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Volatility analysis: causation impacts in retrospect (2007-2011) and preparing for the future

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ULYSSES project assess the literature on prices volatility of food, feed and non-food commodities. It attempt to determine the causes of markets' volatility, identifying the drivers and factors causing markets volatility. Projections for supply shocks, demand changes and climate change impacts on agricultural production are performed to assess the likelihood of more volatile markets. ULYSSES is concerned also about the impact of markets' volatility in the food supply chain in the EU and in developing countries, analysing traditional and new instruments to manage price risks. It also evaluates impacts on households in the EU and developing countries. Results will help the consortium draw policy-relevant conclusions that help the EU define market management strategies within the CAP after 2013 and inform EU's standing in the international context. The project is led by Universidad Politécnica de Madrid.

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Abbreviations and acronyms

AR	Auto-Regressive
BRICS	Brazil, Russia, India, China, South Africa
CFTC	Commodity Futures Trading Commission
CIT	Commodity Index Traders
COT	Commitment of Traders
ENSO	El Niño - Southern Oscillation
EU	European Union
F.O.B.	Free on Board
FED	Federal Reserve
GARCH	Generalized Auto-Regressive Conditional Heteroskedasticity
GDP	Gross Domestic Product
MATIF	Marché à Terme International de France
MiFID	Markets in Financial Instruments Directive
NYMEX	New York Mercantile Exchange
OECD	The Organisation for Economic Co-operation and Development
OTM	Out of The Money
PPP	Purchasing Power Parity
SOI	Southern Oscillation Index
US	United States
USDA	United States Department of Agriculture
VAR	Vector Auto-Regressive
WAOB	World Agricultural Outlook Board
WASDE	World Agricultural Supply and Demand Estimates Report
WTI	West Texas Intermediate

1. Introduction

Price volatility in agricultural markets is still an important matter in the discussion at both the political and the scientific level. Starting from the food price crisis of 2007/08, not only the observation of increasing price levels but also their increased volatility on key markets (most notably grains) has triggered many studies both at the conceptual and at the empirical level. Policy makers have responded, too; policies for stabilising producer and consumer prices have experienced a revival in the discussions surrounding the Common Agricultural Policy reforms, and concerns about the impact of insufficient regulation for derivatives markets with relevance in agriculture have played a role in the ongoing reform process of the EU's financial market regulation. The agreement reached in January 2014 in the trilogue process on the reform of the Markets in Financial Instruments Directive (MiFID), which, among other things, introduced a mechanism for setting position limits and mandatory reporting of positions held, is a case in point.

Despite this focus on agricultural price volatility, there has not yet been reached a full consensus about the question which drivers were shaping price volatility in agricultural markets over the past years. In an overview of the existing literature (Brümmer et al. 2013b), a number of broader categories is identified which were often mentioned in the studies contained in the review. Figure 1 (Brümmer et al. 2013a) gives an overall impression of the frequency at which a given category was addressed in the existing literature. The colour coding allows to split each category according to the way each of the studies treated the corresponding category: When a paper addressed the category in an empirical way, it is counted towards the red segment of the corresponding bar; if no attempt at empirical quantification of the variables' impact was undertaken, the study was counted towards the grey segment.

From Figure 1, it is obvious that financialisation and speculation were by far the most important in overall terms, followed by a set of macro-economic variables (oil prices, exchange rate volatility, and increasing consumption). Biofuel mandates, as an important policy factor, came next, followed by weather shocks. The final two categories were never addressed quantitatively but only discussed at the conceptual level: Underinvestment in agriculture and the impact of ad hoc policy measures are indeed difficult to quantify. There is, however, a major drawback in the vast majority of the existing studies: Usually, the focus is put on one (in rare cases up to three) agricultural markets. To restrict a single study to a narrowly defined subset of agricultural markets is, on the one hand, a very meaningful approach because it allows careful modelling of price volatility and the factors behind it. On the other hand, the opportunity to study a broader set of markets, and the price volatility spillovers among them is missed. Furthermore, the heterogeneity of price volatility developments between markets is easily lost out of sight, too.

Our study aims at addressing this research gap. We provide a thorough analysis of agricultural price volatility for 15 different markets of global importance, grouped into five commodity groups which were formed on the basis of the expected interdependence between the markets. Monthly price volatility is estimated for each product using a standardised GARCH framework. In order to address a broad picture regarding the impact of exogenous drivers and the relevant price volatility spillovers, we employ in a second stage a vector-autoregressive (VAR) model for the estimated volatilities for each of the five groups. In each VAR model, we use the same set of variables as potential exogenous drivers of price volatility. These candidate variable are chosen to represent the most important categories from Figure 1: Financialisation, oil prices, low stocks, exchange rates, increased consumption, and weather shocks. Policy related variables (biofuel mandates, ad-hoc policy interventions) were excluded since it is difficult to define meaningful continuous variables for policy changes. The role of biofuels is, however, not neglected since bioethanol and biodiesel are included in the set of markets analysed.

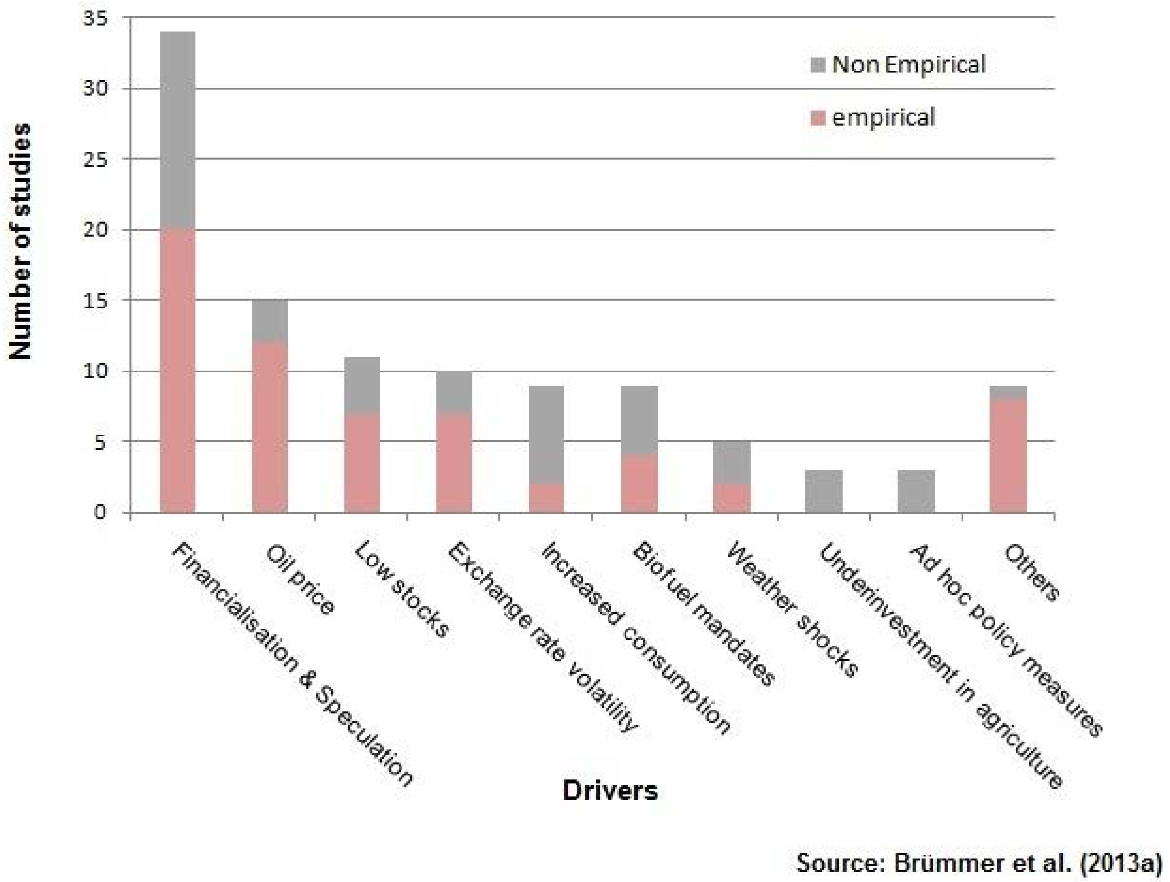

Figure 1: Drivers of food price volatility

In the next section (Section 2), we briefly delineate how we selected the agricultural products (including selected biofuels) in each commodity group, for which we model the estimated volatilities as an interdependent system. We follow up in Section 3 with an explanation of the estimation procedure for price volatility. In the following Section, we explain which variables were used to capture the categories of drivers outlined above. Given that the number of potential candidate variables is huge, we then continue in Section 5 with an explanation of our model selection procedure. We rely on automatic model selection in order to avoid subjective biases in the general-to-specific modelling exercise, and to facilitate reproducibility of our results. The subsequent Section presents the parameter estimates by commodity groups, and discusses the results on two aspects of major relevance: The estimated impact of the drivers, and the identified spillovers among the price volatilities of the commodities included in each group. Section 7 concludes by pointing out the lessons which can be learned from our analysis with regard to policy implications.

2. Identifying relevant commodity groups

As a contribution to the volatility spillover and volatility drivers literature, we develop an innovative spillover - driver model. In order to find influential factors which affect food price volatility and to quantify the effects of these drivers on volatility we select five groups of commodities. Table 1 shows the commodities which are considered in each group. Each group consists of commodities which are likely to be affected by a changing volatility of the other members of the group.

Table 1: Groups and commodities

	Groups				
	Grain	Oilseed	Vegetable oils	Sugar	Meat
Commodities	Wheat (soft) (US)	Soybean (US)	Palm oil (Malaysia)	Raw sugar (World)	Pork (Germany)
	Corn (US)	Rapeseed (EU)	Soybean oil (US, Argentina)	Bioethanol (Brazil)	Corn (US)
	Bioethanol (US)		Rapeseed oil (EU)		Soybean meal (US)
	Ammonia (US)		Sunflower oil (Argentina)		
			Biodiesel (Germany)		

The interrelation between commodities, bioenergy and biofuel markets in different geographical regions is an important issue of our volatility analysis and mainly motivates the composition of the commodity groups.

Group one is called “grains” and consists of wheat, corn, bioethanol and ammonia, all from the US. Bioethanol volatility is chosen as an endogenous variable in this group because it is supposed to be affected by grain price volatility as bioethanol is extracted from corn in the US. Wheat is included because it is usually deemed the lead market for price formation in the grains complex. Additionally, ammonia is chosen because it is the main fertilizer used for grain production. Therefore, it may influence grain price volatilities.

Group two is called “oilseeds” and consists of soybeans from the US and rapeseed from the European Union (EU). The soybean price volatility and rapeseed price volatility are likely related to each other as the protein component in both oilseeds serves as a major source of meal for animal husbandry feed. The oil component is used for human consumption and industrial uses. The latter includes, predominantly in the EU, the use of vegetable oils for biodiesel production. Hence, the markets for oilseeds are characterised by a high extent of substitution possibilities in consumption.

These potentially strong linkages via substitution in consumption is at the core of the composition of our third group, “vegetable oils”. It contains palm oil from Malaysia, soybean oil from Argentina, rapeseed oil from North West Europe, sunflower oil from Argentina and biodiesel from Germany. These agricultural markets are considered jointly with the market for biodiesel as a major use of vegetable oils in the EU. Moreover, this group captures possible volatility spillovers between different geographical regions.

As sugar plays an important role in bioethanol and biofuel production in South America, we have considered a fourth group for sugar and bioethanol from Brazil. The final group is called "meat" and includes pork from Germany as well as corn and soybean meal from the US. The analysis of the volatility spillover effects among meat markets and feed grains is the major objective of the volatility analysis for this group which includes the major exportable meat together with two major feedstock components..

3. Estimating volatility

While food prices are easily observable, price volatilities cannot be observed, but have to be estimated. Several methods of volatility estimation exist, like realised volatilities, model based ex-post volatilities or ex-ante volatilities like option implied volatilities. But not only the estimation approach per se is crucial for the estimation result, also the investigated time frame and the data frequency matter. For our investigation, we choose a monthly data frequency because it is supposed to be a relevant horizon for decision makers in commodity markets. The GARCH (1,1) model[5] is chosen as the most appropriate model for our study because implied volatilities can only be calculated for some commodities due to a lack of sufficient options data, and realised volatilities require higher frequency data to be robust estimators, which is also not available for all commodities.

Price volatilities for all commodities in our study are estimated by fitting a GARCH (1,1) model to monthly continuously compounded returns. If data is available at a weekly or daily frequency, the latest available price within a month is taken for the return calculation. The lengths of the time series for the volatility calculations are different for different commodities, starting with the first available data for each commodity, but not earlier than January 1990. This is done even if the time series used in the VAR model starts at a later point of time due to data unavailability of other commodities in that group.

