2013). Wright (2014) argues that the introduction of biofuel policies fundamentally changed the structure of the agricultural market by significantly lowering the amount of products available for human consumption or livestock feeding.

Crude oil futures are the commodity with the highest average daily trading volume in the CME Group and ethanol futures gained high liquidity only recently. Therefore, in this thesis the focus will be on crude oil futures (CME 2017b). The crude oil futures contract at the

NYMEX has a volume of 1000 barrels and ultimately is settled by delivery. The contracts are listed for the upcoming nine years, with consecutive contracts listed for each month in the following five years and contracts for June and December from the sixth year onward (CME 2017d).

2.5 Volatility in the futures market

The advances in information technology ensure the distribution of information from all around the world and the futures traders incorporate these into the commodity prices. Due to the immediate processing and individual interpretation of new information, prices can vary in the very short-run, which causes price volatility. The volatility of a price is describing the extent of its variability over time, generally measured as the standard deviation of a relative change in prices (Gilbert and Morgan 2010). Unconditional volatility is describing the historic volatility of the time series, i.e. it is not conditioned upon information that is available today and it treats every observation alike. Therefore, it does not depend on time. Conditional volatility does depend on time. It determines volatility that is conditioned upon information that is available today (Enders 2010). Throughout the following chapters volatility refers to the concept of conditional volatility, if not explicitly mentioned differently. In fundamentally related markets, i.e. markets that share common information, a shock to the volatility can spill over from one commodity market into another related market. Therefore, analyzing the volatility interdependency between different markets does provide insights on how information is flowing between them (Liu and An 2011). Volatility spillovers can be separated into two distinct categories. The own price volatility spillover describes volatility that is spilled from a past volatility shock into the current price volatility within one market. Cross volatility spillovers describe the relationship between the current volatility in one market and a past shock to the volatility in another related market (Natarajan et al. 2014). Throughout the thesis the term volatility spillover refers to the concept of cross volatility spillover.

The efficient market hypothesis, based on distinct assumptions about rational decision making, states that a liquid market will drive the futures price of a commodity towards its fundamental price, with informed traders outcompeting less informed traders in the information processing activities (Gosh et al. 2012). The efficient market hypothesis experienced lots of criticism, for example from Akerlof and Shiller (2009), claiming that increasing market liquidity does not necessarily provide more stability due to the irrational behavior of many speculators. The efficient market hypothesis is widely accepted only in its semi-strong form, which states that current information are all included in the price of a commodity and that new information about supply or demand fundamentals will be incorporated continuously (UN 2011). Sanders et al. (2008) claim that the increasing number of speculators in the futures market might be changing the fundamental rules of the game by disrupting the convergence patterns between cash and futures prices and thus creating price distortions.

Recently, increasing evidence has been gathered that the financialization of the commodity futures markets is associated with increasing return- and range-based volatility. Floros and Salvador (2016), including daily CBOT futures data of corn, soybean, sugar and wheat from January 1996 until December 2014 in their analysis, conclude that increasing trade volumes have a significant positive effect on the return volatility of the included commodities. Return volatility measures the volatility of a relative change in prices over a fixed period of time, for example taking the daily closing price of commodities (Gilbert and Morgan 2010). The positive effect implies that higher trade volumes are associated with higher return volatility in futures markets. The authors claim their findings to be in line with leading theories on the relationship between trade volume and conditional volatility in the futures market, like the sequential information arrival hypothesis (Floros and Salvador 2016).

A positive correlation between trading volume in the futures market and weekly return volatility on the spot market has been detected for several agricultural markets by Gosh et al. (2012). Additionally, the authors state that the changes in global supply and demand are not sufficient to figure as the exclusive explanation for increasing prices and volatility, but that the financialization of the futures market also might play a vital role due to significant increases in return volatility during times of high trading volumes. For the energy market Ripple and Moosa (2009) find that increasing trade volumes have a significant and positive influence on the range volatility of crude oil futures, estimated using daily futures data obtained from the NYMEX division of the CME Group for the period between January 1995 and December 2005. Range volatility describes a volatility measure obtained from the difference between the highest and the lowest price in a defined period (Martens and van Dijk 2006). The insight that the trade volume could have a significant positive effect on conditional volatility in commodity futures markets has already been known before the recent drastic increases in trade volumes. Using daily futures data, Bessembinder and Seguin (1993) already showed the positive relationship between daily return volatility and trade volume for the time between 1982 until 1990, including data on agricultural commodities like wheat and cotton.

Although there is evidence for a positive correlation between trading volume and conditional volatility, either return based or range based, this does not yet determine the direction of the causal relationship (Gosh et al. 2012). The question whether higher price variations attract more speculators or whether more speculators lead to higher price variations still needs to be finally answered.

2.6 Volatility spillovers within the agricultural market

The literature regarding volatility spillovers between livestock and feed markets is scarce. One of the few peer-reviewed studies concentrating on the transmission of return volatility between livestock and feed markets was published by Buguk et al. (2003). The authors used monthly average spot prices for corn, soybeans and catfishes in the USA from January 1980 until December 2000 in an exponential generalized autoregressive conditional heteroskedasticity (GARCH) model for their analysis. The choice for the catfish market was based on the assumption of unidirectional volatility spillovers, i.e. catfish markets are assumed to be too small in order to influence corn and soybean markets. The results of the study indicate significant spillovers of return volatility from input markets into the livestock market. Apergis and Rezitis (2003) provide insights for the Greek agricultural market. The authors use monthly indices for spot prices of agricultural input prices, agricultural output prices and food prices from January 1985 until December 1999 to investigate the price volatility relationship between these categories. The results from the multivariate generalized autoregressive conditional heteroskedasticity (MGARCH) model indicate that price volatility from agricultural input markets positively effects volatility in agricultural output markets.

Gardebroek et al. (2016) use CBOT daily, weekly and monthly return volatilities to investigate the relationship between major agricultural futures markets, namely corn, wheat and soybeans from January 1998 until October 2012 in an MGARCH framework. From the daily returns the authors do not obtain significant evidence for return volatility spillovers when using their full sample period. Only when analyzing the post 2008 sample individually, significant return volatility spillovers were identified. The findings indicate that mainly wheat and corn are transmitters of return volatility into others agricultural markets, which is similar to the authors findings for weekly and monthly return volatility analysis. The authors hypothesize that for daily trading the actions on the futures market are more likely to be financially motivated and thus increase with numbers of speculators on the market, although this hypothesis is not confirmed by their data. The significance of weekly and monthly average return volatility spillovers indicates that these measures are not so much driven by speculators but are more likely explained by fundamental relationships between the commodities.

Beckmann and Czudaj (2014) are using daily return volatility for corn and wheat futures from the CBOT and cotton futures from the New York Board of Trade from January 2000 until June 2012 in a GARCH model to analyze the return volatility relationship among some of the most liquid agricultural commodity markets. The results of the authors show significant short-run volatility spillovers between the commodity markets. Goodwin and Zhao (2011) use weekly data on option contracts for the soybean and corn markets between May 2001 and January 2010 for an analysis of the implied volatility in a threshold vector autoregressive (VAR) model. The results indicate that in times of low implied volatility in both markets, implied volatility is only transmitted from the corn market into the soybean market. In times of higher implied volatility in the soybean market, the corn market receives implied volatility from the soybean market. Additionally, the authors use average weekly return volatility of corn and soybeans futures in an MGRACH model, which indicates that return volatility is transmitted and received by both commodities.

Grosche and Heckelei (2014) use daily range volatilities to analyze the range volatility relationships between agricultural, energy, real estate and financial assets. The paper contains volatility spillover indices, based on Diebold and Yilmaz (2012), showing volatility relationships between the included assets. The authors include CBOT corn, soybeans and wheat futures data from June 1998 until December 2013. The results of the authors indicate that corn is mostly a transmitter of conditional range volatility towards soybeans and wheat. The conditional range volatility relationship between soybean and wheat is changing continuously.

2.7 Volatility spillovers between agricultural and the energy market

The introduction of biofuel policies in the USA, Brazil or the EU and the connections they provided between the agricultural and the energy sector initiated an increase in the interest of researchers in the information flow between these two sectors. However, so far publications do not provide a unique perspective on this issue.

Serra and Zilberman (2013) provide a literature review regarding price transmission between the energy sector and the agricultural sector, but also including several studies on the volatility relationship. The authors conclude that based on their literature review it seems like price variations are mostly transmitted by the energy sector and received by the agricultural sector and that this pattern intensified with the rise of the biofuel sector. However, the authors do not specifically distinguish between the different volatility concepts.

Gardebroek and Hernandez (2013) use weekly average crude oil and corn spot price returns with ethanol CBOT futures price returns from September 1997 until October 2011 in various MGARCH model specifications to answer the question whether price volatility in the energy sector influences the volatility in the corn market. The authors cannot find empirical evidence for significant spillovers of conditional mean price return volatility from energy markets into the corn market when analyzing the full sample period. They do find spillovers from the corn market into the ethanol market for a segmented smaller sample. Trujillo-Barrera et al. (2012) use return volatilities of corn, ethanol and crude oil futures from July 2006 until November 2011 to answer a similar research question in an MGARCH framework. The authors' results indicate strong return volatility spillovers from crude oil towards corn and ethanol, with spill-overs being particularly strong towards the latter. Additionally, the authors find significant return volatility spillovers from the corn market into the ethanol market but not vice versa. Guan et al. (2011) use corn spot and CBOT futures return volatility with NYMEX crude oil futures return volatility to investigate their return volatility relationship between January 1992 and June 2009 in a GARCH model. Their analysis shows that return volatility spillovers increased significantly after 2005 and were transmitted from the crude oil market into the corn cash and futures market.

Nazlioglu et al. (2013) utilize daily spot price data between January 1986 and March 2011 to determine the return volatility of crude oil, soybeans, wheat and sugar. The authors split the data in two parts, with the 31st of December 2005 taken as the separation date to have a pre-crisis sample and a post-crisis sample to analyze in the GARCH model. The results of the analysis suggest no return volatility spillovers before the crisis and significant spillovers transmitted from crude oil into the agricultural markets after the crisis. The authors conclude that throughout recent years the interdependency between the energy sector and the agricultural sector increased substantially. Gilbert and Mugera (2014) use daily returns of crude oil, corn, wheat and soybean futures markets from January 2000 until December 2011 in a GARCH and MGARCH framework to identify the return volatility relationship amongst the commodities. The authors find empirical evidence that during the 2008-2009 crisis the return volatility of the crops partly increased due to volatility transmitted to them from the crude oil market, even though this influence was only modest.

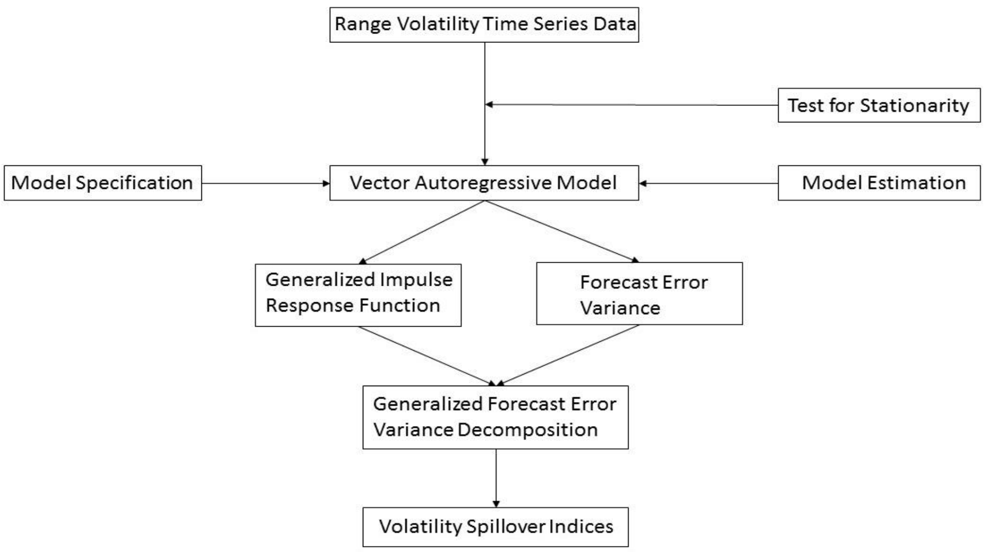
2.8 **Summary**

The changes that the agricultural sector experienced throughout the last two decades are extraordinary. The agricultural futures market experienced an inflow of new market participant and a subsequent surge in trading volumes, which seems to imply an increase in the conditional return or range volatility measures of many commodity markets. Furthermore, the developments in the energy sector further tightened agricultural markets with a wide array of potential implications. So far, the increase in meat consumption hardly caused any interest in the volatility spillover implications that this might have. Anyway, the insights gained from the literature review indicate that in the spot market livestock products receive volatility from other markets. With respect to volatility in futures market it is important to keep in mind that the concepts discussed in this chapter often do not allow to directly compare the results of different studies and generalizations can often not be made due to distinct definitions of certain concepts.

3 Methodology

The research questions as presented in the introduction demand for a rigorous statistical analysis. At the center of this volatility analysis are VAR models, which are used to determine the relationships between the individual range volatilities of the commodities included in the system. VAR models were developed as an answer to the shortcomings of simultaneous equation models and were introduced by Sims (1980) as a means of analyzing the relationships among variables using their common history. In a VAR system, all variables are endogenous and in its standard or reduced form every variable is written as a linear function of the lagged values of all the variables included in the system. The structural analysis of reduced VAR models has been suffering from the shortcoming due to the ordering effect of the Cholesky decomposition of the error covariance matrix, which has been solved by Pesaran and Shin (1998) building on Koop et al. (1996). The generalization of the structural analysis by these authors has been developed into a framework for volatility spillover analysis by Diebold and Yilmaz (2012). This framework allows for the investigation of volatility relationships and thus provides the required insights with respect to the research questions. Figure 2 provides a brief overview of the methodology used for the analysis.

Figure 2: Methodology overview



Source: Own illustration

This chapter follows the logical order of the figure presented above. First the stationarity issue in time series econometrics is briefly introduced, including the most common test for stationarity. Afterwards, there is a presentation of the VAR framework and the derivation of the vector moving average (VMA) representation. Following this the forecast error variance (FEV) is explained as the first element of the generalized forecast error variance decomposition (GFEVD). The next section explains the Generalized Impulse response function (GI) as the second element of the GFEVD. The two elements are subsequently brought together in the sub-chapter regarding the GFEVD. The chapter ends with the introduction of the volatility spillover indices as introduced by Diebold and Yilmaz (2012).

3.1 **Stationarity**

For a stochastic process to be stationary it is required that a change in time does not alter the joint probability distribution of the process. This implies that the probability density function for y_t is constant over time. For most of the cases it is sufficient to use the definition of weak stationarity, which only requires the mean, variance and covariance to be independent of time (Verbeek 2012). A violation of the weak stationarity implies that the past realizations of a variable cannot be used to predict future values since the distribution of the series is changing over time. This change in the distribution over time is mostly caused by a trend or a unit root in the data sample, where the latter can be dealt with by integrating the series. Regarding the estimation of VAR models there is an ongoing discussion whether the variables must be stationary. Sims (1980) argues that integrating variables is taking valuable information out of the system and that the main cause for VAR models is to investigate the relationship between the variables based on this information. Anyway, the majority opinion in applied econometrics is that variables included in VAR systems ought to be stationary (Enders 2010).

