Since the financial and food price crises of 2007, market instability has been a topic of major concern to agricultural economists and policy professionals. This volume provides an overview of the key issues surrounding food prices volatility, focusing primarily on drivers, long-term implications of volatility and its impacts on food chains and consumers.

The book explores which factors and drivers are volatility-increasing and which others are price level-increasing, and whether these two distinctive effects can be identified and measured. It considers the extent to which increasing instability affects agents in the value chain, as well as the actual impacts on the most vulnerable households in the EU and in selected developing countries. It also analyses which policies are more effective to avert and mitigate the effects of instability.

Developed from the work of the European-based ULYSSES project, the book synthesises the most recent literature on the topic and presents the views of practitioners, businesses, NGOs and farmers’ organisations. It draws policy responses and recommendations for policy makers at both European and international levels.

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Chapter 3
Has agricultural price volatility increased since 2007?

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1 Introduction

In this chapter, we assess the development of price volatility in major agricultural markets over the past years. We base this analysis on univariate GARCH models for the commodities under consideration and then analyze these estimated volatilities further, with a specific focus on spillovers between closely related agricultural markets. These volatility dynamics are captured in vector autoregression (VAR) models for five different groups of key agricultural markets. Since volatility is inherently unobservable (and hence must be estimated), we first introduce the major conceptual choices which the researcher faces when conducting analyses of agricultural price volatility. In particular, we discuss the issues of time horizons, ex-ante versus ex-post perspectives, and estimation methods. We then take a closer look at the development of price volatility on key agricultural markets and put those into context with the recent literature. Finally, we provide some additional results on the distinction between short- and long-term volatility.

2 Volatility concepts and measurement

Any attempt to identify the factors that govern volatility in agricultural commodity markets depends on the volatility concept that is applied. Throughout the literature, the following definition is commonly employed: Volatility is the standard deviation of relative price changes (log returns). This definition has several important implications. (i) Since the standard deviation is the square root of the expected squared deviation between the actual (relative) price change and the expected price change, such a volatility concept clearly distinguishes between expected price changes and unexpected price changes. Andersen et al. (2010, p. 69) define volatility as “the component of a given price increment that represents a return innovation as opposed to an expected price movement”. (ii) Since volatility expresses the magnitude of deviations from the expected price movement, any attempt to measure volatility empirically requires in addition the modelling of the price process, e.g., by modelling trends, seasonality, or cyclical components. For example, the popular
assumptions of zero expected returns, or expected returns that are constant over time, imply the absence of any trend, or a simple linear trend, respectively. These simple trend models may be perfectly appropriate for short time intervals like a minute or a day. However, for longer time intervals it is important to deal both with long-term trends and cycles as well as with seasonalities according to harvest cycles. (iii) Since volatility addresses potential price changes, it inevitably refers to a period (over which a price change can happen) and not only to a single point in time. (iv) According to the above definition, volatility is not a directly observable quantity, like a price, but has to be estimated (see e.g., Poon and Granger, 2003, or Andersen et al., 2010).

The concrete measurement or estimation of volatility based on this definition involves a number of additional choices. Because different choices could lead to different volatility estimates, which in turn could lead to different conclusions about volatility drivers and policy implications, we briefly discuss these choices.

**Time horizon**: Volatility always refers to a time period. The end of this time period defines the time horizon. The selection of an appropriate time horizon depends on the goal of the analysis. For example, for an understanding of the effects of volatility on producers and consumers, a time horizon of at least one month seems appropriate. The time horizon does not necessarily coincide with the frequency of the data, which is used to estimate volatility. On the contrary, some estimation methods require that data is available at a higher frequency than the time horizon under study.