The mean process of the returns is modelled either as an AR(12) or AR(1) process, depending on the seasonality of the commodity prices.[6] In case of an AR(1) mean process, Ljung-Box tests with lags 10, 15 and 20 are applied and indicate in all cases that residuals are free of autocorrelation.

The error distribution used for the GARCH estimations is student-t. The resulting GARCH models lead to a stationary volatility process for all selected commodities ($\alpha+\beta<1$). This result justifies the use of the vector autoregressive (VAR) model in volatility levels that we introduce in Section 5 without consideration of non-stationarity and co-integration. Finally, the monthly volatility estimates resulting from the GARCH are annualised by multiplying them with $\sqrt{12}$. Table 2 summarizes the GARCH estimations for the different commodities and provides some descriptive statistics for the resulting volatilities.

[5] See Bollerslev (1986).

[6] The results are robust against controlling for seasonality by using monthly dummy variables in the volatility estimation model.

Table 2 : Description of annualised GARCH (1,1) volatility estimations

Commod.	Group	Region	Start	End	Mean process	Mean	SD	Min.	Max.
Wheat (Soft)	1	US	Feb. 1990	Dec. 2012	AR(12)	33.14%	8.17%	22.99%	58.07%
Corn	1 & 5	US	Feb. 1990	Dec. 2012	AR(12)	28.72%	11.71%	17.72%	79.69%
Bioethanol	1	US	Feb. 1990	Dec. 2012	AR(1)	26.72%	9.16%	13.67%	49.85%
Ammonia	1	US	Oct. 1991	Dec. 2012	AR(1)	53.12%	25.37%	36.88%	251.47%
Soybean	2	US	Feb. 1990	Dec. 2012	AR(1)	26.22%	9.43%	14.96%	70.95%
Rapeseed[7]	2	Europe	May 2003	Sept. 2012	AR(1)	22.38%	6.68%	14.93%	44.52%
Palm oil	3	Malaysia	Feb. 1990	Dec. 2012	AR(1)	23.48%	6.11%	17.11%	54.91%
Soybean oil	3	Argentina	Dec. 1995	Dec. 2012	AR(1)	28.34%	3.70%	22.10%	42.51%
Rapeseed oil	3	Northwest Europe	Oct. 1995	Dec. 2012	AR(12)	22.58%	9.15%	15.63%	67.73%
Sunflower oil	3	Nether-lands	Feb. 1990	Dec. 2012	AR(12)	22.04%	4.73%	18.71%	64.44%
Biodiesel	3	Germany	Aug. 2002	Dec. 2012	AR(1)	11.59%	2.19%	7.67%	15.62%
Sugar (raw)	4	World	Feb. 1990	Dec. 2012	AR(12)	30.17%	7.83%	19.52%	62.12%
Bioethanol	4	Brazil	Dec. 2002	Dec. 2012	AR(1)	44.04%	0.04%	43.72%	44.05%
Pork	5	Germany	Feb. 1990	Dec. 2012	AR(12)	24.25%	8.93%	14.34%	73.22%
Soybean meal	5	US	Feb. 1990	Dec. 2012	AR(1)	22.10%	4.78%	16.37%	47.99%

Source: Own estimates.

4. Incorporating exogenous drivers of volatility

In the following, we present how we measure the potential volatility drivers used in the VAR model. We follow the categories which were identified in the literature review (Brümmer et al. 2013b). Further details on specific steps in the calculations or detailed information on the data sources can be found in the Appendix.

Crude Oil Price Level and Volatility

There are multiple pathways through which oil prices affect agricultural markets. Over the past decades, linkages via the input side have been most important. Fossil fuels are a major direct input in agricultural production, and are also an important raw material in pesticide production. In crop production, nitrogen is limiting in most production system, and its production via the Haber-Bosch procedure relies on cheap energy usually provided by natural gas. On the output side, the increasing role of biomass over the past decade has partially revived an old linkage: Before the industrialisation of agriculture, feed for draught animals was a ma-

[7] Due to missing reliable spot data of European rapeseed, the spot price is approximated with the price of rapeseed futures, traded at MATIF in Paris. Precisely, on the last trading day of each month the closing price of the futures contract with the shortest time to maturity is used as the proxy for the spot price.

jor use of agricultural products. Today, bioenergy, in particular biofuel policies, strengthen the link between energy and food.

These factors suggest that prices for oil (as the dominant fossil energy) and agricultural products are linked in levels. For price volatility, the linkages might be less obvious. Nevertheless, oil prices are notorious for their volatile and sometimes erratic price behaviour, and since linkages have strengthened over the past years, part of the volatility from oil prices might spill over to agricultural product markets. The reverse direction is unlikely to be relevant, given the relative size of the markets. The impacts of oil and oil price volatility should be most visible in markets where biofuels play an important role, and less important in livestock products.

Our main focus are spot markets which are most important for price formation in a global perspective. Hence, the monthly crude oil price level is calculated as the average daily price within a month based on daily data of West Texas Intermediate (WTI) crude oil free on board (F.O.B.) at Cushing, Oklahoma.[8]

Crude oil price volatility is estimated by the implied volatilities of New York Mercantile Exchange (NYMEX) options on crude oil futures. The futures contracts refer to WTI crude oil. Because the volatility is extracted from currently traded options, the estimator needs no historical price data and is therefore not influenced by outdated information. Implied volatility is supposed to lead to better volatility predictions because it extracts the expectations of market participants, which consider recent information in their decisions.[9] The calculation of the implied volatility is based on the model-free approach of Bakshi et al. (2003). This approach has the major advantage over the standard Black-Scholes volatilities that no assumptions on the price or return distribution are needed.

The crude oil price volatility in a specific month is estimated by the volatility that is implied in options traded on the last trading day of the previous month with a time to maturity of thirty calendar days. If there is no option traded with the required maturity, the volatility is linearly interpolated between the implied volatilities of the nearest options with less than thirty calendar days to maturity and with more than thirty calendar days to maturity.

The crude oil price volatility in a specific month is estimated by the volatility that is implied in options traded on the last trading day of the previous month with a time to maturity of thirty calendar days. If there is no option traded with the required maturity, the volatility is linearly interpolated between the implied volatilities of the nearest options with less than thirty calendar days to maturity and with more than thirty calendar days to maturity.

Dollar Strength Level and Volatility

Most of the international trade in agricultural commodities is carried out in US Dollars. Thus, shocks to the US Dollar will have an impact on prices in domestic currencies. Exchange rate pass through in agricultural markets remains an active area of research, with evidence pointing towards a less than perfect pass-through of exchange rate changes to importer markets. The pricing-to-market literature attributes such imperfections often to market power on the

[8] Source: Thomson Reuters Datastream, Code = "CRUDWTC".
[9] See Poon & Granger (2005), Poon & Granger (2003) and Christoffersen et al. (2011) for a documentation of the predominance of implied volatilities for many different markets.

exporter side. In any case, if exchange rate changes are at least partially transmitted to domestic prices, also volatilities in exchange rates might be transmitted to agricultural markets.

The dollar strength is measured by the trade weighted dollar index, which is calculated by the Federal Reserve (FED) on a daily basis and weights the bilateral exchange rates of the US Dollar against seven major currencies according to their importance for trade competition.[10] The monthly dollar strength is the average index value of the respective month.

To capture not only the strength of the US Dollar, but also its volatility, the realised volatility is calculated based on returns, i.e. the daily percentage changes of the trade weighted dollar index. In order to circumvent underestimation of the true volatility if the returns are positively autocorrelated, the applied formula contains a correction term for autocorrelation:[11]

$$\text{Variance}_t = \sum_{i=1}^{N_t} (r_{i,t} - \overline{r_t})^2 \cdot \left[1 + \frac{2}{N_t} \cdot \sum_{j=1}^{N_t - 1} (N_t - j)\hat{\varphi}_t^j\right]$$

with

t = month, N_t = number of daily returns in month t;

r = daily return; $\overline{r_t}$ = mean return in month t;

$\hat{\varphi}_t$ = first - order autocorrelation coefficient of the daily returns within month t

The realised volatility is calculated for each month using the daily returns and annualised afterwards with $\sqrt{12}$.

Speculation and Financialisation

It is theoretically non-controversial that "normal" speculators are necessary for a well functioning liquid market because they base their decisions on fundamental values and therefore have a balancing, price stabilizing effect (Algieri 2012; Borin & Di Nino 2012). However, the volatility effects of both excessive speculation, i.e., an amount of trading by speculators beyond the level needed to balance the demand of hedgers, and investments in commodity index funds aimed to diversify investors' portfolios, remain controversial.

As a measure for excess speculation Working's T-Index is used, which sets speculative activities in relation to hedging needs:[12]

$$Speculation\ Index = 1 + \frac{S_S}{H_S + H_L}\ for\ H_S \geq H_L\ and$$

$$Speculation\ Index = 1 + \frac{S_L}{H_S + H_L}\ for\ H_S < H_L$$

with

$S_S = Speculators' short\ positions\ and\ S_L = Speculators' long\ positions$

$H_S = Hedgers' short\ positions\ and\ H_L = Hedgers' long\ positions$

[10] For details on the construction of the index weights see Loretan (2005).
[11] See Marquering & Verbeek (2009).
[12] See Working (1960).

If there are more short hedgers than long hedgers in the market, there is a need for additional market participants - speculators - to fulfil the net short hedging demand by taking long positions. So in this case speculative short positions are not needed for generating necessary counterparties and a better functioning market, but can be interpreted as excessive speculation. The more speculative short positions are present, i.e. the higher the speculative activities not accompanied by hedging needs are, the higher is the value of the speculation index. For net long hedging demand the situation is the other way round and the index rises again with speculative long positions above hedging needs. The speculative and hedging positions are calculated with data from the weekly U.S. Commodity Futures trading Commission's (CFTC) Commitment of Traders (COT) reports that document trading activities in several commodity futures markets. For the index calculation, non-commercial (commercial) positions are identified as speculative (hedging) positions and the average positions over the month are used. This classification generates some noise because the group of commercial traders may contain some speculators and vice versa. It is supposed that in the last decade this noise has increased due to commodity index funds. A large part of index investors consist of swap dealers, which make their core business with traders that want to diversify their portfolio over the counter and hedge their positions in the futures market. These traders act for the most part for non-commercials that want to invest in commodities but are still classified by the CFTC as commercials, i.e., they are in the same group as producers and consumers, because of their hedging activity in this specific market.

Therefore, besides the speculation measure a financialisation measure is integrated in the analysis, which is intended to measure the inflow of new capital in commodity markets by index investors. The measure is calculated as the relative change of net long positions of commodity index traders (CIT), based on the CFTC supplemental report that supplies information about index trader positions. The change in positions is calculated as the difference between the CIT net long positions on the last day of the relevant month and on the last day of the previous month.[13] As the reports with CIT information are available since 2006, the net position changes in the months before 2006 are extrapolated by approximating the relative position change with the average monthly position change from January 2006 to January 2007. Using this procedure, the financialisation measure is constant until January 2006.

The speculation and financialisation measures are calculated separately for each group and can be interpreted as a benchmark speculation / financialisation measure for the group. If there is only one commodity for which the required data is available, this commodity's speculation index or CIT net position changes are taken as exogenous variables for the whole group. If there is data available on more than one commodity, the measures are calculated for all these commodities and weighted according to the open interest of the individual commodity in the relevant month. The following table shows the commodities that were used for the calculation of the speculation / financialisation measures for the different groups.

[13] If no report is published on the last day of the month, the position is determined by linear interpolation of the positions according to the month's last and the next month's first report.

Table 3: Benchmark commodities for speculation / financialisation measures

Group	Speculation measure	Financialisation measure
Group 1	Wheat (2 types), Corn	Wheat (2 types), Corn
Group 2	Soybeans	Soybeans
Group 3	Soybean oil	Soybean oil
Group 4	Sugar No. 11	Sugar No. 11
Group 5	Corn, Soybean Meal	Corn

Stock data

Grain stock levels changes and the stocks-to-use ratio are also often found to be a major cause of volatility. Stocks data can be a valuable complement to imperfect price data as an indicator of vulnerability to shortages and price spikes because high stock levels can serve as a buffer for growing demand and mitigate shortages (Bobenrieth et al., 2013). Therefore, we use the monthly change of the projection of the stock level at the end of the crop year to capture changing expectations on stocks. Moreover, we calculated the monthly stocks-to-use ratio projection, i.e. the monthly estimated stock at the end of the agricultural year over the monthly estimated consumption for the same agricultural year. The data is based on reports published by the World Agricultural Outlook Board (WAOB) of the United States Department of Agriculture (USDA).

Demand Increase

The general demand increase for food items in developing countries or emerging economies is considered by many researchers as a major driver of food price volatility. The relative change of the sum of the quarterly GDP of the BRICS[14] countries plus Indonesia is considered as a proxy for demand shocks at the global level. The relative change in GDP at the end of each quarter compared to the end of the previous quarter is used in the model as a driver for the next three months.