In the literature, a wide range of test regarding stationarity of a time series process exists. The standard approach to test for stationarity is the Dickey-Fuller (DF) test, introduced by Dickey and Fuller (1979). The test checks the presence of a unit root or certain trends in the data sequence with the H_0 of non-stationarity using a t-test with a critical value distribution specifically designed for this test. The lag length of a time series process must be determined by an information criteria, like the Schwarz Information Criteria (SIC) (Enders 2010). The DF test for a first order autoregressive model comes in three varieties

(1) $$y_t = \tau y_{t-1} + \varepsilon_t,$$

(2) $$\Delta y_t = b_o + \tau y_{t-1} + \varepsilon_t,$$

(3) $$\Delta y_t = b_o + b_1 t + \tau y_{t-1} + \varepsilon_t,$$

with the equations testing for a pure random walk, a random walk with drift and a random walk with drift and a time trend, respectively. The appropriate form has to be selected due to a visual inspection of the data (Enders 2010). A random walk due to a unit root is implied by τ

not being significantly different from zero, which leaves the value of one period equal to the former periods' value plus a white noise term. In that case the series would violate the condition that its second moment must be time-invariant since the variance would increase over time. In case of a random walk with drift due to a unit root, the drift parameter depicts a deterministic trend in the data sequence. If the non-stationarity is due to a deterministic trend and not due to a unit root, i.e. $|\tau| < 1$ and $b_1 \neq 0$ in (22), including *t* in the regression makes the sequence trend stationary. For the latter cases, also the first moment of the series is not constant over time (Enders 2010). In case the model is of higher order, an augmented Dickey-Fuller (ADF) test is applied. For this extension of the DF test consider the process with two significant lags

(4) $$y_t = b_o + b_1 y_{t-1} + b_2 y_{t-2} + \varepsilon_t,$$

rearranging this equation leads to the form used in the ADF test

(5) $$\Delta y_t = b_o + (b_1 + b_2 - 1) * y_{t-1} - b_2 * \Delta y_{t-1} + \varepsilon_t.$$

It is tested whether the term in brackets significantly differs from zero. In case it does not, the ADF test implies that the process has a unit root and should be used in first differences. Like the former version of the DF test also the augmented test can be extended by a trend parameter, which might imply that detrending is necessary to have a stationary process (Verbeek 2012).

3.2 Vector autoregressive models

A VAR system can be represented either in a structural form or in its reduced form, with the latter being derived from the former one. The structural form of the VAR suffers from problems like simultaneous equation biases since the current values of other variables in the system are considered as well. To circumvent these issues and make the VAR more usable it is transformed into its reduced or standard form (Dougherty 2011). Consider the two variables *a* and *b*, which both have time-invariant first and second moments and thus are stationary (Lütkepohl 2007). A simple structural VAR(1) model including the variables *a* and *b* would have the form of

(6) $$a_t = \beta_a - \beta_{a1} b_t + \beta_{a2} b_{t-1} + \beta_{a3} a_{t-1} + e_{at},$$

(7) $$b_t = \beta_b - \beta_{b1} a_t + \beta_{b2} a_{t-1} + \beta_{b3} b_{t-1} + e_{bt},$$

where the error terms e_{at} and e_{bt} having constant and finite variance, zero covariance and zero expectation, which leaves the error terms as white noise. The white noise describes a purely random process that cannot be caught by a model. In case this assumption does not hold for the error term there would still be information in the error term that could be extracted by introducing the appropriate variable to the system. The structure contained in this VAR(1) system allows for feedback between the individual variables and if β_{a1} and β_{b1} are not equal to zero also the error terms indirectly effect the other equation, leaving ordinary least squares a biased and inconsistent estimator (Enders 2010). Transforming (1) and (2) into matrix notation gives

$$(8) \qquad \begin{bmatrix} 1 & \beta_{a1} \\ \beta_{b1} & 1 \end{bmatrix} * \begin{bmatrix} a_t \\ b_t \end{bmatrix} = \begin{bmatrix} \beta_a \\ \beta_b \end{bmatrix} + \begin{bmatrix} \beta_{a3} & \beta_{a2} \\ \beta_{b3} & \beta_{b2} \end{bmatrix} * \begin{bmatrix} a_{t-1} \\ b_{t-1} \end{bmatrix} + \begin{bmatrix} e_{at} \\ e_{bt} \end{bmatrix}.$$

Equation (3) can be rewritten as

$$(9) \qquad A * c_t = \beta_0 + \beta_1 * c_{t-1} + e_t,$$

using $A = \begin{bmatrix} 1 & \beta_{a1} \\ \beta_{b1} & 1 \end{bmatrix}, c_t = \begin{bmatrix} a_t \\ b_t \end{bmatrix}, \beta_0 = \begin{bmatrix} \beta_a \\ \beta_b \end{bmatrix}, \beta_1 = \begin{bmatrix} \beta_{a3} & \beta_{a2} \\ \beta_{b3} & \beta_{b2} \end{bmatrix}$ and $e_t = \begin{bmatrix} e_{at} \\ e_{bt} \end{bmatrix}$. Multiplying (4) with A^{-1} brings the VAR(1) into its standard form

$$(10) \qquad c_t = B_0 + B_1 * c_{t-1} + \varepsilon_t,$$

with $B_0 = A^{-1} * \beta_0$ being the 2 x 1 vector containing the intercepts, $B_1 = A^{-1} * \beta_1$ being the 2 x 2 coefficient matrix and $\varepsilon_t = A^{-1} * e_t$ being the 2 x 1 vector with the error terms (Enders 2010). Equation (5) then contains

$$(11) \qquad a_t = b_a + b_{a3}a_{t-1} + b_{a2}b_{t-1} + \varepsilon_{at},$$

$$(12) \qquad b_t = b_b + b_{b3}b_{t-1} + b_{b2}a_{t-1} + \varepsilon_{bt},$$

which are the reduced forms of (1) and (2), solved for the simultaneous equation bias. Therefore, each individual equation of a VAR model can consistently and unbiasedly be estimated using ordinary least squares (OLS). In a VAR system, all equations are estimated simultaneously, not subsequently, which emphasizes its dynamic character (Enders 2010). Lütkepohl (2007) imposes some additional requirements for the OLS estimator to be consistent, which will be addressed later. The error terms in equations (6) and (7) depict composites of the error terms from the structural equations and are white noise processes. Furthermore, the two error terms are correlated, with the covariance given as

$$(13) \qquad E\varepsilon_{at}\varepsilon_{bt} = -(\beta_{b1}\sigma_a^2 + \beta_{a1}\sigma_b^2)/(1 - \beta_{b1}\beta_{a1})^2,$$

with σ_a^2 and σ_b^2 being the variances of the error terms. Correlation between the error terms implies the possibility that a shock to one error term can cause a shock to other error term as well. For the special case of $\beta_{b1} = \beta_{a1} = 0$ the error terms would not be correlated, which means that no contemporaneous effect exists. However, the correlation between the error terms has no effect on the consistency and unbiasedness of the OLS estimator plus asymptotically it is efficient (Enders 2010). Since all components of the variance/ covariance matrix of the error terms are time-invariant it can be defined as

$$(14) \qquad \Sigma = \begin{bmatrix} \sigma_a^2 & \sigma_{ab} \\ \sigma_{ba} & \sigma_b^2 \end{bmatrix},$$

with σ_{ab} and σ_{ba} being the covariance between variable a and b (Enders 2010). For Σ it is assumed that the inverse exists, i.e. the matrix is nonsingular.

If the data generation process is investigated starting in period $t = 1$ it has the following implication

$$(15) \qquad c_1 = B_0 + B_1 * c_0 + \varepsilon_1$$

$$c_2 = B_0 + B_1 * c_1 + \varepsilon_2 = B_0 + B_1 * (B_0 + B_1 * c_0 + \varepsilon_1) + \varepsilon_2$$

$$c_2 = (I_2 + \ B_1) * B_0 + B_1^2 * c_0 + A_1 * \varepsilon_1 + \varepsilon_2,$$

with I_2 being a $2x2$ identity matrix. Continuing this process until period *t* gives

$$(16) \qquad c_t = (I_2 + \ B_1 + \cdots + B_1^{t-1}) * B_0 + B_1^t * c_0 + \sum_{i=0}^{t-1} B_1^i \varepsilon_{t-i},$$

indicating that the vectors and joint distribution of all c_t are being determined from the joint distribution of the variables $c_0, \varepsilon_1, \dots, \varepsilon_t$ (Lütkepohl 2007). Assuming that the process for c_t started in the infinite past provides some convenient insights. It shows that if all eigenvalues of B_1 have a modulus of less than one it is possible to build the absolute sum of the sequence B_1^i, which is equivalent to the condition

$$(17) \qquad det(I_2 - B_1 z) \neq 0 \ with \, |z| \leq 1.$$

This is called the stability condition for VAR models. If the stability condition for VAR(p) models is met, this already implies stationarity, although the reverse is not true and an unstable VAR does not necessarily have to indicate unstationary in the variables. In case the VAR does not exhibit stability due to a unit-root, differencing the included variables often solves the issue (Lütkepohl 2007). If the stability condition is met it is possible to determine a VAR process beginning in the infinite past,

$$(18) \qquad c_t = (I_2 + \ B_1 + \cdots + B_1^{\varpi}) * B_0 + B_1^{\varpi+1} * c_{t-\varpi-1} + \sum_{i=0}^{\varpi} B_1^i \varepsilon_{t-i},$$

with $\varpi \to \infty$, since the coefficient matrices are absolutely summable. The implication of the limit is that $B_1^{\varpi+1}$ is quickly converging to zero as ϖ approaches infinity, thus the term $B_1^{\varpi+1} * c_{t-\varpi-1}$ can be dropped. Additionally, the term $(I_2 + B_1 + \cdots + B_1^{\varpi}) * B_0$ is converging to $(I_2 - B_1)^{-1} * B_0$ as $\varpi \to \infty$. Therefore, in the limit the standard VAR (1) from equation (5) can be described in the form of

(19) $$c_t = \mu + \sum_{i=0}^{\infty} B_1^i * \varepsilon_{t-i},$$

for all *t* and $\mu = (I_2 - B_1)^{-1} * B_0$ (Lütkepohl 2007).

It is possible to extend these insights to VAR models of any lag length *p* and including *k* variables. The actual lag length of a VAR model needs to be determined using certain techniques. The most common methods are the SIC, Akaike information criterion (AIC) and the Hannan-Quinn information criterion (HQIC). According to Lütkepohl (2007), the AIC is more suitable for smaller samples, while for large samples the SIC and the HQIC more often estimates the correct order of the lag length. The author states that the SIC has superior consistency over the HQIC. Therefore, the SIC will be used to determine the lag length for the empirical analysis. Furthermore, Greene (2008) states that both the AIC and the SIC have their advantages and disadvantages, without one being much superior to the other. However, Greene (2008) adds that the SIC tends to lead to more parsimonious models because of more severe penalties for losses regarding the degrees of freedom, which in the eyes of the author is favorable. Using matrix notation any standard VAR(p) with k variables can be transformed into a standard VAR (1) model. Consider the model

(20) $$y_t = B_0 + B_1 * y_{t-1} + \cdots + B_p * y_{t-p} + \varepsilon_t,$$

for all t, with the $k \times 1$ vector $y_t = (y_{1t}, \ldots, y_{kt})'$, B_0 being the $k \times 1$ matrix containing the intercepts, B_1 being the $k \times k$ coefficient matrix and ε_t being the $k \times 1$ vector including the respective error terms for the k variables. Bringing (20) into the standard VAR (1) form

(21) $$Y_t = \boldsymbol{B}_0 + \boldsymbol{B} * Y_{t-1} + \boldsymbol{\varepsilon}_t,$$

requires to define the $kp \ x \ 1$ vector $Y_t \coloneqq \begin{bmatrix} y_t \\ y_{t-1} \\ \vdots \\ y_{t-p+1} \end{bmatrix}$, the $kp \ x \ 1$ vector $\boldsymbol{B}_0 \coloneqq \begin{bmatrix} B_0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$, the $kp \ x \ kp$ matrix $\boldsymbol{B}$ that contains the $p \ k \ x \ k$ coefficient matrices $\boldsymbol{B} \coloneqq \begin{pmatrix} B_1 & B_2 & & B_{p-1} & B_p \\ I_k & 0 & \cdots & 0 & 0 \\ 0 & I_k & & 0 & 0 \\ \vdots & & \ddots & \vdots & \\ 0 & 0 & \cdots & I_k & 0 \end{pmatrix}$ and the $kp \ x \ 1$ vector $\boldsymbol{\varepsilon}_t \coloneqq \begin{bmatrix} \varepsilon_t \\ 0 \\ \vdots \\ 0 \end{bmatrix}$ (Lütkepohl 2007). In order to obtain the individual process y_t from Y_t a $k \ x \ kp$ selection matrix J is used, with $J \coloneqq [I_k : 0 : \cdots : 0]$. Since y_t is obtained from Y_t using only the selection matrix it exhibits the same characteristics like constant and finite first and second moments (Lütkepohl 2007).

The form that the VAR (1) model takes in equation (14) is called the moving average (MA) representation of the process, which expresses the process c_t as a function of its present and past error vectors and its mean μ. The MA form of any stable VAR(*p*) model including *k* variables is given as

$$Y_t = \boldsymbol{\mu} + \sum_{i=0}^{\infty} \boldsymbol{B}^i * \boldsymbol{\varepsilon}_{t-i}. \tag{22}$$

The MA representation of the individual process y_t can then be found by premultiplying equation (22) with *J* and using the fact that $\boldsymbol{\varepsilon}_t = J' * J * \boldsymbol{\varepsilon}_t$, *giving*

$$y_t = JY_t = J * \boldsymbol{\mu} + \sum_{i=0}^{\infty} J * \boldsymbol{B}^i * J' * J * \boldsymbol{\varepsilon}_{t-i}, \tag{23}$$

ultimately leading to

$$y_t = \mu + \sum_{i=0}^{\infty} \vartheta_i * \varepsilon_{t-i}, \tag{24}$$

with $\vartheta_i = J * \boldsymbol{B}^i * J'$ being the $k \ x \ k$ moving average coefficient matrix, $\mu = J * \boldsymbol{\mu}$, $\varepsilon_{t-i} = J * \boldsymbol{\varepsilon}_{t-i}$ and $\vartheta_0 = I_k$. The unique characteristic of the MA representation is that it uses error terms of the standard VAR representation. The derivation method for the coefficient matrices ϑ_i makes them absolutely summable just like $\boldsymbol{B}^i$ (Lütkepohl 2007). The elements of ϑ_i are so called impact multipliers and they describe the impact of a one unit change in an error term on the respective variable. The transformation of a VAR system into its VMA representation is a key feature developed by Sims (1980), which enables the researcher to specifically investigate the effect that a shock in one variable has on other variables (Enders 2010).