**Ex-post measurement versus ex-ante prediction**: It is important to distinguish between ex-post volatility and ex-ante volatility. In general, ex-post measurement of volatility can use all available information, including the price changes that occurred in the time period of interest (see the previous discussion on the time horizon above) and even price changes that occurred later. In contrast, measurement of ex-ante volatility is entirely based on information up to the beginning of the time period. This distinction has several implications: (i) The preferred approach depends on the objectives of the volatility assessment. Ex-post volatility is most useful in an analysis that aims to explain what has driven volatility in the past, whereas ex-ante volatility helps us to understand expectations about future volatility. Both perspectives are economically relevant. In terms of policy implications, ex-post analyses can be used to guide longer-term reforms, whereas ex-ante measures could provide an early warning system that may indicate the need for immediate action. (ii) Ex-post volatility can be interpreted as an in-sample volatility, whereas ex-ante volatility can be seen as a forward-looking out-of-sample volatility. Ex-ante approaches hence require that the estimated volatility model continues to be valid for the time horizon outside the observation sample. (iii) Different estimation methods are available for ex-post volatility and ex-ante volatility. In particular, implied volatilities based on the expectations of options markets participants can be used as measures of ex-ante volatility.
Estimation method: The most common approach is to use a parametric volatility model and to estimate it with historical data. The major approaches are models in the GARCH class and stochastic volatility models. A GARCH model explains (squared) volatility by past return innovations and past (squared) volatilities (plus potentially some exogenous explanatory variables [GARCH-X]). A stochastic volatility model treats volatility as a random variable and models its evolution via a stochastic process. GARCH models are the most common choice for the analysis of volatility in agricultural commodity markets. Model specification in this context involves several specific choices: (i) To obtain the return innovations, a model for the expected price change has to be specified (see discussion above). In the discussion that follows, we concentrate, however, on the volatility part of the model. (ii) Some general specification issues involve the questions of whether a univariate GARCH model is applied to each market under consideration or several markets are treated simultaneously via a multivariate GARCH model, the integration property of the volatility (stationary, integrated, or fractionally integrated GARCH models), and the question of whether the volatility response to past return innovations is asymmetric (GJR-GARCH) or depends on certain thresholds (TGARCH). For storable agricultural commodities, the fact that demand for storage tends to become more and more elastic at low price levels suggests that asymmetry or threshold effects are likely present. (iii) Lag lengths have to be fixed for both the return innovations and the past volatilities, i.e., the order of the GARCH model has to be chosen. (iv) The data frequency to be used for the estimations has to be selected. And (v) the historical data period has to be selected, too. One disadvantage of the parametric approach inherent to GARCH models is the assumption that the structure of the model remains constant over the whole data period, including any possible forecast horizon.

An alternative to parametric volatility models is a nonparametric approach often called “realized volatility”. The basic idea is that the volatility of a certain time period can be estimated from data of this period only, which is available, however, on a higher frequency. For example, the volatility referring to a certain month is estimated from the daily price changes within this month. The major advantage of this approach is that it does not require the assumption of a fixed model structure over a quite long period of time (the data period used for GARCH models usually contains several years). One disadvantage of the approach is its need for price data measured at relatively high frequencies, which might not be available. Moreover, the issue of how volatility scales over different frequencies appears. For example, if daily data is used to estimate the volatility for a time horizon of one month, we have to convert the daily volatility into a monthly one. Simple scaling rules for the volatility, like the square root of time rule, might not work very well because of dependencies in the daily price changes.
Parametric and nonparametric methods based on historical price data can in principle be used both for the ex-post measurement of volatility and for ex-ante predictions. Prediction is rather straightforward with parametric models. Given the parameter estimates, volatility forecasts for different time horizons are easily obtained from the model. The nonparametric approach delivers a time series of realized volatilities that can build the basis for out-of-sample predictions of volatilities. The specification of the concrete prediction model, however, is an additional task that again entails many choices to be made by the researcher. A completely different approach to ex-ante volatility prediction is the use of options data to back out the volatility expectations of market participants. This leads to the concept of implied volatility. This concept relies on the idea that volatility is an input variable in standard option pricing models. Given observed market prices for options, the corresponding pricing formula can be inverted to obtain a volatility estimate that is in line with observed market prices. A drawback of this approach is its reliance on a particular option pricing model. For example, a standard approach uses Black’s (1976) model for options on futures or a corresponding discrete-time approximation. Alternatively, model-free approaches to estimate implied volatilities have been developed by Britten-Jones and Neuberger (2000) and Bakshi et al. (2003). These are computationally more complex but do not require the assumption of any specific pricing model. The major advantage of the implied approach to volatility estimation is that it does not require any historical data, which might no longer be representative for the future, but relies only on current option prices. It can therefore exploit the most recent information available to market participants in derivatives markets and often leads to better predictions than alternative methods based on historical price data.