Weather Shocks

Several authors emphasize the importance of the climate change on food price volatility (Roache 2010; Algieri 2013). One of the major climatic phenomena are large scale fluctuations in air pressure occurring between the western and eastern tropical Pacific (the state of the southern Oscillation). We used the Southern Oscillation Index (SOI) as exogenous variable, which indicates air pressure patterns typical for El Niño and La Niña events. As both events influence different areas of the world, we disentangle them by separating the SOI Index into an index for the negative values (El Niño) and one for the positive values (La Niña).

5. Specification of a VAR model for volatility analysis

Our empirical study addresses two important questions. (i) What are the main drivers of volatility? (ii) Are there volatility spillovers between interrelated commodity markets? The econo-

[14] Brazil, Russia, India, China, South Africa.

metric framework of vector autoregressive (VAR) models, as pioneered by Sims (1980) is ideally suited to answer these questions. There are different advantages of this framework. First, the approach allows for the analysis of volatility spillovers by including lagged volatilities of all the commodities in a system as explanatory variables. Second, the VAR approach provides specific tools for the analysis of spillovers, in particular the impulse-response function, which shows how a volatility shock in a certain commodity is transmitted through the whole system and potentially affects the volatilities of other commodities. Finally, one can easily include exogenous explanatory variables in the model, which allows us to quantify the effects of potential volatility drivers.

The specification of a VAR model involves three steps. The first one is the choice of a set of potentially interrelated commodities or products. As outlines in Section 2, we choose five groups, namely grains (4 products), oilseeds (2 products), vegetable oils (5 products), sugar (2 products), and meat (3 products). The estimated GARCH return volatilities of the corresponding products, as provided in Section 3, constitute the set of endogenous variables of the five VAR models that we use.

The second step is the selection of exogenous variables, i.e., potential volatility drivers. The specific choices we make are outlined in Section 4. A major contribution of our study is the simultaneous investigation of many potential drivers, which allows us to quantify the *additional* impact of a specific driver on volatility. Such an approach avoids premature interpretations arising from univariate analyses that fail to control for the effects of other drivers and of volatility spillovers from other markets. Therefore, our approach delivers a comprehensive picture of the (relative) importance of different drivers.

Our choice of a rich model dynamics and a large number of exogenous variables potentially leads to very large models with many insignificant variables that make no contribution to the explanation of volatility. Therefore, the specification of a VAR model requires a third step that is inherent in any general-to-specific econometric modelling: the identification of relevant variables and the exclusion of irrelevant ones. Within the framework of general-to-specific modelling, much progress has been made in automatic model selection or data mining. Starting with a general unrestricted model, this approach reduces the complexity of the model step by step. The main idea is to formulate algorithms based on sequential significance testing of variables or blocks of variables, model diagnostics, and backtesting that finally identify adequate models which resemble the true data structure. Several studies have documented the good performance of automatic model selection procedures (see, e.g., Hoover & Perez (1999); Hendry & Krolzig (1999); Hendry & Krolzig (2005)). Automatic model selection is very attractive for our study, because it minimizes any bias introduced by subjective choices and ‘’lets the data speak” which volatility drivers are important. Given the many potential drivers and the many different opinions about their (relative) importance, such an element of objectivity is very helpful.

In our study, we use the autometrics algorithm developed by Doornik (2009), which is a further improvement over previous procedures.[15] The algorithm allows for the specification of some parameters (p-values) that govern how easily a variable is excluded from the model. Because we don’t want to miss out any significant volatility drivers, we choose rather high p-values (10%), which lead to relatively large models. The results that we present in the follow-

[15] For details on the autometrics algorithm see Doornik (2009).

ing section are the final outcome of the model specification process based on the autometrics algorithm.

6. Results and interpretation

6.1. Parameter estimates and price volatility drivers

In this section, the estimation results of the VAR models according to the methodology outlined above are presented. We focus in the first subsection on the exogenous drivers of volatility. Subsequently, the focus is on volatility spillovers among the commodities in each group.

Group 1: The grains complex

At the level of the whole system, it is remarkable that the residuals are barely correlated across equations. Given that the dependent variable is price volatility at the monthly level, however, this outcome is not too surprising. The interdependence of the commodities is mostly driven via the supply side and less via the demand side so that at a given point in time, immediate volatility spillovers are relatively limited. The detailed parameter estimates are shown in Table 4 below.

All endogenous variables respond strongly to their lagged own volatility at lag 1. For wheat, no other variable except for the own stocks-to-use ratio exerts any statistically significant impact. This indicates the high responsiveness of the wheat market to its own market specifics, and hints to the function of the wheat price as a cornerstone of agricultural price formation in the grains complex. For corn, in addition to the past own volatility lagged by one month, the fourth lag is statistically important, too. Further details on the dynamics implied by these estimates are given in the next subsection.

Among the exogenous drivers, two variables are statistically significant. The sign of the relative change of the projected ending stocks is positive. This result might look surprising at a first glance; however, since changes in projections constitute a measure of new information, the positive sign can be explained as an increase in corn price volatility due to larger amounts of new information. Our financialisation proxy, the percentage change in the long positions in the futures market, has a negative sign. This indicates that the liquidity effect seems to dominate. A larger number of long positions reduces corn price volatility.

For bioethanol, in addition to the own lag at period 1, we find a lagged spillover from the wheat market with a negative sign at lag 3. Among all exogenous drivers tested, we find that oil price volatility is statistically significant with the expected sign. At elevated levels of oil price volatility, a higher bioethanol volatility is observed. The effect, however, is rather small in magnitude.

Ammonia is included as one of the major inputs. Here, a number of different lags from wheat and corn volatility are statistically significant so that a parameter-wise interpretation is difficult; we shed some light on the spillovers in the next subsection using impulse response functions. As for wheat volatility, the stocks-to-use ratio is significant with the expected sign: High ending stocks for wheat relative to world consumption reduce price volatility for ammonia, too. In addition, exchange rate volatility is statistically significant with a positive sign, indicating that the price volatility of ammonia, which is intensively traded at the international level, is responsive to volatility of the US dollar exchange rate.

Table 4: Results group "grains"

Variable	Wheat	Corn	Bioethanol	Ammonia
Wheat (soft) volatility.l1	**0.9074** (0.0664)	-0.0869 (0.2876)	0.0626 (0.0455)	0.1158 (0.4456)
Wheat (soft) volatility.l2	-0.0200 (0.0902)	0.2773 (0.3906)	0.0873 (0.0618)	0.7293 (0.6051)
Wheat (soft) volatility.l3	0.0507 (0.0904)	0.1453 (0.3915)	**-0.1922** (0.0619)	-0.0664 (0.6065)
Wheat (soft) volatility.l4	0.0299 (0.0704)	-0.2468 (0.3052)	-0.0236 (0.0483)	**-0.6847** (0.4727)
Corn volatility.l1	0.0035 (0.0144)	**0.4664** (0.0622)	0.0083 (0.0098)	0.0563 (0.0963)
Corn volatility.l2	-0.0025 (0.0147)	-0.0888 (0.0637)	-0.0011 (0.0101)	**-0.1919** (0.0987)
Corn volatility.l4	-0.0135 (0.0129)	**-0.1281** (0.0558)	0.0024 (0.0088)	**0.1490** (0.0865)
Bioethanol (US) volatility.l1	-0.0175 (0.0263)	-0.1142 (0.1139)	**0.9588** (0.018)	-0.2505 (0.1764)
Ammonia volatility.l1	-0.0028 (0.0098)	-0.0366 (0.0426)	0.0000 (0.0067)	**0.7376** (0.066)
Ammonia volatility.l2	-0.0088 (0.0123)	-0.0340 (0.0532)	0.0104 (0.0084)	0.0217 (0.0824)
Ammonia volatility.l3	0.0081 (0.0123)	0.0008 (0.0534)	**-0.0159** (0.0084)	**-0.2803** (0.0827)
Ammonia volatility.l4	-0.0059 (0.0093)	0.0332 (0.0405)	0.0098 (0.0064)	**0.1338** (0.0627)
Crude oil price volatility	0.0115 (0.0165)	0.0932 (0.0714)	**0.0187** (0.0113)	**0.4435** (0.1106)
Dollar strength volatility	0.0774 (0.0629)	0.1456 (0.2727)	-0.0025 (0.0431)	**0.8232** (0.4225)
SOI negative (El Niño)	-0.0028 (0.0028)	-0.0118 (0.012)	-0.0005 (0.0019)	0.0282 (0.0186)
Wheat Stocks-to-use ratio (US)	**-0.0249** (0.0120)	-0.0457 (0.052)	0.0045 (0.0082)	**-0.1352** (0.0806)
Corn (US) Stock Projection (relative change)	0.0155 (0.0113)	**0.2668** (0.0489)	-0.0012 (0.0077)	0.1045 (0.0757)
CITlongChange_rel	-0.0017 (0.0431)	**-0.5337** (0.1867)	0.0078 (0.0295)	-0.1078 (0.2892)
Constant	**0.0244** (0.0119)	**0.2037** (0.0514)	0.0121 (0.0081)	0.0653 (0.0796)
Trend	0.0000 (0)	0.0003 (0.0002)	**0.0001** (0)	0.0002 (0.0003)

Source: Own estimates.

Group 2: Selected oilseeds

For this group, spot prices are not available to the same extent as in the US grains market. Since a major interest lies on EU price volatilities, it was necessary to include the dominant oilseed in Europe, rapeseed. Due to data availability problems, we had to use the futures prices in the EU. This should be kept in mind for interpreting the results.

Table 5: Results group "oilseeds"

Variable	**Soybean**	**Rapeseed**
Soybean (US) volatility.l1	**0.6897** (0.0612)	-0.0358 (0.0478)
Rapeseed (EU) volatility.l1	**0.3449** (0.0969)	**0.7891** (0.0757)
Dollar strength volatility	0.3040 (0.1839)	**0.4114** (0.1436)
Constant	0.0198 (0.0215)	**0.0334** (0.0168)
Trend	**-0.0003** (0.0002)	-0.0001 (0.0001)

Source: Own estimates.

We find the expected strong impacts of the own lagged volatilities. The dynamics are analysed in more detail in the next section. In this group, we find one significant cross effect, lagged rapeseed price volatility affect soybean volatility. This finding might be affected by the fact that rapeseed prices are price quotes from the MATIF futures market while the soybean prices are spot market prices. The former contain forward-looking information, at least up to the maturity of the nearest contract, and this might explain that rapeseed prices are found as the channel for volatility transmission.

Among all the potential exogenous drivers tested, only the volatility of the US dollar exchange rate against a basket of other important currencies proved to be statistically significant. The sign and magnitude of the estimated coefficient indicates a strong positive impact of this volatility on the rapeseed price volatility; for soybean volatility, sign and magnitude are similar but not as precisely estimated from the available data.

Another remarkable feature is the negative sign of the trend parameters, although statistically insignificant in the rapeseed price volatility equation. The magnitude in both equations is small but the sign is consistently negative, indicating that price volatility has decreased over time (albeit at a low rate, about .003 % per month for soybeans). Nevertheless, this estimate indicates that price volatility, against conventional wisdom, did not develop uniformly across all commodities.

Group 3: Selected vegetable oils

The group of vegetable oils, augmented by biodiesel, shows the strongest extent of volatility spillovers. As implied by the GARCH estimations, own lagged price volatility plays an important role in each equation, with the exception of rapeseed oil. The dynamics of the system are rather complex and hence postponed to the next section.

Table 6: Results group "vegetable oils"

Variable	Palm Oil	Sunflower Oil	Soybean Oil	Biodiesel	Rapeseed Oil
Palm oil (Malaysia) volatility.l1	**0.4881** (0.1259)	-0.4123 (0.2859)	-0.1288 (0.1643)	**0.2623** (0.0872)	0.5603 (0.9575)
Palm oil (Malaysia) volatility.l2	**0.3563** (0.1167)	0.4002 (0.265)	0.0122 (0.1523)	**-0.1896** (0.0809)	-1.1738 (0.8876)
Sunflower oil (Netherlands) volatility.l1	**0.1203** (0.0608)	**0.5082** (0.138)	0.0438 (0.0793)	**-0.0767** (0.0421)	0.4301 (0.4623)
Sunflower oil (Netherlands) volatility.l2	-0.0360 (0.0469)	0.0146 (0.1064)	**0.1030** (0.0612)	**0.0896** (0.0325)	**1.1100** (0.3551)
Soybean oil (Argentina) volatility.l1	**0.2576** (0.0767)	**0.5075** (0.1743)	**0.8788** (0.1001)	-0.0664 (0.0532)	-0.9153 (0.5832)
Soybean oil (Argentina) volatility.l2	**-0.2032** (0.0755)	**-0.3862** (0.1714)	-0.0920 (0.0985)	0.0165 (0.0523)	**1.0307** (0.5743)
Biodiesel (Germany) volatility.l1	0.0427 (0.078)	-0.0371 (0.1771)	**0.1844** (0.1018)	**0.8155** (0.054)	**1.2525** (0.593)
Dollar strength volatility	**0.1252** (0.0466)	**0.1971** (0.1057)	**0.1753** (0.0608)	0.0306 (0.0323)	-0.2058 (0.3527)
SOI positive (La Niña)	-0.0010 (0.0017)	0.0053 (0.0038)	-0.0021 (0.0022)	**0.0029** (0.0011)	0.0043 (0.0126)
Constant	-0.0135 (0.0101)	**0.0581** (0.023)	**0.0269** (0.0132)	**0.0131** (0.007)	-0.0878 (0.0771)
Trend	0.0000 (0)	0.0000 (0.0001)	-0.0001 (0)	0.0000 (0)	**-0.0008** (0.0003)

Source: Own estimates.