The Wold Decomposition Theorem, as presented in Lütkepohl (2007), states that every stationary process can be illustrated as the sum of two distinct processes that are uncorrelated. One process is purely deterministic and the other one is an MA process with white noise error terms. For the VAR system, this translates into the statement that if the variables are all stationary and the mean terms are the only deterministic components, the VMA representation does exist. Therefore, the World Decomposition Theorem provides an alternative way of testing whether the VMA form of the VAR exists. Under the fairly weak assumption that the mean term is the only deterministic element in the system, testing for stationarity of the time series can thus replace the stability condition (Lütkepohl 2007). The MA form of the VAR model is then used as a starting point for many of the methods used to investigate the relationships between the variables within the VAR system.

3.3 Forecast error variance

When evaluating VAR models the forecaster usually utilizes a loss function that is associated with the error of the forecast. The optimal forecast will thus minimize the loss function and the characteristics of the loss function will determine the optimal predictor. The loss function will determine for example whether an unbiased estimator is preferred over an estimator having a smaller variance. With respect to VAR models the forecast mean squared error (MSE) is mostly used for minimization since the predictor that minimizes the MSE often also minimizes many other loss functions (Lütkepohl 2007). The forecast MSE of a general VAR(p) model, expressed in its VAR (1) form, can be obtained using the optimal n-period ahead predictor at time *t* for y_{t+n}

$$JY_t(n) = J * \boldsymbol{B}_0 + J\boldsymbol{B}^n Y_t \tag{25}$$
$$y_t(n) = B_0 + B_1 y_t(n-1) + \cdots + B_p y_t(n-p).$$

In this case $y_t(n)$ is the conditional expectations of y_{t+n} at time *t* as long as the error terms are independent white noise. Let the future realization be

$$Y_{t+n} = \boldsymbol{B}_0 + \boldsymbol{B}^n Y_t + \sum_{i=0}^{n-1} \boldsymbol{B}^i \boldsymbol{\varepsilon}_{t+n-i}, \tag{26}$$

where, $\boldsymbol{\varepsilon}_t = (\varepsilon_t, 0, 0, \ldots, 0)'$ with dimension $kp\ x\ 1$. From this, it can be seen that the forecast error is

$$y_{t+n} - y_t(n) = J[Y_{t+n} - Y_t(n)] = \sum_{i=0}^{n-1} \vartheta_i \varepsilon_{t+n-i}, \tag{27}$$

with $\vartheta_i = J\boldsymbol{B}^i J'$, which obtains the same moving average coefficients as in (24), and $\varepsilon_t = J\varepsilon_{t+n-i}$. The forecast MSE can subsequently be obtained as

(28) $$MSE[y_t(n)] = E\left[\left(y_{t+n} - E_t(y_{t+n})\right)\left(y_{t+n} - E_t(y_{t+n})\right)'\right] = \sum_{i=0}^{n-1} \vartheta_i \Sigma \vartheta_i'$$

(Lütkepohl 2007). The forecast MSE is nondecreasing and approaches the covariance matrix of y_t in the limit. The elements on the diagonal of the $k\ x\ k$ MSE matrix constitute the FEVs of the variables included in the VAR model. The FEV of each element *i* contains two distinct components, one describing the share of the FEV due to shocks in the variable itself and the other being the share coming from shocks happening to other variables in the system (Lütkepohl 2007).

3.4 **Structural analysis**

As indicated before, VAR models have the ability to identify the relationships among the included variables. The structural analysis mainly has three distinct components, which all build upon the VMA representation of the reduced VAR model. In short, granger causality identifies cause-effect relationships between variables, while the impulse response analysis measures the impact of an impulse in one variable on another variable and the forecast error variance decomposition (FEVD) determines the shares of the variation in one variable that can be attributed to variations in other variables and the variable itself. In order to determine the desired volatility spillover indices only the latter two are required.

3.4.1 **Generalized impulse response function**

The GI for VAR models has first been introduced by Pesaran and Shin (1988), building upon the work of Koop et al. (1996). Before introducing this method impulse response function for VAR models have been determined using the Cholesky decomposition of the variance/ covariance matrix of the error terms, which orthogonalized the error terms of the VAR and within that procedure made the impulse response function dependent on the ordering of the variables in the VAR. Thus, the initial impulse response function contained a subjective influence of the researcher. Pesaran and Shin (1988) state that the best way for describing the impulse response function is to see it as the result of an experiment that shocks one element of a multivariate time series at point *t* and then compares the series to the non-shocked baseline series at $t + n$. Thus, impulse response functions catch the impact on all variables included in the VAR system due to a shock in one of its variables. In Pesaran (2015) the author states that one of the main causes to determine a GI is to investigate the influence of a shock in one variable on the entire system, meaning whether the system was hit by a shock that only influenced one specific variable or by a shock that has system-wide effects. The total effect of a shock in one variable can be measured by appropriately summing up the GI (Enders 2010). A real-world example for an exogenous shock would be the oil price crisis of 1973. Generally, the impulse response analysis is done in models with the means of the variables set to zero since the matter of interest is the variation around the mean, which is assumed to be reached at $t = 0$ (Lütkepohl 2007).

The derivation of the GI, according to Pesaran and Shin (1988), starts with the VMA representation of a stable VAR(p) model with zero mean

(29) $$y_t = \sum_{i=0}^{\infty} \vartheta_i * \varepsilon_{t-i}.$$

The GI now shocks one individual element h in ε_t of the VMA (∞) model and via an observed historical or an assumed distribution of the errors integrates out the impacts of potential other shocks. Afterwards the GI can be obtained by comparing the outcomes of the shocked expectation with the expectation not experiencing the shock

(30) $$GI_y(n, \rho_h, \varphi_{t-1}) = E(y_{t+n} | \varepsilon_t = \rho_h, \varphi_{t-1}) - E(y_{t+n} | \varphi_{t-1}),$$

where ρ defines the vector containing the shock at its h element and φ_{t-1} contains the information set at $t - 1$ (Pesaran and Shin 1998). Assuming a multivariate normal distribution for u_t, the GI follows as

(31) $$GI_y(n, \rho_h, \varphi_{t-1}) = (\frac{\vartheta_n \Sigma J_h}{\sqrt{\sigma_{hh}}})(\frac{\rho_h}{\sqrt{\sigma_{hh}}}),$$

with Σ depicting the covariance matrix of the error term, J_h is a selection vector of size k x 1 with zeros everywhere apart from its h-th element and $\sigma_{hh}^{-0.5}$ describing the standard deviation of the error term at the h-th position. Scaling the GI by setting the shock equal to one standard deviation of the shocked element h, i.e. $\rho_h = \sqrt{\sigma_{hh}}$, obtains the scaled GI, for any n

(32) $$\Upsilon_h(n) = \sigma_{hh}^{-0.5} \vartheta_n \Sigma J_h$$

(Pesaran and Shin 1988).

3.4.2 **Generalized forecast error variance decomposition**

As mentioned above the FEV of each variable consists of the variance coming from shocks happening to the variable itself and variance originating in shocks happening to other correlated variables. The FEVD provides a method to decompose the FEV of a variable into its distinct components at different time horizons. Before introducing the GI the FEVD was depending on the orthogonalized errors used in the derivation of the impulse response function and thus also was a victim of the ordering effect in the VAR model due to the Cholesky decomposition. The introduction of the GI by Pesaran and Shin (1988) also provided the methodology allowing for generalized forecast error variance decompositions (GFEVD). The GFEVD is conditioned on the non-orthogonal error terms, which specifically allows the shocks to be contemporaneously correlated amongst each other (Pesaran 2015). The GFEVD is a ratio that sets the contribution to the variation of variable *i* by a shock in variable *h* relative to the total FEV of *i*, which is given on the diagonal elements of MSE matrix (Enders 2010).

The intuition behind the GFEVD is that it determines the share of the total change in the variance of *i* accounted for by a shock to the variance of variable *h* over *n* periods. Therefore, it requires that the numerator contains the shock-induced change in the variance of *i*, while the denominator contains the total variance of *i*. The first element for the GFEVD can be obtained as the sum of squares of the GI, which is given as $\sum_{i=0}^{n-1}[\Upsilon_{hi}(n)]^2$ with $\Upsilon_{ih}(n) = \sigma_{hh}^{-0.5} J_i \vartheta_i \Sigma J_h$, resulting in

$$(33) \qquad SS_{GI_{i,h,l}} = \sigma_{hh}^{-1} \sum_{l=o}^{n-1} (J_i' \vartheta_l \Sigma J_h)^2$$

(Pesaran 2010). The total variance for variable i can be extracted from the diagonal of the MSE in equation (28) using a selection vector. The GFEVD as presented in Diebold and Yilmaz (2012) is thus given as

$$(34) \qquad \Psi_{ih}(n) = \frac{\sigma_{hh}^{-1} \sum_{l=o}^{n-1} \left(J_i' \vartheta_l \Sigma J_j\right)^2}{\sum_{l=0}^{n-1} J_i' \vartheta_l \Sigma \vartheta_l' J_i}.$$

The drawback of the implementation of contemporaneous shocks in the GFEVD, i.e. allowing for non-zero elements for the off-diagonal elements in Σ, is that the individual contributions of the model variables to the FEV of *i* do not necessarily add up to unity, i.e. $\sum_{h=1}^{k} \Psi_{ih}(n) \neq 1$, which used to be the case for the orthogonalized error terms from the Cholesky decomposition (Pesaran and Shin 1998). Diebold and Yilmaz (2012), in order to make the method applicable to the calculation of volatility spillover indices, meet this drawback by normalizing each individual component of the GFEVD matrix by the sum of its row, which is indicated subsequently as $\widetilde{\Psi}_{ih}(n)$.

3.5 Volatility spillover indices

The volatility spillover indices used in the analysis were first introduced by Diebold and Yilmaz (2009) and further developed in Diebold and Yilmaz (2012). From the first to the second version the authors replaced the Cholesky decomposition by the generalized forms of the impulse response function and the FEVD and they introduced directional volatility spillover indices. The authors develop the indices starting from the VMA representation of a VAR(p) process. Then generalized variance decomposition makes it possible to break the FEV for every variable in the system up into the distinct shares accounted for by individual socks to the variables of the system (Diebold and Yilmaz 2012). A volatility spillover is defined as the share of the n-period ahead FEV of variable i that is due to a shock happening to variable j, note that in this case $i \neq j$. The case of $i = j$ depicts the share of the variance due to a shock in the variable itself. The normalization of the individual elements of the GFEVD matrix with k variables, due to the reasons mentioned above, takes the form of

(35) $$\widetilde{\Psi}_{ih}(n) = \frac{\Psi_{ih}(n)}{\sum_{h=1}^{k} \Psi_{ih}(n)},$$

therefore, by construction it holds that $\sum_{h=1}^{k} \widetilde{\Psi}_{ih}(n) = 1$ and $\sum_{i,h=1}^{k} \widetilde{\Psi}_{ih}(n) = k$ (Diebold and Yilmaz 2012).

In order to investigate whether volatility spillovers in general have increased over the considered time period Diebold and Yilmaz (2012) construct the total volatility spillover index, which measures the total contribution of volatility spillovers induced by shocks to individual variables in the system to the overall FEV of the system. This index is defined as

(36) $$T(n) = \frac{\sum_{\substack{i,h=1 \\ i \neq h}}^{k} \widetilde{\Psi}_{i,h}(n)}{k} * 100,$$

where due to the normalization the denominator constitutes the total FEV.

Intuitively, this index provides the share of total volatility originating from volatility spillovers in the VAR system. Graphing the results of (36) over time, allows to easily compare the total volatility spillovers and the increase in meat consumption and also allows a simple graphical examination of the total volatility pattern.

The characteristics of the constructed VAR system with the GI and the GFEVD allows for directional volatility spillover indices across the variables included in the system. The directional volatility spillover index is defined in two distinct ways, one measuring the volatility coming to the variable from the other variables in the system and the other measures the volatility radiating from the variable towards the other variables. Afterwards the first can be subtracted from the latter to determine the net volatility spillover of the variable. Volatility received by the variable is defined as

(37) $$DR_i(n) = \frac{\sum_{\substack{h=1 \\ i \neq h}}^{k} \widetilde{\Psi}_{i,h}(n)}{k} * 100.$$

The index measuring the volatility transmitted by the commodity is given as

(38) $$DT_i(n) = \frac{\sum_{\substack{h=1 \\ i \neq h}}^{k} \widetilde{\Psi}_{h,i}(n)}{k} * 100,$$

where again for both equations (37) and (38) the denominator constitutes the total FEV of the system due to the normalization procedure (Diebold and Yilmaz 2012). This measure gives an overview about the contributions of one market to the volatility in other markets and thus reveals who is a net-transmitter of volatility and who is a net-receiver of volatility. The net volatility spillover index, indicating whether a variable transmitted more volatility towards the other variables in the system than it received from them, is therefore calculated as

(39) $$NET_i(n) = DT_i(n) - DR_i(n)$$

(Diebold and Yilmaz 2012). Following the logic of (39) a similar index can be determined for only two distinct variables of the system, which then constitutes the net pairwise volatility spillover index. This measure is defined as the difference of the gross volatility spillover from one market into another distinct market and vice versa relative to the total FEV. This measure is given as

(40) $$P_{ih}(n) = \left(\frac{\widetilde{\Psi}_{hi}(n) - \widetilde{\Psi}_{ih}(n)}{k}\right) * 100,$$

with k again representing the total FEV of the entire system due to the normalization (Diebold and Yilmaz 2012). Intuitively it shows which commodity was a net-receiver of volatility at what time compared to another single commodity. A graphical representation of all the directional volatility spillover indices over time provides a simple way of visualizing the indices and allows to easily spot changes in the volatility patterns among the variables considered.

4 Data and model estimation

This chapter introduces the data for the analysis. The data choice is explained and followed by a description of its transformation into a suitable format for the purpose of the thesis. Afterwards the data is described extensively, separated into distinct paragraphs for the livestock, feed crop and energy futures. The chapter closes with stationarity tests and the specifications of the VAR model.

4.1 Data

As historically the CME Group depicts the largest and most liquid agricultural derivatives exchange, it is the optimal source for long-term data about agricultural commodity prices. New information is incorporated in these prices continuously as it was shown in chapter two. The variables for the analysis have been chosen after careful consideration of the developments in the agricultural commodity sector, emphasizing the increasing meat consumption and energy sector developments. Additionally, the trading volumes and thus pricing potentials of the futures contracts were a vital characteristic during the selection process.

Data has been obtained for CME feeder cattle, live cattle and lean hog futures, CBOT corn, SRW wheat and soybean futures as well as NYMEX crude oil futures. The last one is chosen as a direct substitute for bioethanol and for its traditionally high liquidity. The sample consists of daily data on historic first generic futures prices and trading volumes for each commodity, all received via the Bloomberg Professional Service for all trading days from the 01.04.1986 until the 07.12.2016. Thus, for each variable a total of 7745 observations are available. The prices for the futures contracts were rolled over from the expiring futures contract to the subsequently expiring contract after the last trading day of the nearest expiring contract. Missing data points are linearly interpolated. In the case of feeder cattle and lean hogs no data on trade volume was available for the first observations, thus linear interpolation is not applicable. For feeder cattle, no data on trade volumes was available from 01.04.1986 until 28.01.1988 and for lean hogs no trade volume data was available from 01.04.1986 until 20.01.1987.