3 Estimating volatility on key agricultural markets

Price volatility in agricultural and food markets should not be viewed in isolation. Substitution possibilities between agricultural products in consumption, competition for scarce land in production, and vertical price transmission along the supply chains lead to complex relations between prices. Therefore, we conduct our analysis not in isolated markets but instead form groups of commodities; volatility transmission along the supply chain will be discussed later in Chapter 6 of this volume.

Group one is called “grains” and consists of wheat, corn, bioethanol, and ammonia, all prices taken from the US spot markets. Bioethanol is added to this group because it is supposed to be affected by grain price volatility, as it is extracted from corn in the United States. Wheat is included because it is usually deemed the lead market for price formation in the grains complex (e.g., Goodwin and Schroeder, 1991). Additionally, ammonia as a main nitrogenous
fertilizer is chosen because nitrogen is the main nutrient in wheat production (Piesse and Thirtle, 2009). Therefore, it may influence grain price formation.

Group two is called “oilseeds” and consists of soybeans from the United States and rapeseed from the European Union. These prices are likely related both in levels and volatilities, 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 characterized by a high extent of substitution possibilities in consumption (Busse et al., 2012).

These potentially strong linkages via substitution in consumption are 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 Northwest 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.

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 imported into the European Union. 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.

As discussed above, modelling and data choices matter in volatility analyses. For our investigation, we chose a monthly data frequency because it is supposed to be a relevant horizon for decision makers in commodity markets. The GARCH (1,1) model 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 realized volatilities require higher frequency data to be robust estimators, which are 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. The source of the price data and the unit of each series are presented in the appendix. If data are 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 in 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. 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 (α+β<1). Finally, the monthly volatility estimates resulting from the GARCH are annualized by multiplying them with \sqrt{12}. Table 3.1 summarizes the GARCH estimations for the different commodities and provides some descriptive statistics for the resulting volatilities.

In order to analyze volatility spillovers, we employ the econometric framework of vector autoregressive (VAR) models, as pioneered by Sims (1980), by including lagged volatilities of all the commodities in a system as explanatory variables. 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. We estimate a separate VAR for each of the commodity groups and include a number of additional exogenous potential drivers of price volatility. For details on this latter aspect, see Brümmer et al. (2014).

In the following, we describe the detailed findings for agricultural price volatility group by group.