For the exogenous drivers, only two of all candidates considered turned out to be statistically significant. The volatility of the strength of the US dollar has a positive impact on the price volatility of palm oil, sunflower oil and soybean oil. The point estimates for all commodities point into the same direction, with the exception of rapeseed oil. This difference in signs, however, is not surprising since rapeseed oil price formation is largely intra-EU (and heavily policy driven in most EU member states).

The only exogenous driver of biodiesel price volatility that is statistically significant is the positive part of the Southern Oscillation Index, i.e., the observations which capture a "La Niña" constellation. Since an impact of "La Niña" are dry summers in the Northern hemisphere, negative impacts on the harvest in Northern Europe and therewith on the input factors for biodiesel production are expected. Hence, "La Niña" has an increasing effect on biodiesel price volatility.

Another interesting result is the negative and statistically significant estimate for the trend parameter in the rapeseed oil equation. Once more, we find a downward trend in price volatility here - possibly a consequence of the policy framework driven by the EU renewable energy directive.

Group 4: World sugar and Brazilian bioethanol

The remarkable result in this group is the lack of any statistically significant cross effects of lagged price volatility. Both price volatilities are driven by their own lagged volatility but not by those on the corresponding other market in this group.

Table 7: Results group "sugar"

Variable	Sugar No.11	Bioethanol (Brazil)
Sugar (World) volatility.l1	**0.6167** (0.0702)	0.0006 (0.0111)
Bioethanol (Brazil) volatility.l1	0.1365 (0.4764)	**0.5751** (0.0753)
Crude oil price volatility	**-0.1069** (0.0434)	-0.0023 (0.0069)
Speculation	**-0.4744** (0.1455)	0.0184 (0.023)
Constant	**0.6037** (0.3016)	**0.2141** (0.0476)
Trend	-0.0001 (0.0002)	0.0000 (0)

Source: Own estimates.

Statistically significant estimates for the potential drivers are only found in the sugar equation. These were price volatility of crude oil and our proxy for excessive speculation (Working's T index). Both have a negative sign, among which the negative sign for oil price volatility might look surprising at a first glance. However, in this group, the volatility decreasing impact of oil price volatility can actually be explained from the specific interdependence between the two markets. In Brazil, most sugarcane processing factories can easily switch between the production of sugar and the production of bioethanol. Crude oil, bioethanol and sugar price levels have been found cointegrated by Serra et al. (2011). In particular, ethanol price levels were found to follow crude oil prices. Then, from the perspective of a sugar processor in Brazil, elevated oil price volatility makes returns from ethanol production more uncertain. Hence, sugar production will be *ceteris paribus* more attractive than with lower oil price volatility. This supply response in sugar markets will then relax the balance between supply and demand on the sugar market, and thus pave the ground for more stable sugar prices.

The negative impact of the speculation proxy on price volatility is in line with a growing body of literature (Brümmer et al. 2013b) which points towards a stabilising impact of speculation. The increased liquidity, and the information brought into the market by additional speculators seems to reduce price volatility, at least in the sugar market.

Group 5: European pork and major feedstock components

In this group, the interdependencies in price volatility are found among the feedstock components but not with the pork prices. This might be caused by the different spatial dimension of the markets considered (pork prices are from the EU). Nevertheless, there is a strong interdependency between corn and soybean meal which will be discussed below.

Table 8: Results group "meat"

Variables	Pork	Corn	Soybean meal
Pork (Germany) volatility.l1	**0.8893** (0.0285)	0.0472 (0.061)	0.0103 (0.0174)
Corn volatility.l1	-0.0057 (0.0267)	**0.4807** (0.0571)	**0.0884** (0.0163)
Corn volatility.l2	-0.0104 (0.029)	**-0.1623** (0.062)	-0.0206 (0.0176)
Soybean meal (US) volatility.l1	-0.0202 (0.1026)	**0.4256** (0.2195)	**0.6572** (0.0625)
Soybean meal (US) volatility.l2	0.0536 (0.0973)	**-0.3933** (0.2082)	**0.1540** (0.0593)
SOI positive (La Niña)	0.0015 (0.0044)	**0.0197** (0.0095)	-0.0043 (0.0027)
CornProjectionUsDiff_rel	**0.0395** (0.0208)	**0.2413** (0.0446)	0.0022 (0.0127)
CITlongChange_rel	-0.0550 (0.076)	**-0.7211** (0.1625)	-0.0053 (0.0463)
Constant	**0.0304** (0.014)	**0.1519** (0.0299)	**0.0196** (0.0085)
Trend	0.0000 (0)	**0.0002** (0.0001)	0.0000 (0)

Source: Own estimates.

The exogenous drivers are mainly found in the US corn equation. This is the only case for all groups analysed, except for the quantitatively small impact on biodiesel in the vegetable oil group, where the "Southern Oscillation" index is statistically significant. Only the positive part of it has a positive impact on price volatility. Since this scenario typically leads to dry summers in the Northern hemisphere, and this is unfavourable for corn production in the US, the volatility-increasing effect of a high positive impact is expected.

This equation also is the only case where the information-related proxy is statistically significant. New information, in this case in the form of a large change to the USDA's WASDE[16] ending stocks projection, drive up price volatility. This result is also found in the pork price equation, albeit at a quantitatively much less important level.

Finally, the financialisation variable, which is constructed as the relative change in long positions from the CTFC data, is statistically significant. The sign is again negative, indicating that financialisation has a price volatility reducing impact.

[16] World Agricultural Supply and Demand Estimates Report

In order to give a comparative perspective on the impact of the potential drivers on price volatility across all commodity groups, we provide a summary of the parameter results in Table 9 below. We reuse the categories which were defined in the introduction to summarize the various potential drivers in the first column. The second column contains the number of commodities for which each driver was tested. This number is then distributed over the following columns, whether we find an increasing, statistically insignificant, or decreasing effect of the driver on price volatility.

Table 9: Identified drivers

	commodities tested	increasing effect	not significant	decreasing effect
Financialisation & Speculation	15	0	12	3
Oil	15	2	12	1
Low stocks	13	2	11	0
Revison of stock projections	13	2	11	0
Exchange rate	15	6	9	0
Increased consumption	15	0	15	0
Weather shocks	15	2	13	0

Source: Own estimates.

The most striking result is the low number of statistically significant parameter estimates; for each of the categories in the rows of Table 9, the number of insignificant parameters clearly dominates. This finding, however, should not be viewed too critical, though. The estimated price volatilities are based on the residuals of a GARCH model, where, besides the temporal dynamics of the conditional heteroscedasticity, the residuals are assumed to be white noise. It is not surprising that the conditional standard deviations are then hard to explain by adding additional information in the form of the potential drivers.

Nevertheless, we find that exchange rates, more precisely the volatility of the strength of the US dollar, to be significant in 40% of the markets analysed. This finding highlights the general relevance of macro-economic factors in shaping price formation on agricultural markets, and in particular, the role of the volatility of the US dollar. Although the role of the US dollar for international agricultural trade has certainly not increased over time, the dollar volatility remains a major driving factor because there are at least two channels through which it affects price volatility on agricultural markets. First, there is a direct impact since a huge share of international agricultural trade is carried out in US dollars. Second, there is an indirect channel since elevated levels of dollar volatility are indicative of high uncertainty of the general macro-economic environment, thus affecting agricultural markets mainly via the demand side.

This second channel is also important for oil, where price volatility of only two of the tested commodities is a statistically significant volatility driver. Direct transmission takes place via the biofuels channel, this is at least suggested by the fact the oil price volatility was only statistically significant in systems where at least one biofuel was included.

Weather shocks are surprisingly seldom an identifiable driver of price volatility. This might be related to the measure of weather shocks which was used here. The Southern oscillation index captures more the general, longer term tendency towards 'El Niño', or 'La Niña', respectively. A localized and temporally more fine-grained measure would most likely yield more impressive results in such an ex-post analysis.

Consumption, as proxied by, the GDP growth variable, is not statistically significant in any of our monthly volatility systems. As with weather shocks, it is difficult to construct an appropriate short-run measure of consumption changes that would better be able to explain price volatility at this temporal resolution.

Finally, we do not find any hint that financialisation or speculation act as volatility increasing factors, as was discussed in the public over the past years. This is in line with the majority of the recent literature (Brümmer et al. 2013b), which points to the same pattern as we found here: If there is any statistically significant impact of financialisation or speculation proxy variables on price volatility, then it is likely to be volatility-reducing.

6.2. Volatility spillovers

The VAR model allows us to detect and quantify volatility spillovers between different commodities by means of lagged volatilities of all products within a product group. There are two main issues that we address in our analysis of volatility spillovers. The first one is the statistical significance of lagged volatilities referring to other products within the VAR model. The second issue is the economic significance of spillovers. Such economic significance is particularly strong if the initial effect on volatility is large and persists over long periods. The first issue can be judged via t-statistics. The second issue is addressed via impulse-response functions that quantify the effects of volatility shocks and show how these effects accumulate or fade out over time. We provide a graphical depiction of the impulse responses below. The dashed lines in the figures indicate 95% bootstrapped confidence intervals. We discuss our results separately for each group of commodities.

Grains: For all four products in this group we observe that the own lagged volatility is significant with the expected positive sign (see Table 4). This result shows the well known volatility persistence that we capture with our GARCH model. For wheat and corn, no lagged volatility of any other product is significant, i.e., there is no indication of a volatility spillover from any of the markets to the wheat or corn market. Bioethanol and ammonia show a different picture. There are some significant coefficients for the lagged volatilities of other markets. However, the specific effects are difficult to judge because the coefficients have different signs and more than one other market is involved. We therefore have to study the dynamics of the whole system. The impulse-response functions are very instructive in this respect. They are presented in Figure 2. The reactions of wheat and corn to volatility shocks confirm the lack of volatility spillovers. The only significant effect is a shock in the own volatility. For bioethanol, we observe a significant volatility increase due to a volatility shock in the wheat market. However, the effect is not immediate but materializes with some time lag due to system effects. For ammonia, we observe an immediate volatility increasing effect of a shock in the corn market. In summary, our results for the group of grains show that wheat and corn are unaffected by spillovers but the volatilities of bioethanol and ammonia react to volatility shocks in the wheat or corn market.