As already indicated in chapter two, the volatility of a price series is a latent factor that needs to be estimated, which itself leaves some scope to the researcher (Andersen et al. 2003). So far, there is no methodology that estimates volatility in a way that has been proven superior to all others (Engle and Gallo 2006). However, the range volatility, defined as the difference between the highest and the lowest price of a fixed time interval, provides a more efficient volatility estimator as the return based estimation for the purpose of this analysis. In the short-run, the difference between the highest and the lowest price of a series in a fixed period provides more information than the difference between two closing prices. Furthermore, the range volatility is less fragile regarding noise in the microstructure of the data, for example bounces in the bid-ask spread (Chou et al. 2010). The basis for range-based volatility estimation depicts the Parkinson (1980) range estimator, which is given for commodity *i* over time *t* as

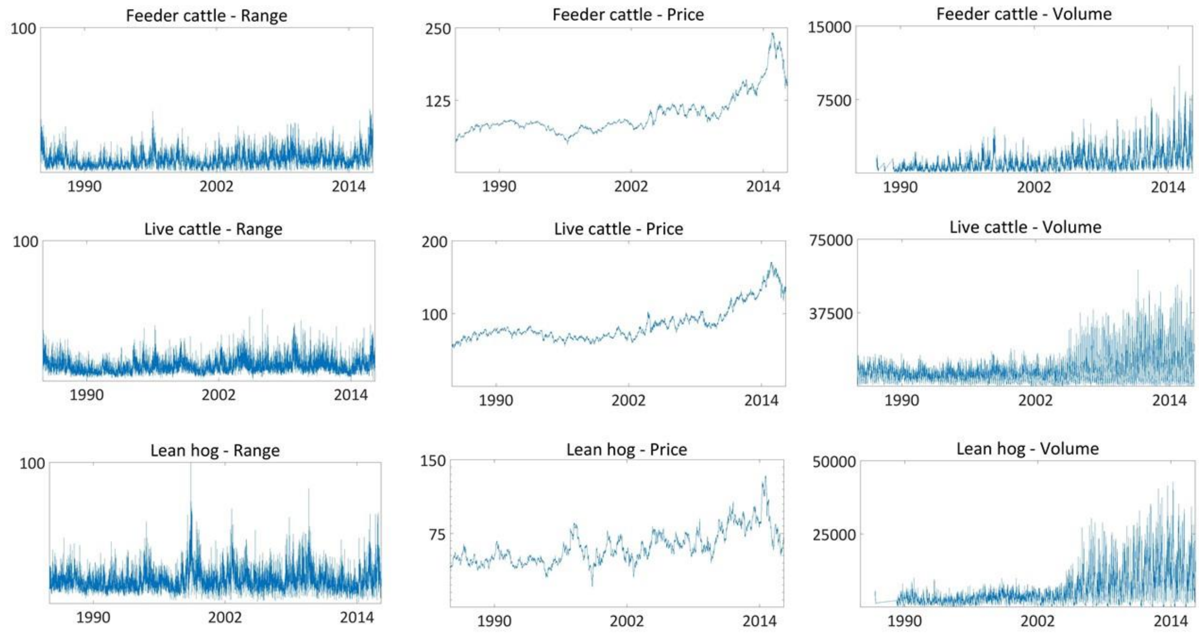
$$R_{it} = 0.361(lnP_h - lnP_l)^2, \tag{41}$$

with lnP_h and lnP_l being the highest and lowest logged price for the chosen time horizon *t* of commodity *i* respectively. Using the Parkinson (1980) range estimator the futures prices are transformed into range-based volatilities, with P_h being the highest price for each trading day and P_l the lowest. Since the main objective of the estimated VAR model is forecasting, it is beneficial to transform the volatilities for each variable into logged range volatilities, which often increases the precision of the forecasts (Lütkepohl and Xu 2012).

4.2 Annualized range volatilities, closing prices and trade volumes

Figure 3 displays the annualized range volatilities, the closing prices and the trading volumes of the livestock futures included in the analysis. Range volatility of feeder cattle futures experienced its peak in April 1996, which comes together with a low in feeder cattle prices and a high in feeder cattle trading volume. During that time, the market in the USA experienced an oversupply of beef meat, starting in the early 1990s and climaxing in 1996 (USDA 1999). The continuously falling price in the beef market might have caused producers to increasingly hedge their production risk at the futures market. In the live cattle market, the price development was less distinct during those years and an increase in trade volume hardly occurred. Anyway, range volatility in live cattle futures also spiked in April 1996. For live cattle futures, another important range volatility spike happened in late 2004 and the beginning of 2005, coinciding with high prices and volatility in the soybean market. During the commodity price crisis in 2008, cattle futures closing prices and range volatility only slightly increased. Closing prices in the cattle futures markets started surging from 2010 onwards, including the sample peak of the closing prices for feeder and live cattle in November 2014 and April 2015 respectively. The average trade volume in the feeder cattle market more than doubled since the financialization of the futures markets in 2006. Between 01.04.1986 and 30.12.2005 the average daily trading volume was 701 contracts per day, since then this number went up to 1765. The relatively low market liquidity in the feeder cattle market restricts the amount of information that is stored in the price since not many traders contribute to the pricing process, which can impose restriction when interpreting the results of the analysis. In the live cattle market these numbers changed from 6067 between 1986 and 2005 to 12088 after 2006.

Figure 3: Livestock futures data



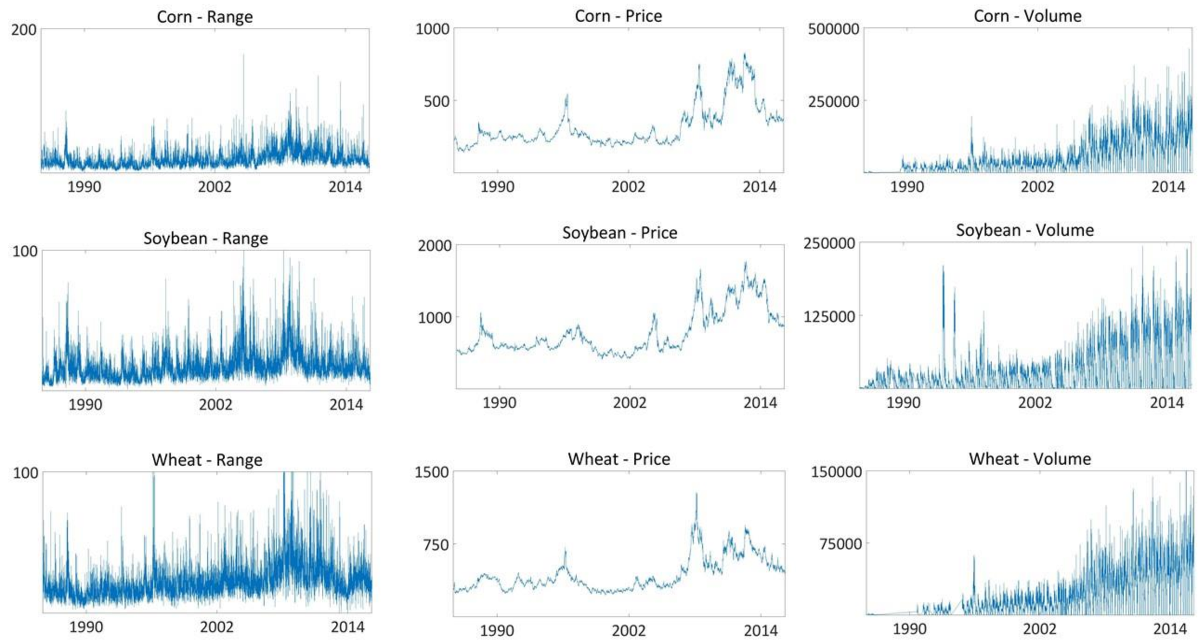
Source: Own illustration

The range volatility of lean hog futures experienced its peak in July 1998. After having the highest average prices ever in hog markets in 1996 and 1997, prices starting plummeting. The lowest closing price for lean hog futures was reached in December 1998. This was followed by a shake-out in the hog production market and a shift towards larger production facilities in the USA (Luby 1999). The closing price of lean hog futures follows a nicely visible Cobweb pattern, intensifying after 1996, which coincides with the development towards larger production facilities. Despite the Cobweb pattern the trend in closing prices for the lean hog futures market was positive after the low in 2000 until July 2014 where prices reached an all-time high of 133.88 US dollars per futures contract and a subsequent drop to 58 US dollars by March 2015. The spikes in range volatility for lean hog futures indicate a cyclical pattern like its closing prices, with spikes every three to four years. Outstanding spikes in magnitude occurred in August 1994 and November 2007. The average daily trading volume for lean hog futures contracts increased from 2796 contracts between 1986 and 2005 up to 10125 contracts after the financialization in 2006. Therefore, the trading volume before the financialization of lean hog futures also has to be interpreted carefully due to limited information content.

Figure 4 shows the developments of annualized range volatilities, closing prices and trading volumes for corn, soybeans and wheat futures respectively. In the feed crop futures markets the first spike in range volatility and closing prices of corn and soybeans appears in July 1988, which was the year the USA experienced a severe drought, which lasted into the 1990s (Hunt and Gordon 1991). The trading volume of soybeans shows two extraordinary spikes with more than 200000 trades in September 1993 and more than 160000 contracts traded in September 1994, which in both cases depicts the soybean harvesting season in the USA. According to FAOSTAT, the soybean harvest in the USA in 1993 decreased by approximately 15 per cent compared to 1992. In 1994 the production quantity increased by more than 30 per cent. A grain price shock hit the US markets in 1996, following a drought in 1995 and a rising export demand for feed grains (Light and Shevlin 1998). The closing price of corn and wheat spiked that year and the range volatility in the wheat market experienced its peak for the sample period in March 1996. In the soybean market the closing price, after a small spike in 1997, declined until 1999, with range volatility spikes in July 1997, July 1998 and July 1999, which in the USA always depicts the time shortly after soybean planting. In March 2004 the soybean price spiked, after harvests in South America fell way short of their USDA forecasts (USDA 2006). September 2004 also constituted the month with the range volatility peak in the soybean futures market for the sample period. These developments also coincide with the accession of China to the WTO in late 2001 and its quick surges in soybean imports. In the corn market the range volatility peak for the sample period was on 14.09.2004, which is the day the USDA Feed Outlook for 2004 was published, announcing corn production volume records for that year (USDA 2004). The peak in range volatility was accompanied by a spike in trading volume that same day. On May 8th in 2003 the European Union introduced its Directive 2003/30/EC, announcing that until 2010 a mandatory blending in of biofuels into ordinary fuels up to 5.75 per cent had to be reached. This announcement was followed by a short spike in range volatility in the corn futures market during those days. Similar actions can be observed after the introduction of the Energy Policy Act in July 2005 in the USA, announcing mandatory increases in bioethanol production levels. The commodity price crisis in 2008 lead to price spikes and range volatility spikes in all three markets. For wheat, the closing price dropped quickly and afterwards did not return to the crisis levels, whereas for corn and soybeans closing prices even surpassed the crisis spikes and remained on record levels from July 2011 until July 2014 for soybeans and from August 2010 until July 2013 for corn. Corn prices reached their highest level in August 2012 during a major drought in the USA. The drought of

2011/2012 depicted a multi-billion dollar disaster for the agricultural sector in the USA, which was similar to the drought results of 1988 (Rippey 2015). Since the second half of 2014 closing prices in the feed markets remained relatively calm. Between 01.04.1986 and 30.12.2005 the average daily trading volumes for corn, soybean and wheat were 21567 contracts, 7683 contracts and 17361 contracts respectively. For the sample period after 03.01.2006, these number increase to daily averages of 103288 contracts, 39142 contracts and 59507 contracts.

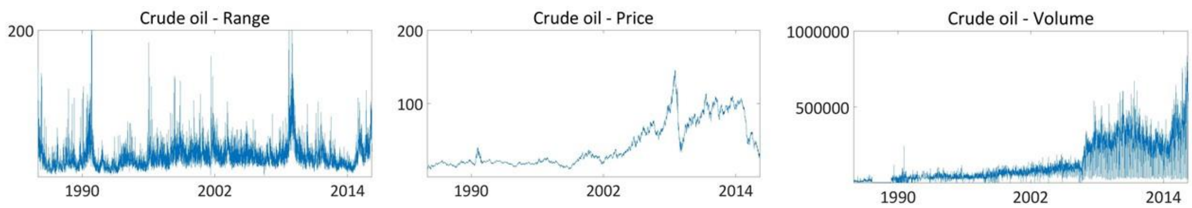
Figure 4: Feed crop futures data



Source: Own illustration

Figure 5 contains the development in the crude oil futures market regarding annualized range volatility, closing price and trade volume. The peak in range volatility for the crude oil futures market sample occurred in January 1991, the time of the second Gulf War, which involved major crude oil producers like Kuwait and Iraq. The price spike that followed this dispute doubled the closing price of the oil price futures quickly. Frequent changes in expectations also had a severe impact on the range volatility during these times. Furthermore, a spike in the trading volume occurred. A volatility spike in February 1996 followed directly on an accident of a Liberian oil tanker in the Irish sea, spilling more than 70000 tons of crude oil (BBC 2002). This event hardly had an impact on closing prices or trade volumes in the crude oil market. After decreasing oil prices throughout 1997, the Organization of the Petroleum Exporting Countries decided to decrease production volumes to increase prices. An agreement had been reached in March 1998 (CNN 1998) and was followed by a spike in crude oil futures range volatility. In September 2001, the range volatility of crude oil futures spiked again after a terroristic attack took place in the USA, which increased the likelihood of another intervention of the US military in the Gulf region. In August 2003 the crude oil futures range volatility experienced another spike on the day the invasion of Iraq by the US military began (CBS 2003). In 2003 the closing prices of crude oil futures started to increase and in 2007 the commodity price crisis became obvious in the crude oil market. The closing price increased from 50.48 US Dollars on 18.01.2007 up to 145.9 US Dollars on the 03.07.2008. Afterwards, crude oil futures closing prices dropped down to 36.87 US Dollars on 19.12.2008. The range volatility spike for crude oil started almost on the peak of the crude oil closing futures prices in 2008, reaching the highest range volatility of that spike on 22.09.2008. After the low in the closing prices, they increased again from 2009 until July 2014. Since then prices are dropping again towards price levels before 2003. The average trading volume of crude oil futures increased from 48767 contracts for the sample period before 2006 up to 282508 contracts afterwards.

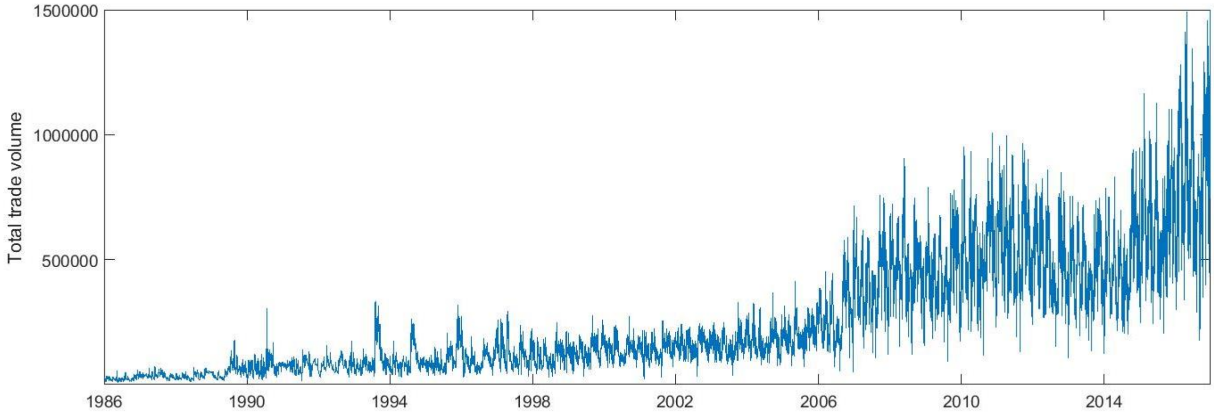
Figure 5: Crude oil futures data



Source: Own illustration

Figure 6 displays the total trading volume of all included assets. The second Gulf War marks the first big spike in total trading volume. The subsequent spikes originate in the soybean market, followed by the grain price shock from 1996. After the grain price crisis, the pattern of the total trading volume remained rather unobtrusive. The year 2006 depicts the start of vast increases in the total trading volumes, initiated by the financialization of the futures market. The years of the commodity price crisis, i.e. 2007 and 2008, depict an intermediate spike of the total trading volume, subsequently decreasing at the end of 2009. After a decrease from 2011 until 2014, currently it is unclear whether the trading volumes spiked in late 2016 or are still moving on an upward trend. The average daily trading volume for the sample period before 2006 depicts 104942 contracts, which afterwards increases to 508424 contracts.

Figure 6: Total trading volume



Source: Own illustration

4.3 Stationarity tests

Before estimating the VAR model, the individual logged range volatility series are tested for stationarity using the ADF test, as presented in chapter three. Non-stationary data would be unsuitable for forecasting values, which is required for the analysis. For each series, the optimal number of lags is determined using the SIC, given as

(42) $$SIC = \ln \frac{1}{T}(\varepsilon' * \varepsilon) + \frac{K}{T} * \ln T,$$

with T being the number of observations and K being the number of coefficients that need to be estimated. The target is to find the lag length p from which on the value of the SIC increases, thus the second term is punishing higher lag lengths (Greene 2008). The visual inspection of the range volatilities allows to omit the trend parameter for all variables. Therefore, for every variable, an ADF test of the form

(43) $$\Delta y_t = b_o + \tau y_{t-1} + \sum_{i=2}^{p} b_i * \Delta y_{t-i+1} + \varepsilon_t,$$

with p being the number of lags, is conducted. The results for the individual range volatilities are summarized in Table 1. As the H_o of the ADF test is non-stationarity and each test statistic is larger than the specific one per cent critical value of the ADF test, it can be concluded that all series are stationary.

Table 1: Results ADF test

Variable	Lags	Test statistic	p-value*
Corn	15	|7.664|	0.0000
Crude Oil	20	|6.412|	0.0000
Feeder Cattle	20	|9.176|	0.0000
Live Cattle	16	|9.597|	0.0000
Lean Hogs	21	|12.843|	0.0000
Soybean	14	|8.178|	0.0000
Wheat	15	|8.644|	0.0000
* Critical value (1%): 3.430|			

Source: Own illustration

4.4 Model specification and estimation

To estimate the VAR model, it is first necessary to determine the lag length of the model. Therefore, as discussed in chapter three, the SIC is used again.

Table 2 displays the results of the SIC criterion as obtained from STATA. The SIC suggests an optimal lag length of five for the VAR model if applied to the entire sample. For the HQIC criterion, STATA determines an optimal lag length of 10, while for the AIC criterion no optimal lag length could be determined in this context due to limitation regarding the size of matrices within the STATA software package. Values for the AIC still are decreasing with a lag length of 15 and further calculations exceed the limitations of STATA. However, since the SIC is the crucial information criterion in this context, this does not cause further issues.

After selecting the lag length, the model could be estimated. Lütkepohl (2007) derives that a multivariate least squares estimator for VAR(p) models, which is identical to the OLS estimator, is consistent and asymptotically normal if the VAR model is stationary and stable with normally distributed error terms. To be stable, all the Eigenvalues of the VAR model must have a modulus less than one. Considering the entire sample at once, the modulus of all the $k \ x \ p$ Eigenvalues, as can be seen in Appendix 1, are smaller than one, which leaves the VAR (5) stable and confirms the stationarity of the model. Normality of the error terms is confirmed using the Jarque-Bera test in STATA. The normality of the error terms was expected due to the results of Alizadeh et al. (2002), showing that logged range volatilities are distributed approximately Gaussian.

However, due to the various changes in the economic environment of the agricultural and the energy sector throughout the sample period, it seems unlikely that a single model with fixed parameters is applicable to the entire sample. To deal with this, Diebold and Yilmaz (2012) suggest to use a rolling estimation procedure to determine the volatility indices. The authors claim that this makes it more likely to detect cyclical or secular movements in the sample data. A rolling estimation is a common tool to analyze financial data. It uses a fixed-seize window that is rolled through the data sample and estimates new parameters for each window. After estimating the first window, the estimated model is used to make predictions for the upcoming *h* values. From this, prediction errors can be calculated later and the window is rolled forward by a predetermined increment. This procedure is repeated until no more *h*-step ahead predictions can be made (Zivot and Wang 2006). Afterwards, the determined prediction errors of the rolling estimation can be used to calculate connectedness measures, such as the volatility spillover indices (Diebold and Yilmaz 2011).

Table 2: Results SIC (full sample)

	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
SIC	19.7021	18.0829	17.7263	17.5935	17.532	17.51*	17.5236

Source: Own illustration

The SIC criterion selected a lag length of five for the entire sample period, which also is going to be applied during each window of the rolling estimations. Following Grosche and Heckelei (2012), the chosen window length is 252, which depicts the average number of trading days per year. The h-step ahead forecast horizon always contains the subsequent ten observations. Diebold and Yilmaz (2011) suggest choosing this specific predictive horizon since it also depicts a common choice when calculating the Value at Risk in many finance applications, such as risk management or portfolio management. The authors claim this choice to be of high importance since it directly relates to issues in the measurement of dynamic contagions. Finally, these choices leave 7494 observations for each variable to determine the volatility indices as presented in chapter three. The last observation of the first estimation window, i.e. 27.03.1987, depicts the first observation to calculate the indices. The entire estimation procedure is conducted in the software package MATLAB, based on code provided by Grosche and Heckelei (2014).

A conducted sensitivity analysis is included in Appendix 2, depicting changes in the total volatility spillover index when altering major variables in the estimation process, such as window size or lag length. The biggest differences occur when reducing the window size by half, shifting the total volatility spillover index significantly upward, while excluding crude oil futures from the analysis only has very minor impacts on the results.

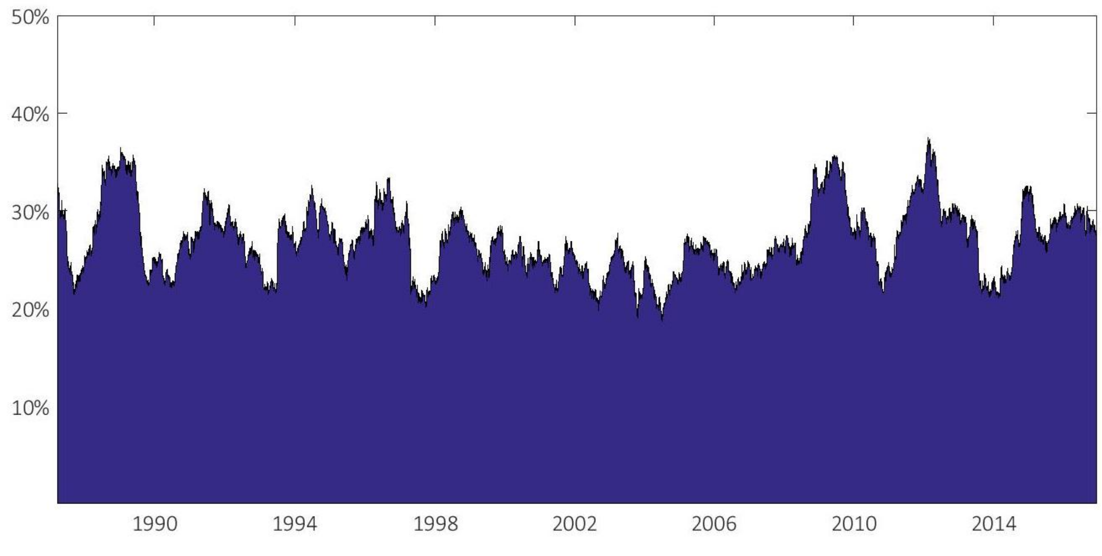
5 Empirical results

The volatility indices as introduced by Diebold and Yilmaz (2012) and as presented in chapter three are determined using the specifications obtained in the former chapter. The indices are divided into three categories. First, the total volatility spillover index for the entire sample, subsequently the directional and net volatility spillovers. The pairwise volatility spillover indices are following towards the end of this chapter. After presenting the results of the spillover indices, a brief discussion linking the results to the insights from chapters two and four is conducted.

5.1 Total volatility spillover index

Figure 7 displays the total volatility spillover for the entire sample period. This index adds up all the range volatility transmitted by all assets in the sample. The average total volatility spillover index for the entire sample period is 26.87 per cent. From Figure 7, three distinct sub-periods can be determined. The first period depicts the sample between 1987 until February 1997. It is characterized by a plateau, which is reached in June 1988, and lasting until June 1989, plus three cyclically appearing spikes. In January 1989, the total volatility spillover index takes a value of 36.48 per cent, which is the second highest value for the entire sample. The other three spikes have maximum values of 32.26 per cent in May 1991, 32.59 per cent in June 1994 and 33.39 per cent in August 1996. The average total volatility spillover for this first period is 27.67.

Figure 7: Total volatility spillover index



Source: Own illustration

The second period starts in March 1997 and ends in June 2007. Within this second phase the total volatility spillover index depicts a negative trend until June 2004, which ends with the lowest value of the entire sample period of 18.67 per cent in July 2004. Afterwards, the trend is switching to a positive value. Throughout the negative trend period the spikes occur regularly, approximately once every year. The average total volatility spillover index for this period is 24.69 per cent. The third segment contains the peak value, i.e. 37.51 per cent, for the entire sample in February 2012. For the first spike of this period the peak value of 35.69 per cent was reached in June 2008. The last spike with a value of 32.04 per cent occurred in December 2013. For this third segment the average total volatility spillover index is 28.75 and spikes occur again approximately once in three years. When splitting the sample in only two parts, before and after 2006, the average total volatility spillovers are 26.19 and 28.24 percent respectively.

5.2 **Directional and net volatility spillover indices**

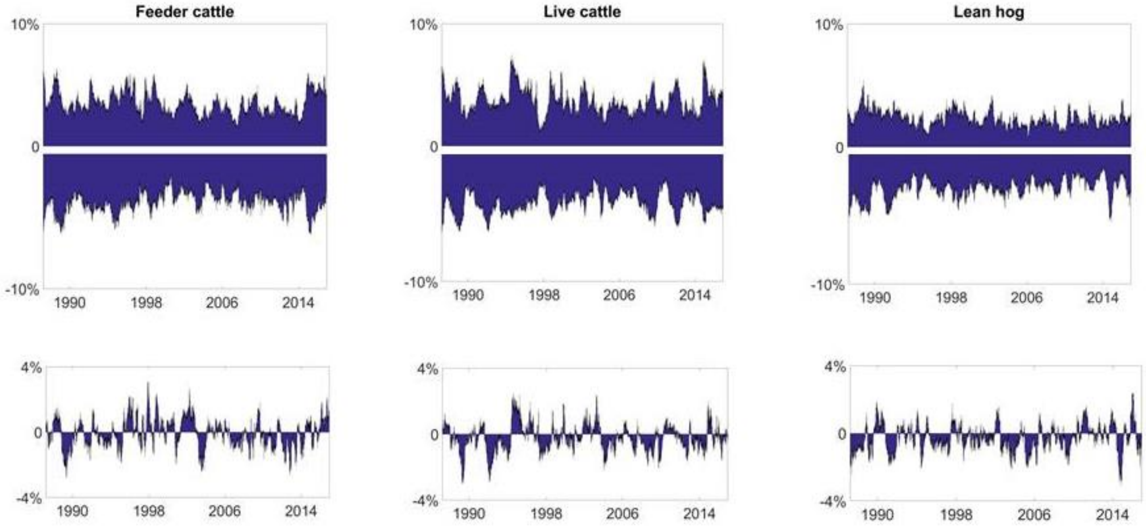
The directional volatility spillover indices measure the range volatility transmitted by each asset towards the range of all other assets and the range volatility received by each asset from all other assets in the sample. In the following figures a positive value indicates range volatility transmitted by an asset towards the ranges of all other assets, while a negative value indicates range volatility received from the ranges of all other assets. The figure for the net volatility spillover indices of each asset follows directly below the figures for the directional volatility spillovers of each asset. Only in the case of crude oil the net volatility spillover index figure is to the right of the figures for the directional volatility spillover indices.

5.2.1 **Livestock**

In Figure 8 the directional and net volatility spillover indices for the livestock futures range volatilities are displayed. Feeder cattle futures start with its peak value for transmitting range volatility in August 1988 with a value of 6.37 per cent, which is directly followed by a spike in range volatility received by all other assets in February 1989. The spikes in feeder cattle range volatility transmitted to all other assets appear cyclical, but with higher frequency before the year 2000. Since the beginning of 2014 the range volatility received and transmitted by feeder cattle futures increased substantially, after a period of receiving and transmitting lower average range volatility between 2000 and 2014. Between June 1995 and April 2002, the feeder cattle net volatility spillover shows a sequence of many positive spikes in a row, with the average net volatility spillover index being 0.51 per cent. From 2006 until 2015 the net volatility spillover index is mostly negative, with an average of -0.54, between November

2011 and June 2013 the average goes down to -1.1 per cent. In total feeder cattle is a net range volatility receiver from all other assets.

Figure 8: Livestock directional and net spillover indices



Source: Own illustration

Live cattle futures are a net range volatility receiver and even more so than feeder cattle futures, especially within the periods between January 1998 until March 2004 with an average value of -0.74 per cent and between November 2003 and September 2014 with the average value of -0.46 per cent. The spikes in range volatility received and transmitted by all other assets show a cyclical pattern. A very steep increase in range volatility transmitted to all other assets occurred in April 1994, reaching the sample period peak in August 1994 with a value of 7.44 per cent. Spikes in live cattle range volatility transmission occur approximately every 3.5 years. Range volatility received by the range volatility of live cattle futures peaked twice with a value of 6.2 per cent, first in January 1989 and then in February 1992.