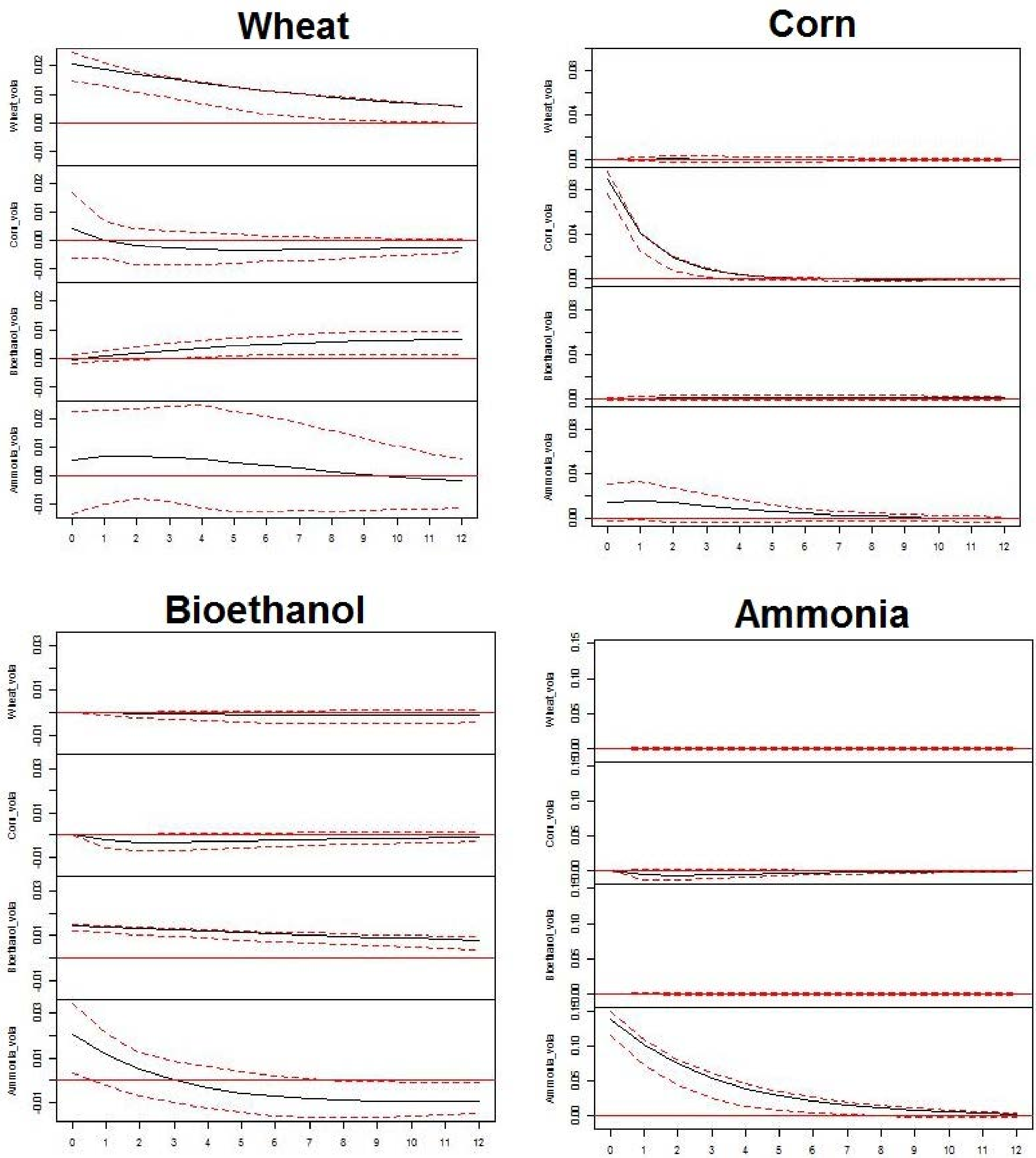

Figure 2: Impulse response functions for group 1 (wheat, corn, bioethanol, ammonia)

Oilseeds: The dynamic effects of volatility shocks in this second group are rather straightforward (see Table 5). There is volatility persistence for both soybeans and rapeseeds, a lagged impact of the previous month's rapeseed volatility on the volatility of soybeans, and a rather strong contemporaneous effect (residual correlation of 0.37). The lagged impact of rapeseeds on soybeans is likely to be caused by the fact that rapeseed volatilities are estimated from futures prices, whereas soybean volatilities are obtained from spot prices. Because the former are (partially) based on expectations of the market developments until maturity of the futures, they may well have explanatory power for next month's spot price. This effect would explain the lead of the futures market over the spot market. However, from the economic functioning of the soybean and rapeseed markets, we would expect a lead of the former. Therefore, for the impulse-response analysis, we attribute the contemporaneous effects to a shock in the soybean market. The results of this analysis are provided in Figure 3. As the impulse-response functions show, there are significant spillover effects in both directions.

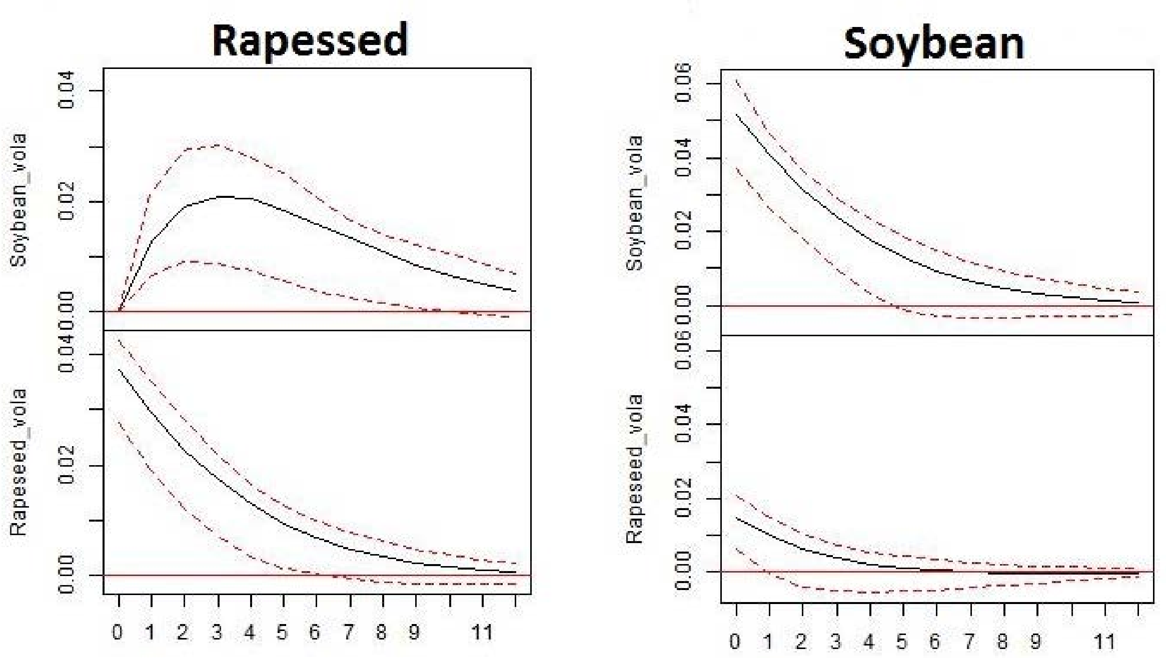

Figure 3: Impulse response functions for group 2 (soybean, rapeseed)

Vegetable oils: The group that contains the vegetable oils has the most complicated dynamic structure of all groups. For each of the five products, there is at least one lagged volatility of another product that shows a statistically significant impact (see Table 6). In such a complex system, the best way to understand the spillover effects is via the impulse-response functions. These are shown in Figure 4. Because of some high contemporaneous correlations in the residuals, it is important to specify if a shock in one product affects other products simultaneously. The results that we show are based on the following ordering of contemporaneous effects: palm oil, soybean oil, rapeseed oil, sunflower oil, and biodiesel. The first product in this list (palm oil) affects all other product contemporaneously, but not vice versa. The second product (soybean oil) affects rapeseed oil, sunflower oil, and biodiesel, but is not affected by them, etc.

According to the impulse responses, there are significant effects of palm oil volatility on all other products. However, the impact on rapeseed oil and biodiesel price volatility is not immediate but shows a delay of two months. A shock in soybean oil volatility significantly increases the volatilities of sunflower oil and rapeseed oil. Sunflower oil has an impact on rapeseed oil. Finally, shocks in rapeseed oil and biodiesel have no impact on the volatilities of the other markets. In summary, our results show a very high interconnectedness between the five products in terms of volatility spillovers. Moreover, there is some evidence that the markets for palm oil and soybean oil take a lead and the markets for rapeseed oil and biodiesel mainly react.

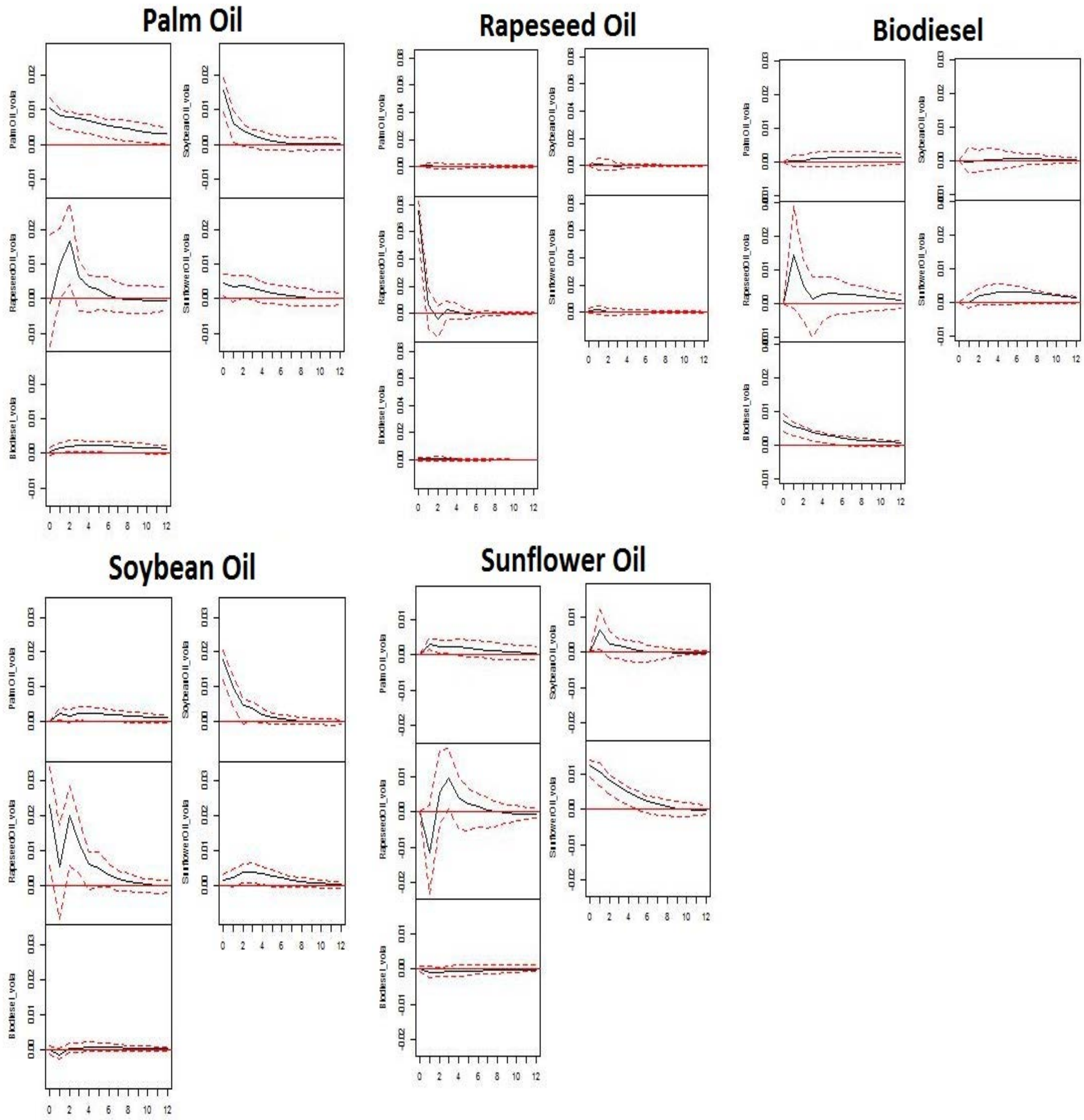

Figure 4: Impulse response functions for group 3 (palm oil, rapeseed oil, biodiesel, soybean oil, sunflower oil)

Sugar: The dynamic structure of the resulting VAR model is very simple for the group with sugar and bioethanol. As the results of Table 7 show, there is persistence in both volatilities and no spillover, neither via lagged volatilities nor via a contemporaneous correlation of the residuals (it takes a value of -0.03). This observation is fully confirmed by the impulse-response functions as provided in Figure 5.

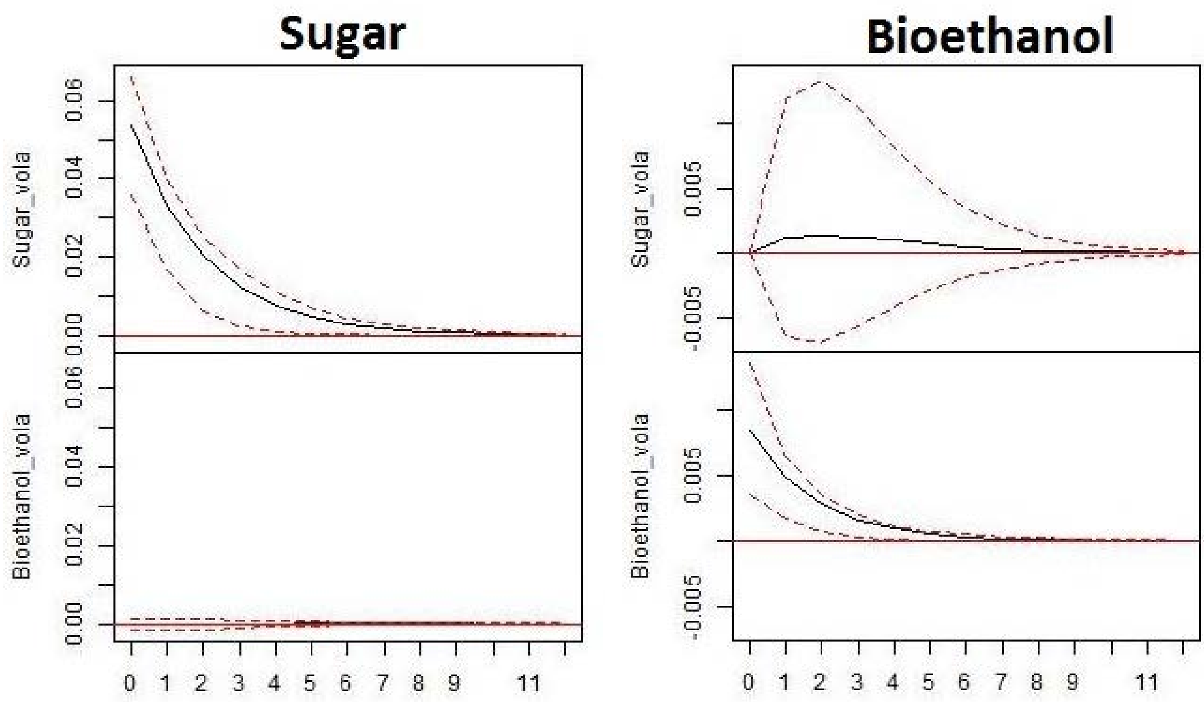

Figure 5: Impulse response functions for group 4 (sugar, bioethanol)

Meat: An interesting question for this group is whether volatility in pork prices is affected by volatilities in the major feeds soybean meal and corn. The answer given by our VAR model is that no significant spillovers exist. There are no significant coefficients of the feeds' lagged volatilities (see Table 8) and the residual correlations are very low. This result is fully confirmed by the impulse-response functions Figure 6. Soybean meal and corn, however, are clearly interrelated. There are spillovers in both directions, from soybean meal to corn and from corn to soybean meal.

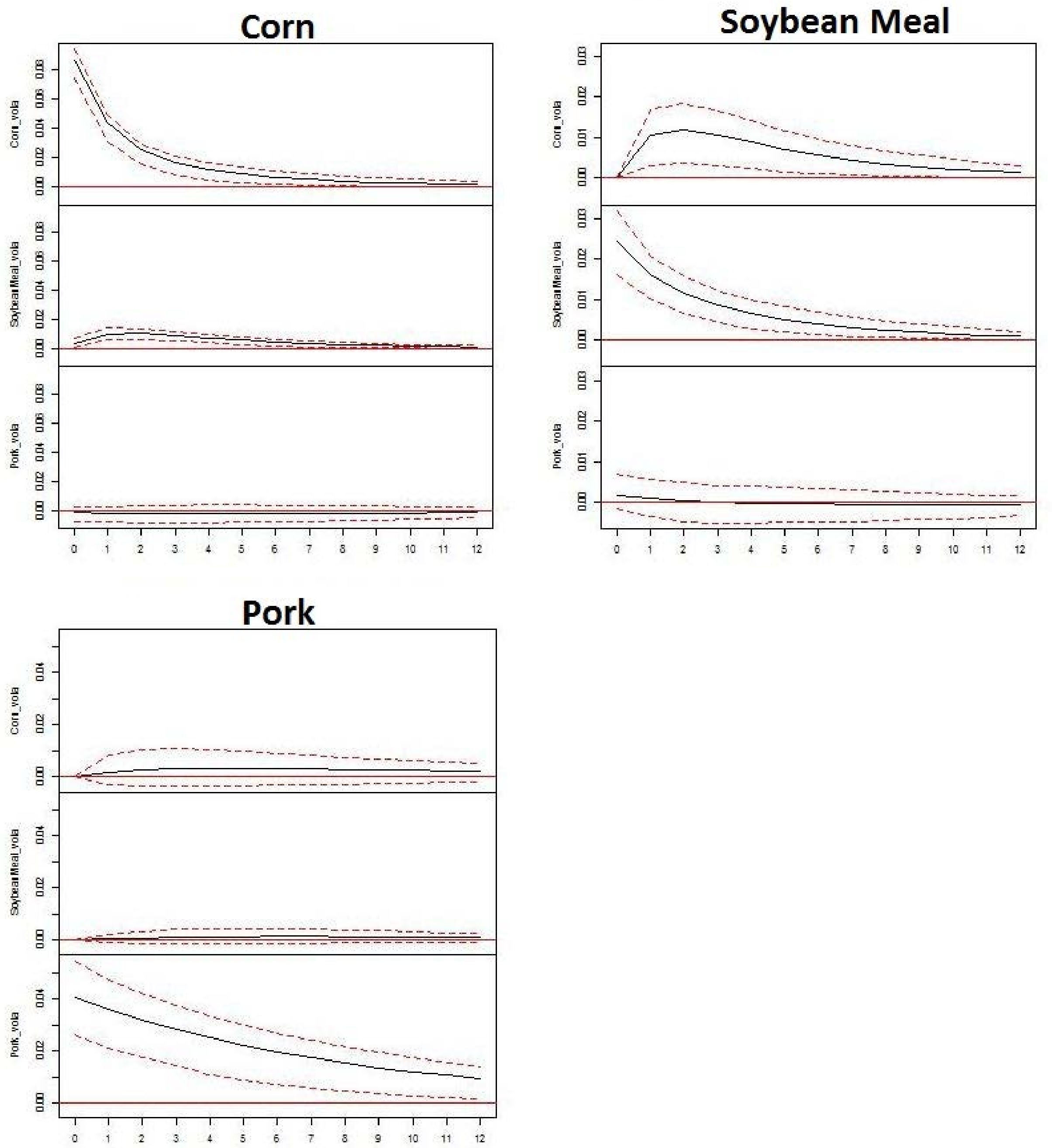

Figure 6: Impulse response functions for group 5 (corn, soybean meal, pork)

7. Conclusions

In this study, we have addressed a comprehensive price volatility assessment for five major agricultural commodity groups. Estimating price volatility on each market in a standardised GARCH framework opened up the possibility of shedding light on the dynamics in each group by analysing the estimated price volatilities in a VAR system. In particular, we were able to identify the role which was played by a number of 'suspects' which had been previously discussed in the existing literature.

The findings indicate that price volatility developments are far from homogenous across the markets considered. In some markets, price volatility exhibits an increasing trend over the sample period, in others, the trend was the other way around. In consequence, a uniform impact of the drivers tested in the VAR framework cannot be generally expected.

The findings of the VAR approach support this view since many of the potential drivers which we tested did not show any statistically significant impact on agricultural price volatility. This result is not unexpected since price volatility is notoriously hard to explain.

The most frequently identified impact is found for the exchange rate volatility, as measured by the volatility of the strength of the US dollar. In the 40% of the cases where a statistically significant impact was found, exchange rate volatility turns out to be driving price volatility of agricultural commodities upwards. In a similar vein, the impact of low stocks, measured by the corresponding stocks-to-use ratio, was in the same direction whenever it was statistically significant. Relatively low stocks exert an upward pressure on price volatility, too. Finally, weather shocks and oil prices were also of importance for price volatility developments in specific markets.

Although a statistically insignificant parameter estimate should not be misinterpreted as a definite proof that the corresponding variable has no impact at all, the results on financialisation and speculation are striking. We never observe the often postulated volatility increasing impact of financialisation and speculation. On the contrary, when any of the variables was found to be statistically significant, the impact of agricultural price volatility is volatility decreasing.

Looking at price volatility spillovers within each group, we find varying degrees of dynamics between the markets included. The most complex picture emerges in the vegetable oils group. One explanation for this is the relatively high extent of substitution possibilities among the vegetable oils. Palm oil price volatility has the strongest impacts on all other markets, followed by soybean oil. On the other hand, price volatilities of biodiesel and of rapeseed oil do not exert any visible impact on the two aforementioned markets. In the grains complex, interdependence in price volatility for wheat and corn was found to be of less importance. This suggests that the price volatility dynamics are mostly driven by market-specific factors, a result that is corroborated by the small role which the potential drivers play in these markets.

What do these findings now imply for future policy design? One important implication emerges from the observed heterogeneity in the results. There is no silver bullet for coping with excessive levels of price volatility in agricultural markets. The development of price volatility over time differs a lot, and the impact of the potential drivers does so as well. In particular, we find no evidence that financialisation and speculation are among the culprits for elevated levels of agricultural price volatility. In consequence, our findings do not support the notion that the introduction of position limits, a key element of the MIFID reform, helps in curbing price volatility on agricultural markets.

An unanimous picture (although tainted by a dominating share of statistically insignificant parameter estimates) emerges for the role of stocks. However, this does not necessarily suggest that storage polices are a viable policy option. First, it should be noted that we never find a statistically significant impact of the stocks kept in a single country (in our analysis, the US stocks which were included in several cases). This might point to the futility of country-specific buffer stocks. However, global buffer stocks schemes are unlikely to be viable because of their relatively high costs, and the incentives for free-riding. On the other hand, improving the access to public information on stocks might be a more promising way, as also supported by our findings on the role of revisions of stock projections in the price volatility of corn.

One common pattern across all groups and markets within each group is the strong role played by lagged own price volatility. In combination with the overall picture of a limited and heterogeneous contribution of our broad set of potential drivers, this suggests that price volatility on agricultural markets is largely driven by factors which are specific to each market. Thus, policies for limiting price volatility would have to be fine-tuned to the market in question. Given that price formation for the agricultural products which we have analysed takes mostly place on a global scale, this amounts to an almost insurmountable barrier for effective policy. This suggests that a more promising approach might rely on policies which help producers and consumers to *cope* with price volatility, instead of trying to *curb* price volatility.

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Appendix 1. Drivers' details

Crude oil price volatility: Calculation of model free implied volatilities

The approach of Bakshi et al. (2003) requires an infinite continuum of strike prices of European options. Because only out of the money (OTM) options are needed, the implied volatilities of all existing OTM American options[17] are extracted via finite differences method. The risk free rate is approximated with the US treasury bill rate.[18] To overcome the problem that only a finite range of discrete strike prices is available, a continuum of strike prices is generated by applying the curve fitting method to implied volatilities for interpolating between the minimum and maximum available strike prices and by constant extrapolation for strike prices below (above) the minimum (maximum) strike price (see (Jiang & Tian 2005)).[19] Finally, thousand values are extracted from the volatility curve on the interval $[0.003 \cdot S(0); 3 \cdot S(0)]$ with $S(0)$ being the price of the underlying futures contract, and the respective European option prices are calculated using Black's formula.[20] Finally, with trapezoidal numerical integration the implied volatilities can be calculated following the procedure of Bakshi et al. (2003). (for a similar procedure of adopting the model free volatility calculation see Chang et al. (2009)).

Speculation / Financialisation

Table 10: Futures trading data basis for speculation (S) and financialisation (F) measures

Commodity	Commodity Exchange		Basis for
Wheat	Chicago Board of Trade		S and F
Wheat	Kansas City Board of Trade		S and F
Corn	Chicago Board of Trade		S and F
Soybeans	Chicago Board of Trade		S and F
Soybean oil	Chicago Board of Trade		S and F
Sugar No. 11	Coffee, Sugar & Cocoa Exchange	Jan. 1990 - Dec. 2004	S
	New York Board of Trade	Jan. 2005 - Aug, 2007	S and F (since 2006)
	ICE Futures U.S.	Sept. 2007 - July 2012	S and F
Soybean meal	Chicago Board of Trade		S

Stock Data

Every month USDA publishes a summary report of the United States', world's and some important countries' monthly projection of beginning stock, production level, imports, domestic

[17] An option is filtered out from the further calculations if the option's price does not lie inside the pricing boundaries or the option's strike price is lower than 0.5 times the underlying's price and higher than 1.5 times the underlying's price to filter out deep out of the money options that may cause noise because they are rarely traded.
[18] For options with a time to maturity between 1 and 31 days, the 1 month treasury bill rate is used, for options between 32 and 93 days to maturity, the 3 month treasury bill rate is used and so on.
[19] To get reliable results, this procedure is only done, if at least two Call and two Put options are available for a specific day.
[20] Black's formula is the adaption of the Black-Scholes-formula to options on futures, see Black (1976).

consumption, exports and ending stock for some major agricultural crops such as wheat, coarse grain, corn, rice, cotton, soybean, soybean meal, soybean oil. The monthly projection of each month is for the end of the same agricultural year. In this report, they estimate the same variables for the last two agricultural years. The agricultural year ends in May each year for the majority of crops and in June or July for some others. The data is available approximately for most of the crops mentioned above since 1973[21]. The projection and estimation approach can be reviewed in WAOB (1999). The USDA does the same projection for some crops or products limited to the US such as sorghum, barley, oats, sugar, dairy products and meat. In this study, we have extracted the projection data for wheat, corn, soybean, soybean meal and soybean oil since 1990. This data is used to calculate the monthly projection changes and monthly stock to use ratio as influential factors on food price volatility. Figure 7 shows the stock to use ratio trend since 1990 for the major crops. As no more projection are available for the month May (or any month which is the last month of the agricultural year) in this data series, we have used the last estimation value of the last agricultural year to cover the loop in the data series for change in stock projections at the end of the agricultural year.