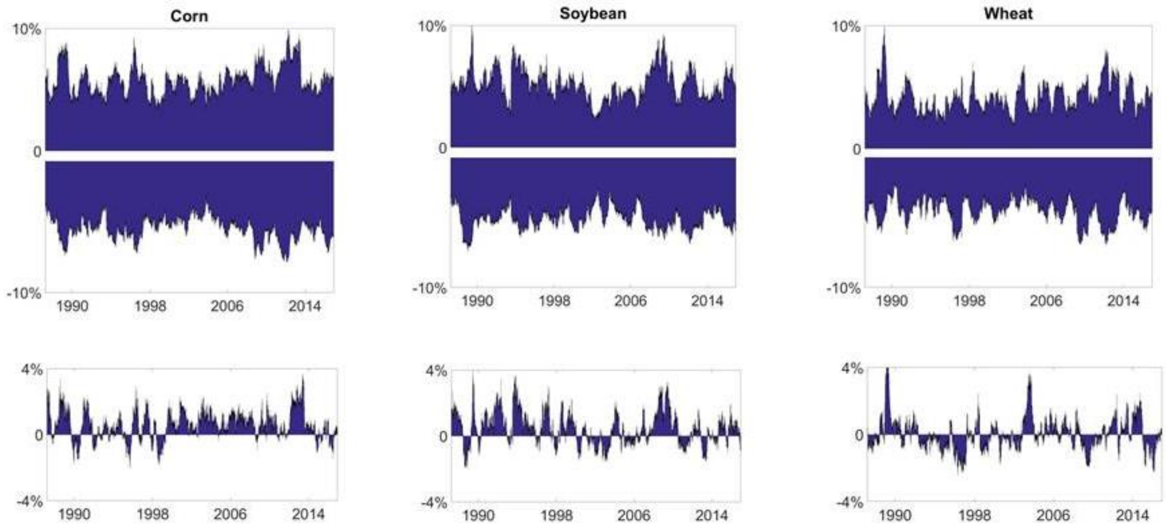
Lean hog futures range volatility transmitted to all other assets peaked in November 1988 with a value of 5.43 per cent. This peak in range volatility transmitted is accompanied by a peak in range volatility received, which repeats itself in May 1991. The peak of range volatility received from all other assets for the entire sample period occurs in October 2014. Over the entire sample period the average range volatility transmitted by lean hog futures to all other assets is as low as 2.32 per cent, while for feeder cattle and live cattle these values were 3.49 per cent and 3.69 per cent respectively. In total, lean hog futures are a net receiver of range volatility like the other livestock futures range volatilities. Its total value approaches the value of live cattle and is thus higher than the value for feeder cattle.

5.2.2 **Feed crops**

Figure 9 contains the directional and net range volatility spillover indices for corn, soybean and wheat futures. For corn the major spikes in range volatility transmitted as well as range volatility received by all other assets in the sample occur around February 1989, April 1996, October 2008 and April 2012. The average range volatility transmitted by corn to all other assets over the entire sample period is 5.77 per cent, while the average range volatility received by all other assets is 5.18, making corn the strongest net transmitter of range volatility in this analysis. Corn hardly received any range volatility throughout the period from April 1999 until June 2008. The peak of net range volatility received by corn futures happened in September 1995 with a value of 2 per cent, the peak for net volatility transmitted occurred in May 2013. From October 2003 until June 2013 range volatility transmitted and received by corn futures were increasing on average in absolute terms.

The second strongest range volatility transmitting commodity are soybeans. The range volatility transmitted by soybean futures to all other assets in the sample peaked in August 1989 with a value of 10.38 per cent, which is the second highest value for all assets. In January 1989 soybean futures received the highest range volatility from all other assets in the entire sample with a value of 7.26 per cent. After a vast increase in range volatility transmitted by soybean futures in June 1993, range volatility transmitted by soybean futures to all other assets followed a negative trend until August 2006. Afterwards, a big spike occurred that peaked in June 2009. The average range volatility transmitted by soybean futures to all other assets for the entire sample period is 5.2 per cent; the value for range volatility received is 4.77 per cent.

Figure 9: Feed directional and net spillover indices



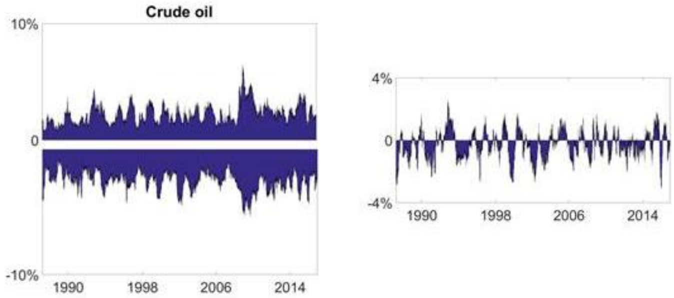
Source: Own illustration

The highest value for range volatility transmitted to all other assets, i.e. 10.51 per cent, occurred on 03.04.1989 and originated in wheat futures. This also provided the highest value for net range volatility transmission, which was just short of 6 per cent on that same day. Spikes in the wheat futures occur approximately every two years with 1994 and 2002 depicting exemption from this pattern. In those years, range volatility transmitted by wheat futures was lower than expected from the other observations. A spike in range volatility transmitted by wheat futures, which was accompanied only by a very minor spike in range volatility received from all other assets occurred in September 2003. Two major spikes in range volatility received by the range volatility of wheat futures appeared in June 2009 and June 2012. In total, wheat futures almost break even with respect to range volatility transmitted and range volatility received from all other commodities throughout the sample period. The average range volatility transmitted by wheat is 4.18 per cent, which is just the same as for range volatility received by wheat futures.

5.2.3 **Energy**

For the sample period, the range volatility of crude oil futures depicts a net range volatility receiver, similar to the extent of lean hog futures and live cattle futures ranges. As can be seen in Figure 10, for most of the time, spikes in range volatility transmitted by the range of crude oil futures are directly followed by spikes in range volatility received by the range of crude oil futures. The spikes occur approximately every two years. The peak for range volatility transmitted by crude oil futures to the ranges of all other assets in the sample occurred in December 2008 with a value of 6.53 per cent.

Figure 10: Crude oil directional and net spillover indices



Source: Own illustration

5.3 Pairwise volatility spillover indices

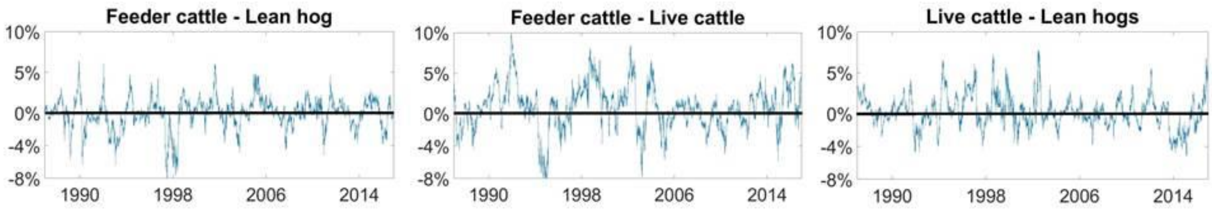
The following sub-sections contain the pairwise volatility spillover indices as presented in chapter three, which always take two commodities at a time and determine the flow of range volatility between these two commodities. First the range volatility spillovers between the livestock futures are presented. Subsequently, the range volatility relationship between livestock futures and feed crop futures is discussed, followed by the energy futures and livestock futures relationship and the relationship amongst the feed crop futures. Lastly, the range volatility spillovers between the individual feed crops and the energy futures are presented. The figures included in this section always contain the range volatility spillovers of the two commodities mentioned on top of the individual figure. Values above zero imply that the commodity mentioned first spills over volatility towards the other commodity and vice versa.

5.3.1 Livestock-Livestock

Figure 11 displays the pairwise range volatility spillover indices between the distinct livestock futures. Feeder cattle and lean hog futures exchange range volatility to high magnitudes within the first years of the sample period. From May 1997 until August 1998 a large spike occurred, with range volatility spilled over from lean hog futures to feeder cattle futures. This spike also includes the peak value between the two commodities, i.e. 11.19 percent. In total, feeder cattle futures are a net receiver of range volatility from lean hog futures. The volatility relationship between feeder and live cattle is denoted by some distinctive range volatility spikes, namely in February 1992, June 1994, August 1998 and April 2003. The first and the third one spills range volatility from feeder cattle to live cattle futures, while the second one spills range volatility from live cattle towards feeder cattle futures. Furthermore, the spike in

1994 depicts the peak spillover between the two commodities with a total value of 9.63 percent. In total feeder cattle is transmitting more range volatility to live cattle than vice versa.

Figure 11: Livestock pairwise volatility spillovers



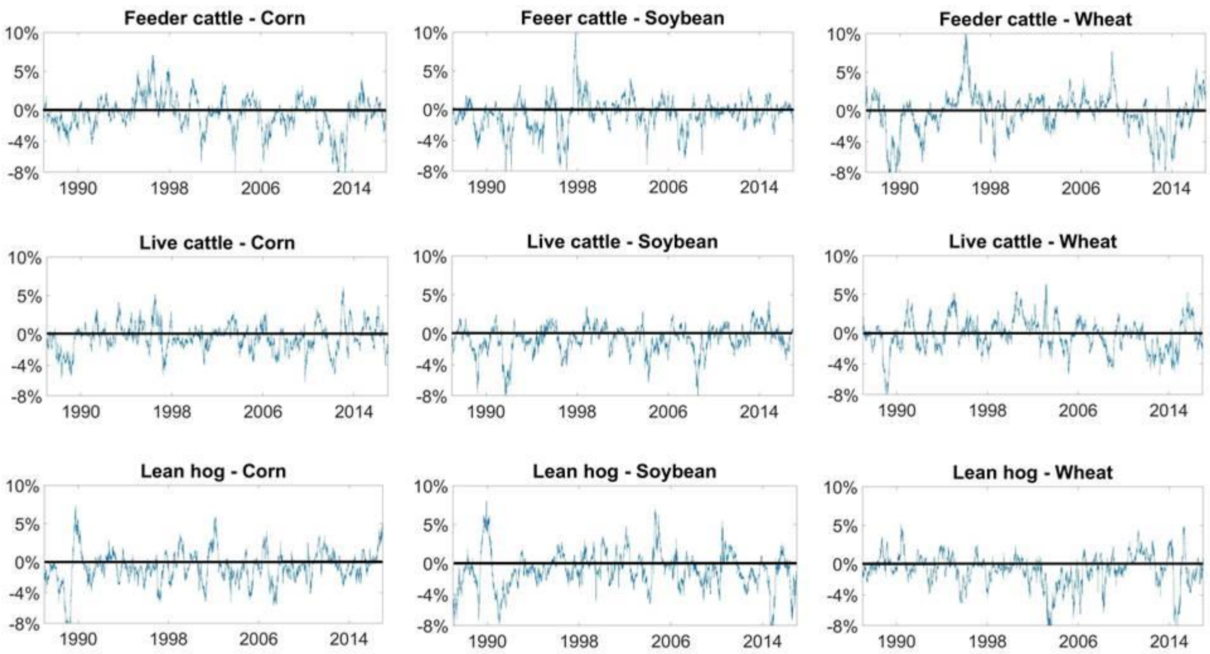
Source: Own illustration

For live cattle and lean hog futures the most significant spikes in range volatility spillovers flowed from live cattle to lean hog futures in June 1994, August 1998 and June 2002. The range volatility spillovers between live cattle and lean hog futures decreased in magnitude from 2006 onwards, although the absolute average range volatility spillover increased from 1.41 percent to 1.51 percent. For the remaining relationships, volatility spillovers on average decreased since 2006 in absolute terms. Between feeder cattle and live cattle the average absolute range volatility spillover before 2006 was 2.4 per cent, while after 2006 it decreases to 1.6 per cent. For feeder cattle and lean hog the values are 1.52 and 1.12 respectively. Additionally, the magnitude of the spikes also decreases for latter two range volatility relationships.

5.3.2 Livestock–Feed

Figure 12 depicts the pairwise range volatility spillover indices between the livestock and feed crop futures. Livestock futures are displayed from left to right, while feed crop futures are displayed from top to bottom. For most of the time, feeder cattle futures receive range volatility from corn futures, with spikes in November 2000, October 2003 and April 2006. The peak of this spillover series occurred in October 2012 with a value of 9.72 percent towards the range of feeder cattle. A long period of feeder cattle spilling over range volatility towards corn futures started in September 1994 and lasted until June 1998 with a peak in September 1996. After the year 2000, the spillovers occurring from the range of corn towards the range of feeder cattle magnified substantially. The range volatility relationship between feeder cattle and soybeans futures is characterized by several major spikes, spilling over from soybean to feeder cattle futures. These spikes peaked in April 1992, August 1996, March 2004, June 2007 and December 2008. Anyway, the absolute peak value for this series occurred in December 1997 and spilled range volatility from feeder cattle towards soybean futures. Since the spike in December 2008, the magnitude of the spillovers has decreased. The peak value for range volatility spilling over from wheat to feeder cattle futures occurred in April 1989, followed by another spike with the same direction of impact in March 1993. In November 1995, with an absolute value of 10.1 percent, the peak value between wheat and feeder cattle futures spilled over from feeder cattle towards wheat. Between September 1999 and January 2009 the average spillovers from wheat to feeder cattle decreased continuously. However, afterwards several spillover spikes from wheat towards feeder cattle futures happened, for example in May 2012 or May 2013. Since March 2014, the trend is again in favor of feeder cattle. In total, feeder cattle futures are net receivers of range volatility from each distinct feed crop.

Figure 12: Livestock-Feed pairwise volatility spillovers



Source: Own illustration

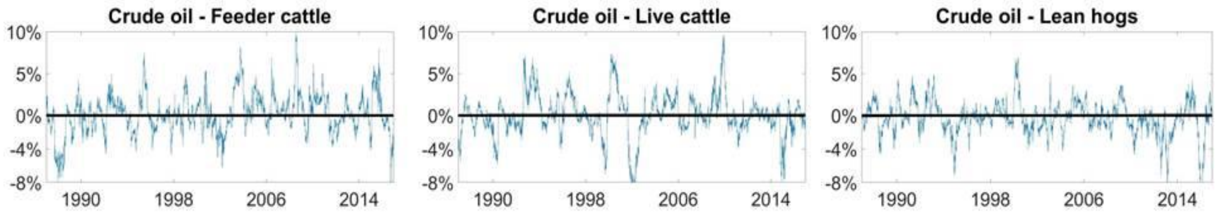
Just like feeder cattle, live cattle futures are receiving more range volatility from each feed crop than they transmit to them. Nevertheless, the spillover index between live cattle and corn futures can be separated into three distinct phases. The magnitude of volatility spillovers decreased after February 1998 and only increased again after September 2009. A distinctive spike in range volatility spilled over from live cattle to corn futures in August 1996, which was followed by another significant spike in range volatility spilling over the other way around, peaking in April 1997. A reversed revision of this pattern can be observed in the third segment, with a spike in spillovers from corn to live cattle futures in April 2012, followed by the absolute peak value for this series in January 2013, spilled over from live cattle to corn futures range volatility. From soybean futures, live cattle futures are receiving range volatility almost all the time in the sample period. The most significant spikes for range volatility spill-overs from soybean to live cattle futures happened in June 1989, November 1991, April 2004 and August 2008. The value in August 2008, i.e. 8.25 percent in absolute terms, depicts the peak of this series. The relationship with wheat futures is not as one-sided for live cattle as it is with soybean futures. April 1989 depicts the peak value for this series, spilling over from wheat to live cattle futures. Afterwards, a period of range volatility mainly spilling over from live cattle towards wheat futures started in June 1990 and lasted approximately until June 2004. Throughout this distinct period live cattle is spilling over more range volatility towards wheat than vice versa.

The range volatility relationship between lean hog, corn and soybean futures is characterized by peaks in the beginning of the sample period. The range volatility spillover from corn into lean hog futures peaked in April 1989 with the reversed spillover peak in December 1989. With soybean these values have been reached in June 1989 and January 1990 respectively. Another significant spike of range volatility spilling over from lean hog to corn futures occurred in April 2002. Distinctive spikes from corn to lean hog futures happened in April 1997, April 2001, July 2003, March 2005 and June 2007. Range volatility spilled from lean hog to soybean futures spiked in September 2004 and July 2010. In recent years volatility spillovers from soybean to lean hog futures spiked in October 2014 and January 2016. Regarding wheat, lean hog futures mostly receive range volatility. The peak spillover from wheat to lean hog futures happened in August 2003 with an absolute value of 13.8 percent. Another major spill-over in this direction occurred in September 2014 with an absolute value of 10.2 percent. A trend towards less range volatility spillover flowing from wheat towards lean hog futures can be detected in the period between September 2003 and April 2011.

5.3.3 **Energy–Livestock**

Figure 13 depicts the pairwise range volatility spillover indices between crude oil and live-stock futures. Crude oil transmits more range volatility towards both the cattle futures than it receives from them, but vice versa for its relationship with lean hog futures. For none of the relationships distinct changes in spillover patterns can be detected for the sample period. Feeder cattle futures spill over high levels of range volatility to crude oil futures in April 1988, April 2002 and just recently in August 2016. The other way around, spikes occurred in August 1995, October 2003, August 2008 and July 2015. Live cattle futures spill over large chunks of range volatility towards crude oil futures in April 2002 and September 2014. The other way around spillover spikes are detected for October 1992, May 2000 and November 2009. The spikes of range volatility spilling over form lean hog into crude oil futures are placed in January 1995, July 2012 and January 2016. The latter one depicts the peak of the series with an absolute value of 14.65 percent. From crude oil into lean hog futures range volatility spillover spikes occur in April 1990, June 1991, October 1992, May 1993 and March 2000. In total, crude oil futures are net receivers of range volatility from lean hog futures.

Figure 13: Energy-Livestock pairwise volatility spillovers

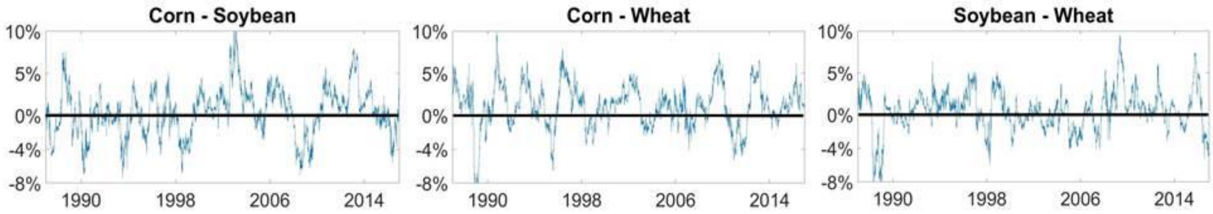


Source: Own illustration

5.3.4 **Feed-Feed**

The range volatility relationships among the feed crop futures included in the analysis is displayed in Figure 14. Between corn and soybean futures distinct periods can be detected where range volatility flows mainly unidirectional. The first period starts in July 1999 and ends in January 2008 with range volatility flowing towards soybean futures. Afterwards, range volatility spills over from soybean into corn futures between February 2008 and June 2010 and again vice versa until August 2014. Spikes in range volatility spillovers from corn into soybean futures occurred in December 1988, December 2003 and July 2012. The other way around, spikes are observed in June 1990, August 1993, August 1998 and July 2008. For soybean as for wheat, corn futures are net transmitters of range volatility over the sample period. Wheat futures range volatility spillovers into corn futures peak in March 1989 with 13.25 percent. Further spikes occurred in September 1995 and December 2010, opposed by spikes flowing the other way around in January 1991, June 1996 and September 2009. The volatility relationship between soybean and wheat futures is characterized by four major spikes, happening in July 1988, May 1998, May 2009 and October 2015. The latter two spikes spilled over range volatility from soybean into wheat futures, while the first two spikes worked the other way around. Over the entire sample period more range volatility is transmitted from soybean into wheat futures than vice versa.

Figure 14: Feed-Feed pairwise volatility spillovers

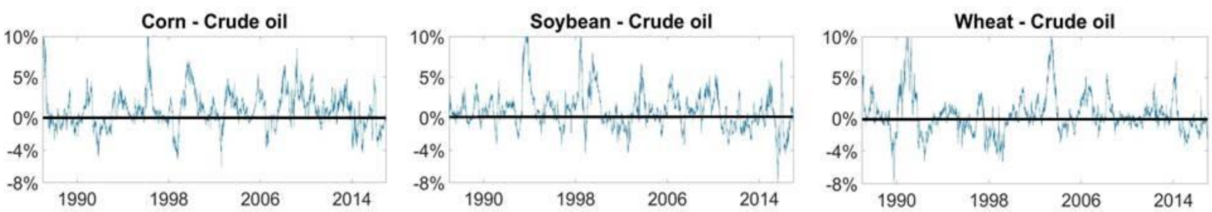


Source: Own illustration

5.3.5 **Feed–Energy**

Range volatility spillovers between feed crop and energy futures are depicted in Figure 15. Over the entire sample period crude oil futures mostly receive range volatility from corn futures, although since mid-2009 this trend seems to revert itself. A downward trend in this relationship can be seen, starting after the commodity price crisis of 2007 and 2008. The range volatility between corn and crude oil futures peaks in May 1996 with an absolute value of 11.95 percent, spilling over from corn into crude oil futures. Other peaks in this direction occurred in October 1999 and March 2009. The average absolute volatility spillover between corn and crude oil futures before and after May 2003 is moving around 1.7 percent. Furthermore, crude oil futures also receive range volatility for most of the sample period from soybean futures with spikes happening in August 1993 and June 1998. Minor spikes can be observed in September 2003, February 2006 or October 2015. The only distinctive spillover from crude oil into soybean futures took place in July 2015. Wheat futures received a major spillover of range volatility from crude oil futures in December 1989, followed by a reversed spike in January 1991. The latter one depicts the absolute peak value for this series with a value of 12.55 percent. The next spike, originating in the wheat futures, is in June 2003, followed by minor spikes in May 2006 and April 2008 in the same direction. Generally, crude oil futures depict a net range volatility receiver from all three feed crop futures for the sample period.

Figure 15: Feed-Energy pairwise volatility spillovers



Source: Own illustration

5.3.6 Summary

From the net volatility spillover measures it is possible to determine the strongest transmitters of net range volatility, as well as the strongest receivers of net range volatility. The most net range volatility has been transmitted by corn futures, followed by soybean futures. Wheat futures almost even out the range volatility they receive with the range volatility they transmit to all other assets. Net range volatility receivers are feeder cattle, live cattle and lean hog futures. The strongest receiver of net range volatility spillover ends up being crude oil.

Years with particularly high total volatility spillovers were determined from Figure 7. The highest values have been reached in 1989, 2008 and 2012. Other years with high total volatility spillovers are 1991, 1994 and 1996. An important time of the year regarding range volatility spillover spikes throughout the distinct indices and assets has been identified around June, which depicts an important period regarding the plantation and harvesting dates for the feed crops, as already indicated in chapter two.

The pairwise range volatility relationships for all assets are summarized in Appendix 3, which provides the answer to the third research question. A plus indicates the horizontally listed asset to be a net transmitter of range volatility to the vertically listed asset. Corn is the only commodity that is a net transmitter of volatility in each pairwise range volatility relationship, while the livestock futures are only receiving net range volatility from the non-livestock assets, except for the crude oil and lean hog futures relationship.

5.4 Discussion

The applied methodology does not provide any form of statistical evidence for causal coherences between range volatility spillovers and certain events in time. However, it is still worth it to qualitatively evaluate the empirical findings with respect to the previously gained market insights and results from the literature review. Therefore, this sub-chapter only discuses simultaneously occurring phenomena but not causal relationships.

The total volatility spillover index does not reveal a significant trend towards increasing range volatility spillovers over time. It has anyway been divided into three different segments, starting with a turbulent time in the late 1980s and 1990s. The one year plateau in 1988 and 1989 occurred to the same time when the USA was hit by a major drought, largely influencing all three crop markets. The spike in June 1994 also happened at a time of drought in the USA, whilst the in 1996 the range volatility spillover spike emerged together with the climax in the cattle market oversupply and a grain price shock induced by a preceding drought. All three of these spikes have been accompanied by local highs in the total trading volume. After a ten-year period of decreasing average total volatility spillovers, the commodity price crisis of 2007 and 2008 hit the markets, characterized by price jumps in crude oil and the feed crops futures and a big spike in the total range volatility spillover index. The commodity price crisis has been accompanied by the financialization of the futures markets, but as already mentioned before might not have been caused by it. The peak in total range volatility spillovers in 2012 evolved around another major drought in the USA, comparable only to the drought in 1988, which depicts the second highest total volatility spillover index value. The average total volatility spillover index in the third segment is higher than in the first segment, but it also contains a major drought in the USA, the commodity price crisis of 2007 and 2008 and the financialization of the futures market. Comparing Figure 6 and Figure 7 does not leave a categorical impression on the relationship between market liquidity and total range volatility spillovers since the vast increases in trading volume seem not to have caused an increase of comparable magnitude in total range volatility spillovers. Furthermore, from evaluating the results with respect to the first research question regarding the relationship between the demand for feedstock and total volatility spillovers, no evidence can be detected supporting a positive correlation between these two factors. The reason for this result cannot be pinned down to single causes, but an important factor is the short-term data used during the analysis relative to the log-term structural changes underlying the increasing demand for feedstock, which has been indicated by Gardebroek et al. (2016). The short-term data mostly catches unforeseen immediate events that directly impact commodity supply and demand, which is represented best by the frequent spikes evolving around the droughts. Furthermore, the increasing production volumes of the feed crops might have prevented increasing pressure on the markets by sufficiently answering increasing demand with increasing supply.

The directional range volatility indices and the subsequent net directional range volatility measures reveal corn and soybeans as the major transmitters of volatility in the system, which comes as no surprise if considering their importance in the American agricultural sector. The fact that these two commodities are emitting a lot of range volatility translates into the hypothesis that the key drivers influencing these markets are likely to also influence other markets (Grosche and Heckelei 2014). Additionally, it is noteworthy that the futures with the highest liquidity are the major range volatility transmitters, not considering crude oil futures. Therefore, it seems plausible that information is flowing from these central markets into other subordinate markets in the agricultural market. The spikes in range volatility transmitted by corn futures to all other assets concentrate on the drought years in the USA and the commodity price crisis. The peak in directional volatility transmitted by soybeans occurred in the drought year 1989 and also the spike in 1993 was accompanied by a significant decrease in the total soybean harvest in the USA. Wheat transmitted a lot of range volatility during the drought of 1989, but in total does not represent a net range volatility transmitter. Severe droughts inside a major producer like the USA can have significant effects on the future price expectation of speculators for several commodities in the derivative exchanges due to their various linkages. Weather is hard to predict accurately and traders need to adjust their price expectation continuously, even more so in times of extreme weather events that have significant effects on production volumes. Therefore, it is no surprise that a lot of information is exchanged among the markets in times of droughts. The livestock futures hardly transmit net range volatility to the other assets, despite feeder cattle after the climax of the beef market oversupply. But they do frequently receive net range volatility spillovers during times of drought in the USA, which again is not surprising since droughts directly influence the main input for livestock production and the information regarding changes in the feed markets is directly processed into the future expectation of traders in the livestock sector. When looking for patterns in the net directional range volatility indices for the livestock futures no trend towards more volatility transmission towards other assets can be qualitatively detected in later periods of the sample.

The pairwise volatility spillovers confirm the scarce results from the literature review regarding volatility spillovers from feed into livestock markets. The results of the studies by Buguk et al. (2003) and Apergis and Rezitis (2003) both indicate that volatility spills over from feed into livestock markets, based on GARCH models and spot prices. However, from Figure 12 more detailed insights can be obtained. Feed crop futures are all ultimately net range volatility transmitters towards livestock futures, but in the mid-1990s feeder cattle futures have transmitted range volatility to each feed market, either in spikes as to soybean and wheat futures or during an extended time period to corn futures. It would thus be worthwhile to further investigate the implications of the beef market oversupply in the USA during the 1990s for the feed markets. Speculators might expect production volumes to go down in the cattle market substantially and thus also expect a decrease in feed demand, which ultimately alters the speculators expectation of future feed crop prices. Problematic for this period is that the trading volumes of feeder cattle futures averages around 700 traded contracts per day, which restricts the amount of information that is stored in the market. Another interesting observation in the pairwise livestock-feed relationship is the volatility spillover peaks from lean hog futures into soybean and corn markets in 1989. Figure 3 indicates that 1990 depicted the end of one of the hog marketing cycles, although it did not have major price effects or range volatility effects on lean hog futures themselves. Towards the end of a marketing cycle traders could already assume feed demand to change soon and thus alter their expectations accordingly in the markets. A lack of data regarding the trade volumes for lean hog and corn futures provides an obstacle in the interpretation of this situation. It depicts a possibility that the trading volumes in the lean hog futures market to that time was too thin to actually allow for any meaningful results since the amount of information stored in the market is not sufficient. Ultimately, Figure 12 does not provide any evidence for a trend of increasing range volatility spillovers from livestock futures into feed crop futures throughout the recent decades, although there has been a positive trend between lean hog and wheat futures between 2003 and 2011. A similar trend can be observed between feeder cattle and wheat between 1999 and 2009.

Within the feed crop futures markets corn and soybean futures are both net range volatility transmitters towards wheat futures and corn is a net range volatility transmitter towards soybeans. This represents also the ordering in the number of acres devoted to each plant, with wheat only obtaining half the amount of acres of soybeans and roughly 45 percent of corn acreage in 2015 (USDA 2016). Anyway, to the time of the first major drought in the USA in 1989, wheat futures spilled over large portions of range volatility towards the other feed crops. After the 1989 drought soybeans depict a range volatility transmitter towards wheat futures in times of drought like 1996 or 2012. Corn on the other hand receives range volatility from wheat futures during these two particular drought years. In non-drought years corn is mostly transmitting range volatility into wheat futures. The information flow within these sectors could be influenced by the differences in planting and harvesting dates, which can allow for years with soybean and wheat production but hardly allows for wheat and corn production combined. Furthermore, corn as the strongest volatility depicts the most liquid market with the most information stored in its price. The liquidity of the soybean futures market is lower than the liquidity in the wheat market, translating into information being transmitted from the less informed market into the market with higher information content.

Looking into the pairwise range volatility relationships of crude oil futures does not allow for conclusive statements on the impact of developments within the energy sector on the information flow between it and its related markets. Just in recent times all three livestock futures transmitted significant spikes of range volatility into the crude oil futures market. Lean hog futures even constitute a net range volatility transmitter towards crude oil futures, although, this result has to be considered in the light of the large differences of the trading volumes between the two markets. The information concentrated in the livestock futures only constitutes a fraction of the information stored in the crude oil market. The counterintuitive result from the analysis that information is transmitted from livestock markets into the crude oil market, especially before the financialization of the futures market might be a result of this large difference. Further investigation on this matter is required to make more decisive statements.