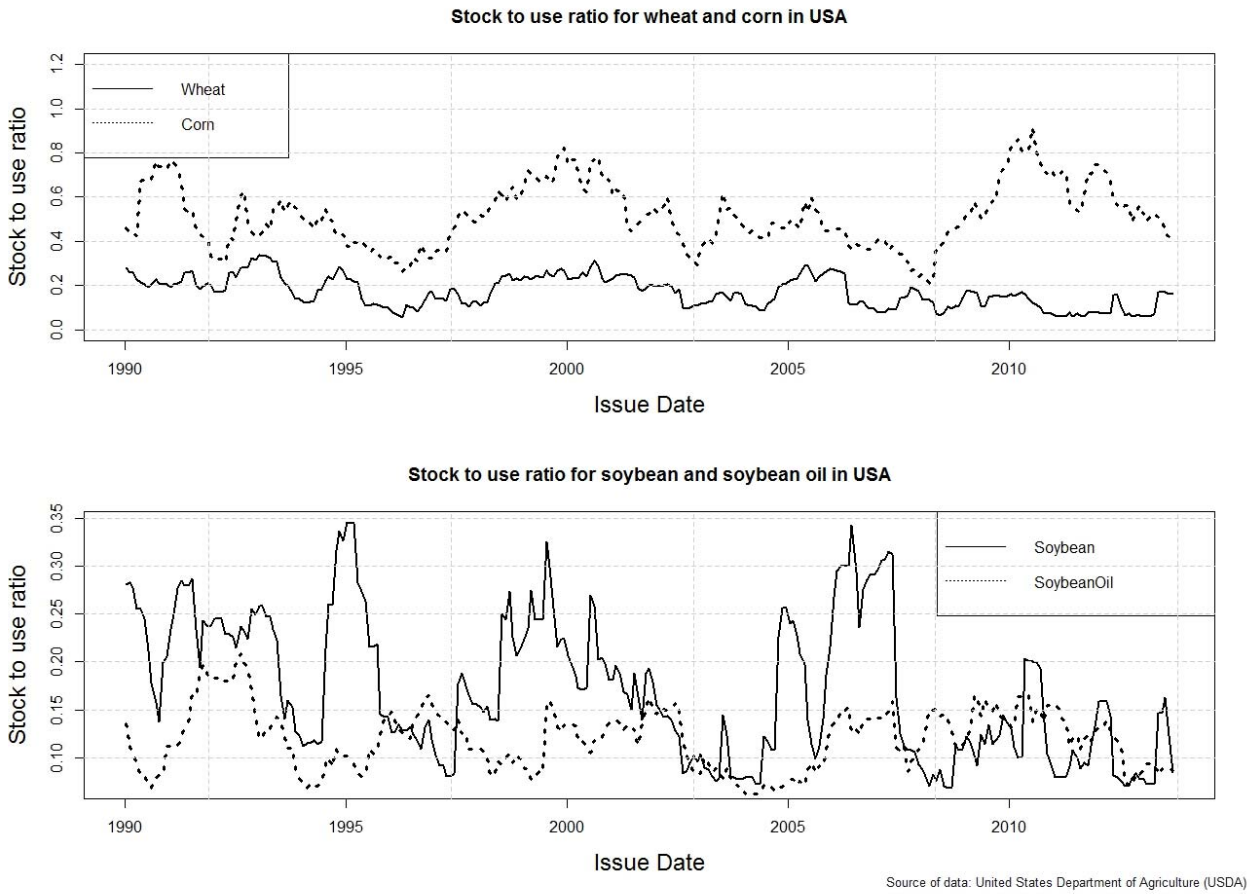

Figure 7: Stock to use ratio for wheat, corn, soybean and soybean oil in USA since 1990

[21] http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1194

Demand Increase

The quarterly GDP of the emerging economies is calculated by using the OECD database[22]. The current purchasing power parity (PPP) for current prices is used for Brazil, Russia, India, South Africa and Indonesia from this database. For China, the quarterly data is used from the current prices' estimation (with current exchange rate) of china statistical center[23]. Figure 8 shows the change of the sum of the quarterly GDP of the above mentioned countries. As we could not find quarterly GDP for some of the countries in OECD database for the beginning of 1990s, we have used the annual data and turned them to quarterly level.

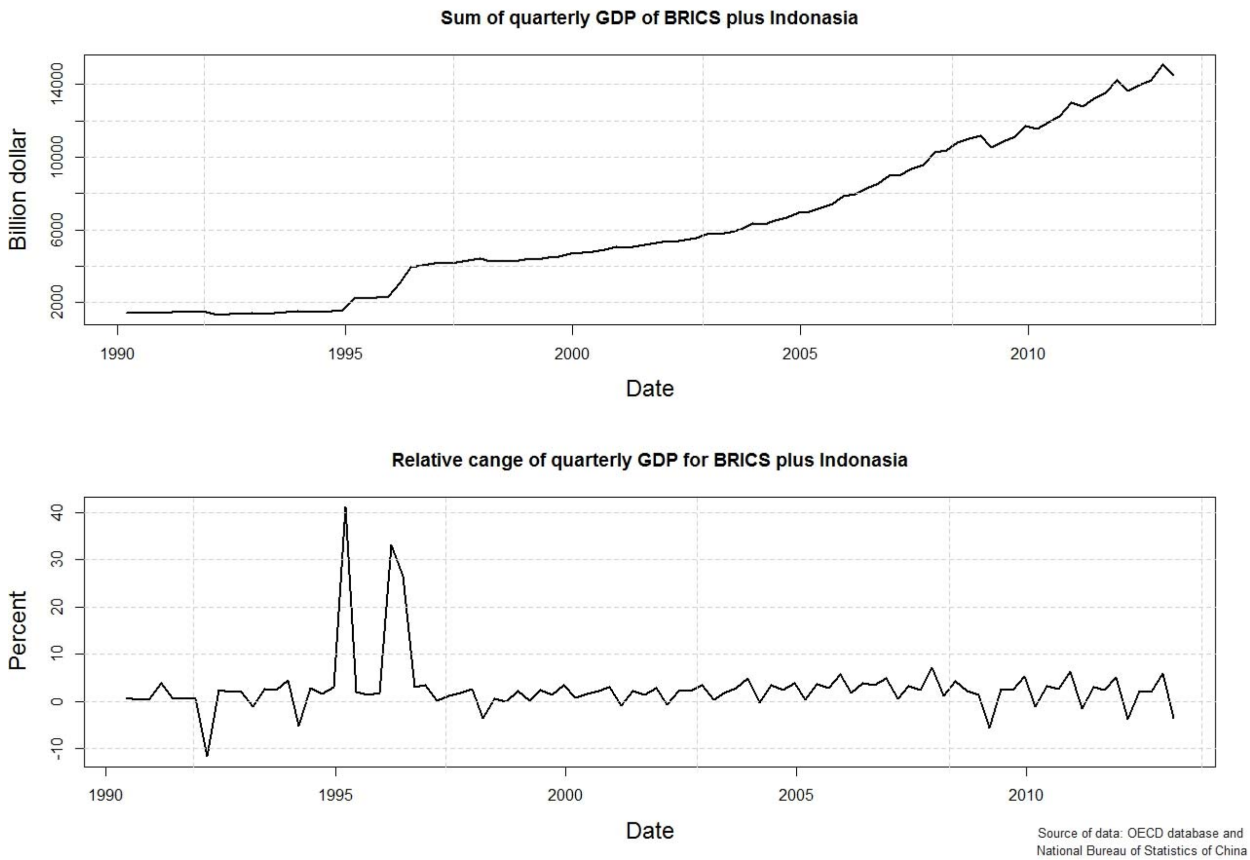

Figure 8: The GDP growth trend and relative changes of the quarterly GDP of the BRICS plus Indonesia

Weather Shocks

El Niño and La Niña: El Niño and the Southern Oscillation, also known as ENSO is a periodic fluctuation in sea surface temperature (El Niño) and the air pressure of the overlying atmosphere (Southern Oscillation) across the equatorial Pacific Ocean (NOAA 2014a). La Niña is the counterpart of El Niño. In El Niño years, when the rain area that is usually centered over Indonesia and the far western Pacific moves eastward into the central Pacific, the waves in the flow aloft are affected, causing unseasonable weather over many regions of the globe

[22] http://stats.oecd.org/Index.aspx?DatasetCode=SNA_TABLE1# , last access: 27.01.2014.

[23] http://data.stats.gov.cn/workspace/index?a=q&type=adv&m=hgjd&x=index&y=time&z=region&index=A010101&region=000000&time=-1,1986A&selectId=000000, last access: 27.01.2014.

(NOAA 1995). These two events are companied by a group of extreme weather in different parts of the world.

Global El Niño Impacts: The impacts of El Niño upon climate in temperate latitudes show up most clearly during wintertime. For example, most El Niño winters are mild over western Canada and parts of the northern United States, and wet over the southern United States from Texas to Florida. El Niño affects temperate climates in other seasons as well. But even during wintertime, El Niño is only one of a number of factors that influence temperate climates. El Niño years, therefore, are not always marked by "typical" El Niño conditions the way they are in parts of the tropics. See list of impacts on the U.S. and list of impacts on other countries (NOAA 1995).

Global La Niña Impacts: Globally, La Niña is characterized by wetter than normal conditions west of the equatorial central Pacific over northern Australia and Indonesia during the northern hemisphere winter, and over the Philippines during the northern hemisphere summer. Wetter than normal conditions are also observed over southeastern Africa and northern Brazil, during the northern hemisphere winter season. During the northern hemisphere summer season, the Indian monsoon rainfall tends to be greater than normal, especially in northwest India. Drier than normal conditions are observed along the west coast of tropical South America, and at subtropical latitudes of North America (Gulf Coast) and South America (southern Brazil to central Argentina) during their respective winter seasons (NASA 2014).

SOI: The Southern Oscillation Index (SOI) is a standardized index based on the observed sea level pressure differences between Tahiti and Darwin, Australia. The SOI is one measure of the large-scale fluctuations in air pressure occurring between the western and eastern tropical Pacific (i.e., the state of the Southern Oscillation) during El Niño and La Niña episodes. In general, smoothed time series of the SOI correspond very well with changes in ocean temperatures across the eastern tropical Pacific. The negative phase of the SOI represents below-normal air pressure at Tahiti and above-normal air pressure at Darwin. Prolonged periods of negative (positive) SOI values coincide with abnormally warm (cold) ocean waters across the eastern tropical Pacific typical of El Niño (La Niña) episodes (NOAA 2014b). Figure 9 shows the SOI general trend. SOI is calculated as below (NOAA 2014b):

$$SOI = \frac{\text{Standardized Tahiti} - \text{Standardized Darwin}}{\text{MSD}}$$

$$\text{Standardized Tahiti} = \frac{(\text{Actual Tahiti SLP} - \text{Mean Tahiti SLP})}{\text{Standard Deviation Tahiti}}$$

where

$$\text{Standard Deviation Tahiti} = \frac{\sqrt{(\sum (\text{Actual Tahiti SLP} - \text{Mean Tahiti SLP})^2)}}{N}$$

where $N = Number\ of\ months$

and

$$\text{MSD} = \text{Monthly Standard Deviation} = \frac{\sqrt{(\sum (\text{Standardized Tahiti} - \text{Standardized Darwin})^2)}}{N}$$

where N = Number of months in the summation.

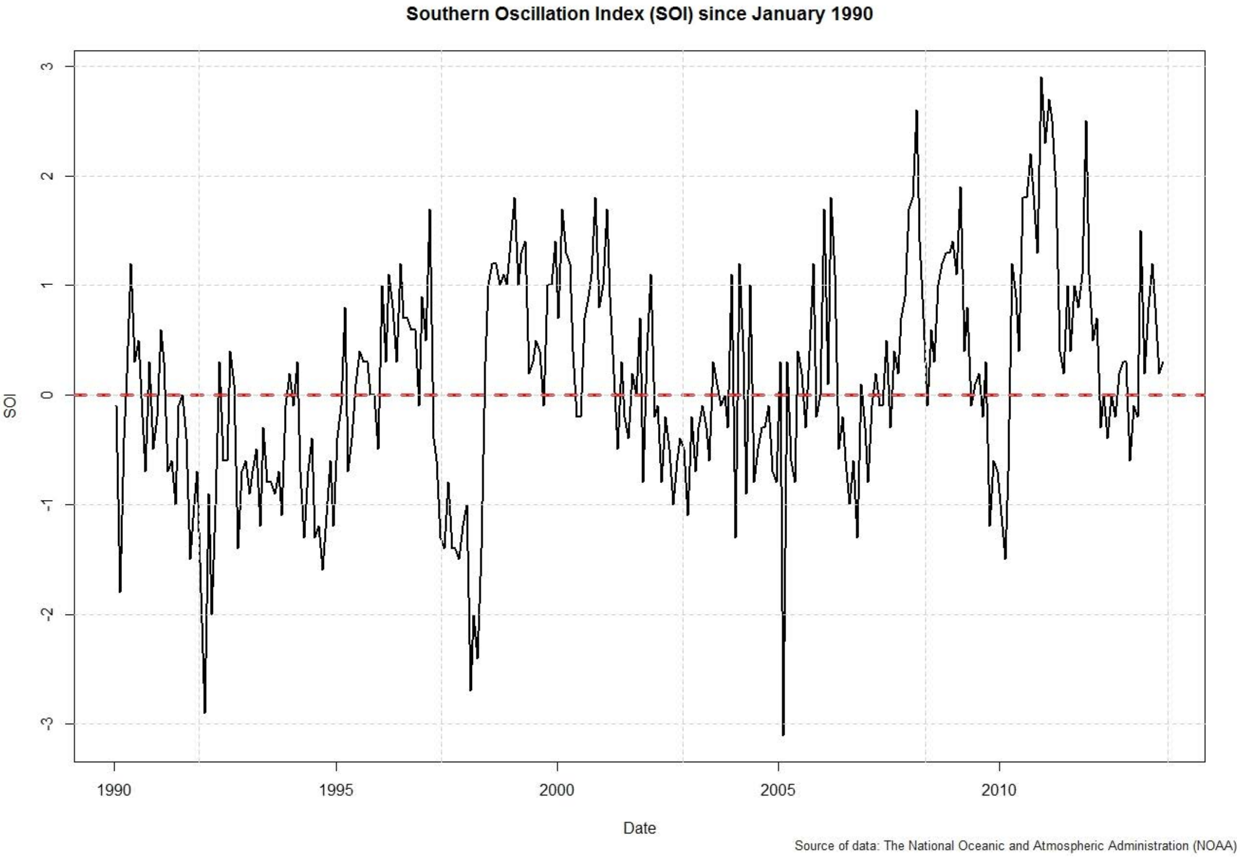

Figure 9: SOI trend since 1990

Appendix 2. Group specific overview of drivers

The following tables show a summary of the endogenous variables and the exogenous drivers for the different groups. As the starting point is different in each group, those drivers that are in common in all groups have in each group different starting dates and therewith different characteristics. Therefore, the tables are separate for each group and capture those characteristics that are in the specific dataset used for the VAR model.

Table 11: Group 1, grains (October 1991 - July 2012)

Variable	Mean	SD	Minimum	Maximum
Crude oil price ($/Barrel)	43.111	29.376	11.346	133.890
Crude oil price volatility	36.34%	11.83%	17.49%	104.13%
Dollar strength (in base year = 100)	87.711	10.627	69.005	112.196
Dollar strength volatility	0.060	0.026	0.013	0.175
GDP %- change	2.89%	6.61%	-11.70%	41.15%
SOI positive	0.469	0.646	0.000	2.900
SOI negative	0.352	0.554	0.000	3.100
Speculation Index grains	1.115	0.050	1.020	1.258
Financialisation grains	1.93%	3.53%	-19.90%	19.42%
Year-End Stock Projection %-change wheat	0.05%	6.95%	-19.43%	25.95%
Year-End Stock Projection %-change corn	0.14%	12.43%	-47.69%	50.61%
Stock-to-use ratio wheat	0.509	0.146	0.211	0.914
Stock-to-use ratio corn	0.170	0.070	0.058	0.336
Wheat (Hard) volatility	30.59%	8.15%	20.03%	59.15%
Wheat (Soft) volatility	33.67%	8.27%	24.67%	58.07%
Corn volatility	29.21%	11.74%	18.00%	79.69%
Bioethanol volatility	26.81%	9.58%	13.67%	49.85%
Ammonia volatility	53.38%	25.55%	36.88%	251.47%

Table 12: Group 2, oilseeds (May 2003 - July 2012)

Variable	Mean	SD	Minimum	Maximum
Crude oil price ($/Barrel)	70.103	24.412	28.183	133.890
Crude oil price volatility	39.48%	12.81%	25.18%	104.13%
Dollar strength (in base year = 100)	79.116	6.291	69.005	94.232
Dollar strength volatility	0.069	0.028	0.027	0.175
GDP %- change	2.42%	2.57%	-5.63%	7.13%
SOI positive	0.613	0.764	0.000	2.900
SOI negative	0.223	0.443	0.000	3.100
Speculation Index soybean	1.115	0.051	1.047	1.224
Financialisation soybean	1.10%	5.57%	-20.67%	14.32%
Year-End Stock Projection (US) %-change soybean	0.02%	17.32%	-38.46%	113.76%

Year-End Stock Projection (World) %-change soybean	-0.05%	4.28%	-10.80%	14.96%
Stock-to-use ratio soybean (US)	0.149	0.077	0.068	0.343
Stock-to-use ratio soybean (World)	0.231	0.030	0.159	0.299
Soybean (US) volatility	32.81%	10.89%	17.76%	70.95%
Soybean (US, Kentucky) volatility	32.04%	6.16%	24.52%	58.80%
Rapeseed volatility	22.49%	6.69%	14.93%	44.52%

Table 13: Group 3, vegetable oils (August 2002 - July 2012)

Variable	Mean	SD	Minimum	Maximum
Crude oil price ($/Barrel)	67.675	26.330	26.401	133.890
Crude oil price volatility	39.94%	12.70%	25.18%	104.13%
Dollar strength (in base year = 100)	80.657	8.359	69.005	104.087
Dollar strength volatility	6.75%	2.78%	2.70%	17.52%
GDP %- change	2.41%	2.48%	-5.63%	7.13%
SOI positive	0.567	0.749	0.000	2.900
SOI negative	0.245	0.442	0.000	3.100
Speculation Index soybean oil	1.094	0.047	1.017	1.196
Financialisation soybean oil	1.05%	7.30%	-19.21%	34.45%
Year-End Stock Projection (US) %-change soybean oil	0.75%	8.16%	-23.08%	23.53%
Year-End Stock Projection (World) %-change soybean oil	0.55%	5.85%	-18.37%	19.00%
Stock-to-use ratio soybean oil (US)	0.117	0.031	0.062	0.165
Stock-to-use ratio soybean oil (World)	0.064	0.010	0.046	0.093
Soybean Oil (US)	20.60%	3.33%	16.06%	32.28%
Palm Oil (Malaysia)	22.76%	4.04%	17.98%	35.96%
Rapeseed Oil (North West Europe)	23.36%	9.03%	15.69%	58.89%
Sunflower Oil (US)	22.04%	3.37%	18.83%	38.82%
Sunflower oil (Argentina)	26.47%	7.37%	18.86%	53.64%
Soybean oil (Argentina)	29.22%	3.47%	23.79%	42.51%
Biodiesel	11.63%	2.22%	7.67%	15.62%

Table 14: Group 4, sugar (December 2002 - July 2012)

Variable	Mean	SD	Minimum	Maximum
Crude oil price ($/Barrel)	68.461	25.114	28.183	133.890
Crude oil price volatility	40.01%	12.96%	25.18%	104.13%
Dollar strength (in base year = 100)	79.951	7.322	69.005	101.651
Dollar strength volatility	6.81%	2.81%	2.70%	17.52%
GDP %- change	2.42%	2.53%	-5.63%	7.13%
SOI positive	0.586	0.758	0.000	2.900
SOI negative	0.234	0.443	0.000	3.100
Speculation Index sugar	1.078	0.041	1.009	1.178

Financialisation sugar	2.14%	7.48%	-28.08%	25.83%
Sugar (raw) volatility	31.33%	8.00%	20.35%	62.12%
Bioethanol (Brazil) volatility	55.03%	1.09%	52.02%	63.33%

Table 15: Group 5, meat (February 1990 - July 2012)

Variable	Mean	SD	Minimum	Maximum
Crude oil price ($/Barrel)	41.635	28.779	11.346	133.890
Crude oil price volatility	36.92%	13.10%	17.49%	104.13%
Dollar strength (in base year = 100)	87.835	10.277	69.005	112.196
Dollar strength volatility	6.05%	2.56%	1.28%	17.52%
GDP %- change	3.01%	6.77%	-11.70%	41.15%
SOI positive	0.447	0.631	0.000	2.900
SOI negative	0.356	0.551	0.000	3.100
Speculation Index feed grains	1.093	0.048	1.012	1.234
Financialisation corn	1.74%	3.51%	-20.42%	19.01%
Year-End Stock Projection %-change corn	-0.02%	12.19%	-47.69%	50.61%
Year-End Stock Projection %-change soybean meal	0.16%	6.94%	-25.93%	42.86%
Stock-to-use ratio corn	0.173	0.069	0.058	0.336
Stock-to-use ratio soybean meal	0.009	0.002	0.006	0.017
Pork volatility	24.32%	8.99%	14.34%	73.22%
Corn volatility	28.59%	11.63%	17.72%	79.69%
Soybean Meal volatility	22.05%	4.81%	16.37%	47.99%

Appendix 3. Estimated volatilities of the commodities

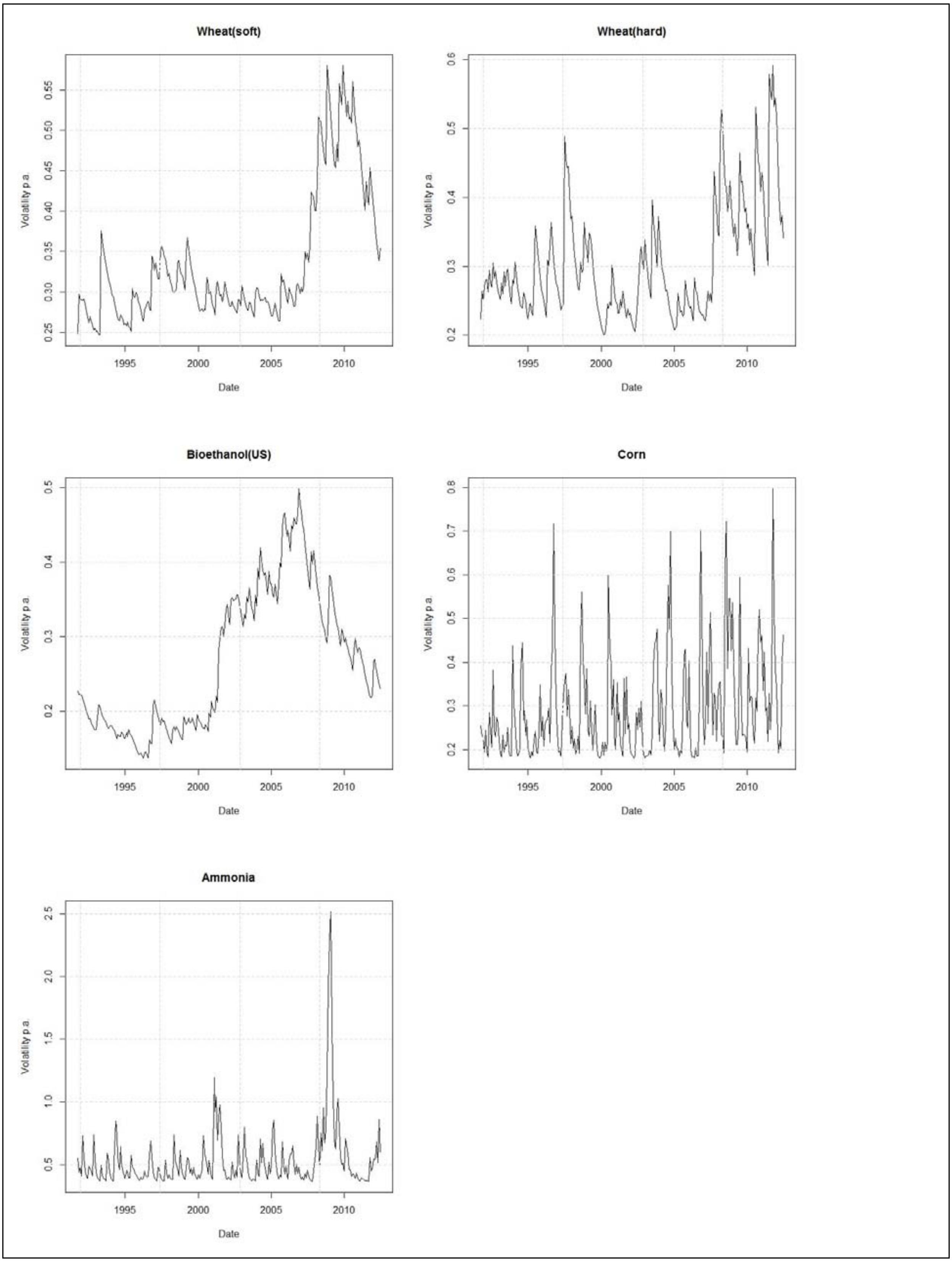

Figure 10: Example for Group 1