The downward trend for range volatility spillovers specifically from corn into crude oil futures since the end of the commodity price crisis could be a result of the biofuel sector developments and the linkages that have been created by it. This would be in line with the return-based GARCH model results of Guan et al. (2011) in so far as a trend towards increasing volatility spillovers from crude oil into corn markets can be detected in recent times. The results of the analysis contradict the findings of Nazlioglu et al. (2013) and Gilbert and Mugera (2014), based on GARCH models and return volatility, in so far that during the crisis range volatility spilled over from corn into crude oil futures and not vice versa. Furthermore, the results of the analysis contradict the results of the literature review regarding the direction of the information flow between corn and crude oil futures. In this set-up, the latter is a net range volatility receiver from corn futures and not a transmitter of volatility. Range volatility spikes from crude oil into corn futures concentrate only occurred around certain events, like the end of the Gulf war in 1991. In general, information is flowing from all feed crop markets into energy markets and not so much vice versa. As for the livestock market, this result seems rather counterintuitive since crude oil depicts an input in the production process of all feed crops and furthermore is the much more liquid futures market. Leaving crude oil futures out of the analysis in a sensitivity scenario shows that range volatility spillovers actually increases during the spikes before the turn of the millennium. This constitutes a further counterintuitive result, which might originate in often missing and generally low trade volumes to that time in the other markets, despite corn and wheat futures markets. Less information contained in the futures prices could cause prediction errors to increase and thus increase the volatility measures. The energy sector thus provides a lot of liquidity to the sample period with a particular strong impact on the time before the financialization of the futures market.

6 Concluding remarks

The commodity market turmoil of recent years has created considerable interest in the volatility linkages between different commodities. The purpose of this thesis was to evaluate whether the trend towards higher meat consumption in the human diet has had effects on the volatility spillovers in the futures market. Furthermore, the linkage of the livestock and agricultural sector with the energy sector due to policy interventions in several countries since the turn of the millennium has been investigated.

The results of the analysis, using daily futures data for seven distinct commodities to calculate volatility spillover indices as introduced by Diebold and Yilmaz (2012), imply that the increasing demand for feedstock in the livestock sector did not translate into higher total range volatility spillovers in the sample period between 1986 and 2016. The total range volatility spillover index reveals increasing average spillovers since 2007, but this period is also characterized by the commodity price crisis of 2007 and 2008 and the major drought in the USA of 2012. Furthermore, the late 1990s and early 2000s experienced a declining average total range volatility spillover index even though meat consumption did also increase throughout that time period as well. In total, no evidence for a positive correlation between meat consumption and short-term range volatility spillovers can be obtained from this analysis.

A substantial impact of the developments in the energy sector on the total range volatility index also cannot be observed. However, a potential outcome of the development might be spotted in the pairwise range volatility index between corn and crude oil futures, which shows a changing trend since the end of the commodity price in 2008, but if this trend will reverse the pattern of net range volatility flowing from corn into crude oil futures remains to be seen.

The results of the analysis, however, do provide evidence that range volatility is not flowing unidirectional from one market into the other. Range volatility spillovers do change their direction, which implies that traders react to economic and political events, such as droughts or political turmoil that alter their expectations of the future price of commodities. However, range volatility spillovers do mostly occur from input into output markets, but are by no means exclusively doing so. A vital problem for analyses of livestock futures markets is the low liquidity before the financialization of the futures market in 2006. This reduces the validity of the insights that can be obtained from analyzing these markets since the amount of information stored in the prices is rather limited. Therefore, results such as lean hog futures constituting a net range volatility transmitter into crude oil futures have to be evaluated very carefully. The trading volume constitutes a crucial factor while analyzing futures markets, but the analysis does not deliver strong evidence that the financialization of the futures market did cause significant increases regarding the volatility spillovers between distinct commodity futures markets.

Despite the lean hog futures range volatility relationship with crude oil futures, the livestock futures depict net range volatility receivers for each relationship with non-livestock assets included in the sample. Increasing demand from the meat sector did not cause this relationship to change its patterns between 1986 and 2016. Thus, increasing meat consumption is not associated with higher range volatility transmission by livestock futures towards others assets within the CME Group. The increasing production volumes of the crops throughout the last decades might have mitigated the effects of increasing demand and released most of the pressure that might have developed if market conditions would have actually become tighter. Anyway, future growth of crop production volumes is expected to slow down, while meat consumption is expected to start increasing in many new regions, such as Sub-Saharan Africa. Furthermore, the level of meat consumption in the emerging economies did not yet reach the levels of developed countries. According to FAOSTAT, the per capita consumption of meat in China in 2011 did not quite reach the level of meat consumption of the USA in the 1960s. Thus, increasing meat consumption in the upcoming decades might put pressure on agricultural markets and the issue might require reinvestigation.

Another vital aspect for the results is the data frequency used in the analysis. As it has been stated by Gardebroek et al. (2016), long-term structural changes in the agricultural sector are more likely to be detected by lower frequency volatility measures, such as monthly averages. Thus, an interesting prospect could be to compare the results of this analysis to results obtained using monthly averages instead of daily data. Additionally, using data sourced from commodity exchanges in emerging economies poses another variation with the potential to obtain different results. The increasing liquidity of Chinese commodity exchanges in recent years offers interesting opportunities to apply the methodology to other markets.

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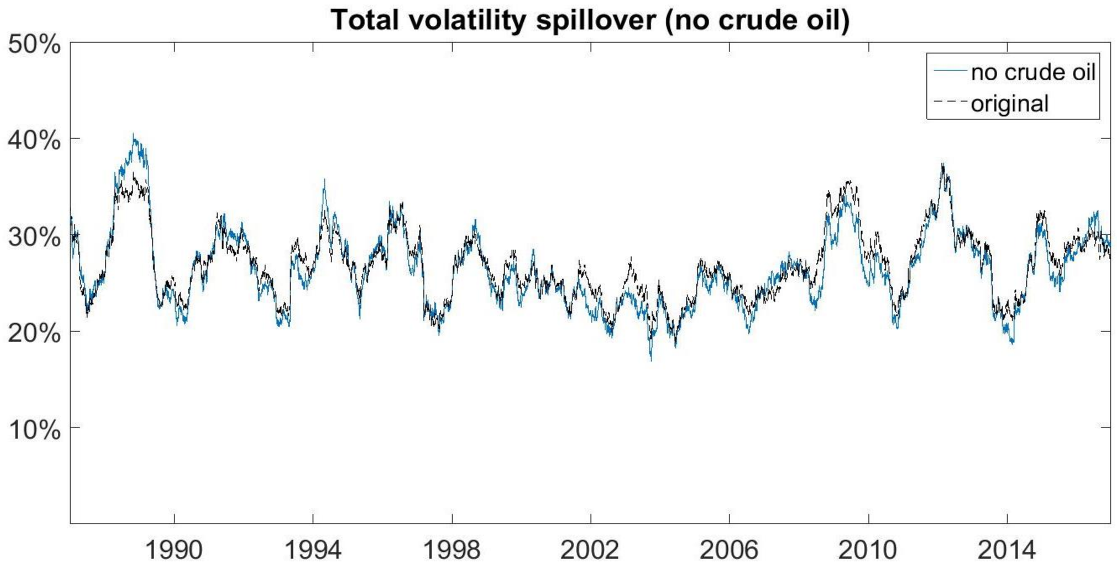
Appendix

Appendix 1: Eigenvalues VAR (5)

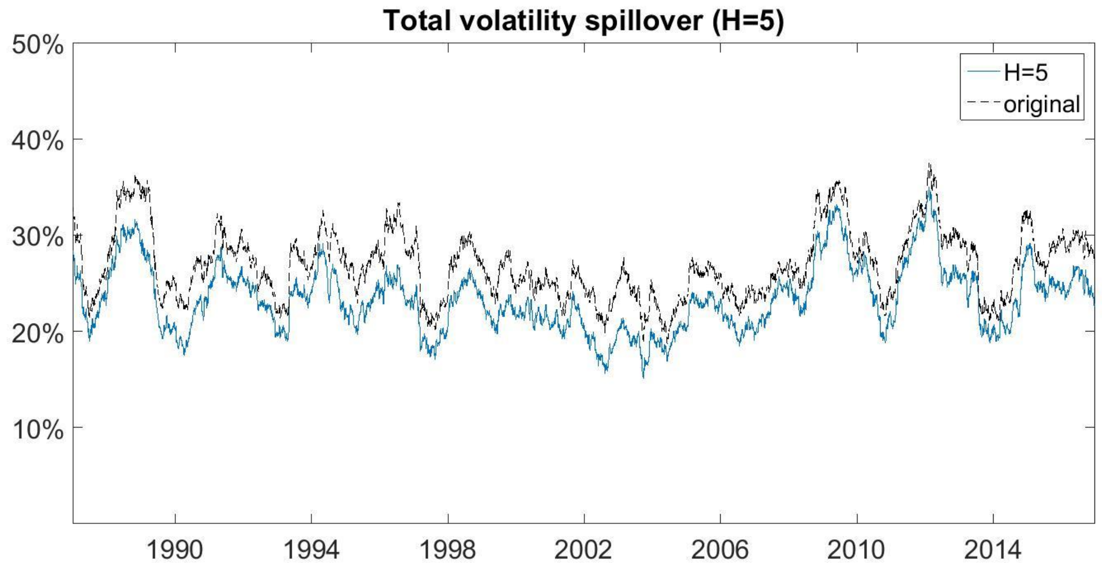
B1	0.947206
B2	0.907663
B3	0.880302
B4	0.865337
B5	0.825658
B6	0.777588
B7	0.757344
B8	0.668892
B9	0.668892
B10	0.632141
B11	0.632141
B12	0.627079
B13	0.627079
B14	0.602602
B15	0.602602
B16	0.590692
B17	0.590692
B18	0.590642
B19	0.590642
B20	0.580421
B21	0.580421
B22	0.568631
B23	0.568631
B24	0.550955
B25	0.550955
B26	0.548088
B27	0.548088
B28	0.542674
B29	0.542674
B30	0.535039
B31	0.535039
B32	0.525707
B33	0.525707
B34	0.420927
B35	0.420927

Source: Own illustration based on STATA

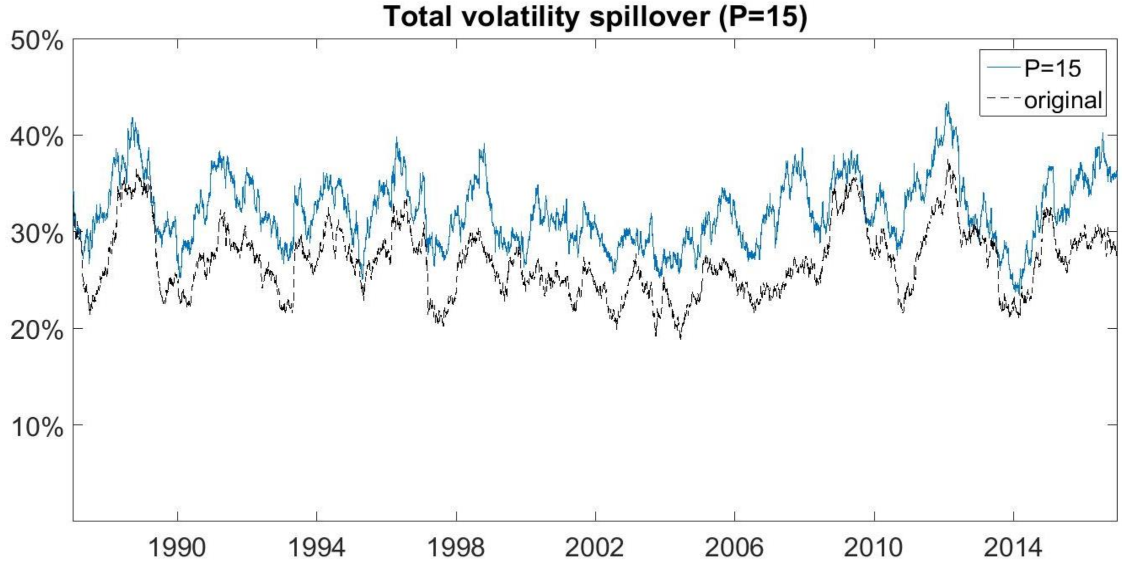
Appendix 2: Results of sensitivity analysis



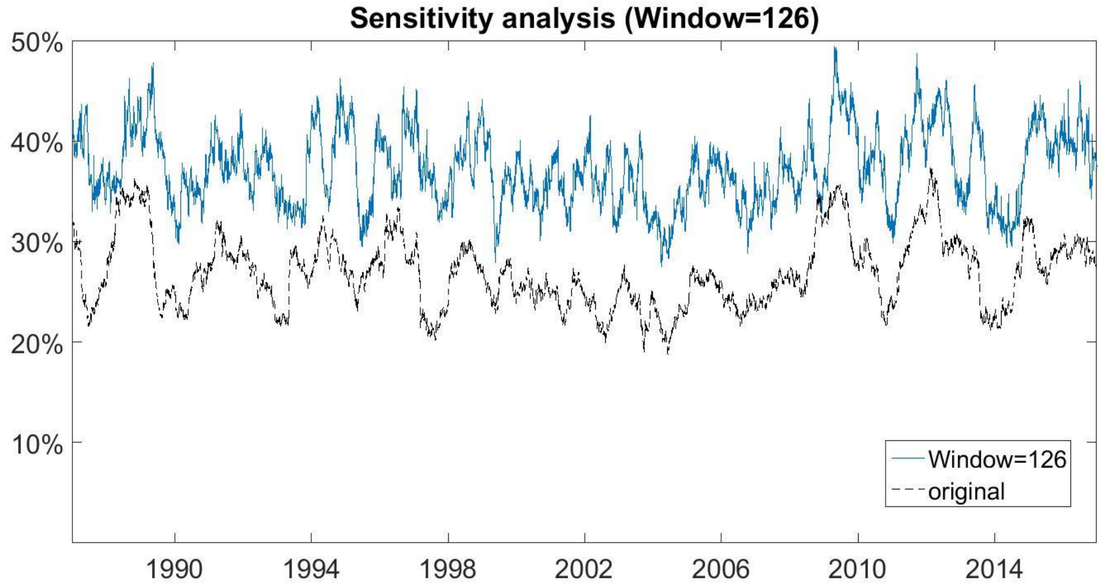
Source: Own illustration



Source: Own illustration



Source: Own illustration



Source: Own illustration

Appendix 3: Pairwise net volatility relationships

	Corn	Crude oil	Feeder cattle	Live cattle	Lean hog	Soybean	Wheat
Corn		+	+	+	+	+	+
Crude oil	-		+	+	-	-	-
Feeder cattle	-	-		+	-	-	-
Live cattle	-	-	-		+	-	-
Lean hog	-	+	+	-		-	-
Soybean	-	+	+	+	+		+
Wheat	-	+	+	+	+	-	

Declaration

I hereby affirm that I have prepared the present paper self-dependently, and without the use of any other tools, than the ones indicated. All parts of the text, having been taken over verbatim or analogously from published or not published scripts, are indicated as such. The thesis hasn't yet been submitted in the same or similar form, or in extracts within the context of another examination.

Hennef, 30.05.2017

Student's signature