Table 3.1 Description of annualized GARCH (1,1) volatility estimations

<table>
<thead>
<tr>
<th>Commod. Group</th>
<th>Region</th>
<th>Start</th>
<th>End</th>
<th>Mean</th>
<th>Mean</th>
<th>SD</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corn</td>
<td>US</td>
<td>Feb. 1990</td>
<td>Dec. 2012</td>
<td>AR(12)</td>
<td>28.72%</td>
<td>11.71%</td>
<td>17.72%</td>
<td>79.69%</td>
</tr>
<tr>
<td>Soybean 2</td>
<td>US</td>
<td>Feb. 1990</td>
<td>Dec. 2012</td>
<td>AR(1)</td>
<td>26.22%</td>
<td>9.43%</td>
<td>14.96%</td>
<td>70.95%</td>
</tr>
<tr>
<td>Rapesseeed 2</td>
<td>Europe</td>
<td>Feb. 1990</td>
<td>Dec. 2012</td>
<td>AR(1)</td>
<td>18.18%</td>
<td>2.97%</td>
<td>14.34%</td>
<td>30.62%</td>
</tr>
<tr>
<td>Palm oil 3</td>
<td>Malaysia</td>
<td>Feb. 1990</td>
<td>Dec. 2012</td>
<td>AR(1)</td>
<td>23.48%</td>
<td>6.11%</td>
<td>17.11%</td>
<td>54.91%</td>
</tr>
<tr>
<td>Soybean oil 3</td>
<td>Argentina</td>
<td>Dec. 1995</td>
<td>Dec. 2012</td>
<td>AR(1)</td>
<td>28.34%</td>
<td>3.70%</td>
<td>22.10%</td>
<td>42.51%</td>
</tr>
<tr>
<td>Rapesseeed 3</td>
<td>Northwest Europe</td>
<td>Oct. 1995</td>
<td>Dec. 2012</td>
<td>AR(12)</td>
<td>22.58%</td>
<td>9.15%</td>
<td>15.63%</td>
<td>67.73%</td>
</tr>
<tr>
<td>Sunflower oil</td>
<td>Netherlands</td>
<td>Feb. 1990</td>
<td>Dec. 2012</td>
<td>AR(12)</td>
<td>22.04%</td>
<td>4.73%</td>
<td>18.71%</td>
<td>64.44%</td>
</tr>
<tr>
<td>Biodiesel 3</td>
<td>Germany</td>
<td>Aug. 2002</td>
<td>Dec. 2012</td>
<td>AR(1)</td>
<td>11.59%</td>
<td>2.19%</td>
<td>7.67%</td>
<td>15.62%</td>
</tr>
<tr>
<td>Bioethanol 4</td>
<td>Brazil</td>
<td>Dec. 2002</td>
<td>Dec. 2012</td>
<td>AR(12)</td>
<td>36.56%</td>
<td>27.94%</td>
<td>0.05%</td>
<td>140.93%</td>
</tr>
<tr>
<td>Pork 5</td>
<td>Germany</td>
<td>Feb. 1990</td>
<td>Dec. 2012</td>
<td>AR(12)</td>
<td>24.25%</td>
<td>8.93%</td>
<td>14.34%</td>
<td>73.22%</td>
</tr>
<tr>
<td>Soybean meal</td>
<td>Europe</td>
<td>Feb. 1990</td>
<td>Dec. 2012</td>
<td>AR(1)</td>
<td>19.14%</td>
<td>4.66%</td>
<td>13.86%</td>
<td>45.28%</td>
</tr>
<tr>
<td>Corn 5</td>
<td>Europe</td>
<td>Mar. 2000</td>
<td>Dec. 2012</td>
<td>AR(12)</td>
<td>26.18%</td>
<td>7.7%</td>
<td>20.64%</td>
<td>61.6%</td>
</tr>
</tbody>
</table>

Source: Own estimates.
4 Volatility spillovers across commodity markets

4.1 Group 1: grains

Grains: Figure 3.1 shows the estimated volatility for four commodities in the grain group. The fertilizer (ammonia) shows the most volatile price development during the estimated period. For all four products in this group, we observe that the own lagged volatility is significant with the expected positive sign in the VAR model illustrating the volatility persistence inherent to the 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 markets. 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 3.2. 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.

![Figure 3.1 GARCH (1,1) volatility estimation for group 1: wheat, corn, ammonia, and bioethanol.](image-url)
Figure 3.2 Impulse-response functions for group 1 (wheat, corn, bioethanol, ammonia).
Figure 3.2 Continued
Figure 3.3 GARCH (1,1) volatility estimation for group 2: rapeseed and soybean.

4.2 Group 2: oilseeds

Oilseeds: Figure 3.3 shows the estimated volatility for the two commodities in the oilseeds group. The rapeseed price shows increased volatility after 2003. The dynamic effects of volatility shocks in this group are rather straightforward. There is volatility persistence for both soybeans and rapeseeds, a lagged impact of rapeseed volatility on the volatility of soybeans and vice versa, and a contemporaneous effect. The relative sizes of soybean and rapeseed markets should imply a leading position of the former in volatility spillovers. Hence, we attribute the contemporaneous effects to a shock in the soybean market for the impulse-response analysis in Figure 3.4. As the impulse-response functions show, there are significant spillover effects in both directions. This statement holds even with changed ordering.

4.3 Group 3: vegetable oils

Vegetable oils: Figure 3.5 shows the estimated volatility for five commodities in the vegetable oil group, with remarkably different volatility patterns for the commodities. The vegetable oils group 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. The impulse-response functions are shown in Figure 3.6. Because of some high contemporaneous correlations in the residuals, the ordering of the markets is particularly important. The results in Figure 3.6 are based on the
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Figure 3.4 Impulse-response functions for group 2 (soybean and rapeseed).

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 products contemporaneously, but not vice versa. The second product (soybean oil) affects rapeseed oil, sunflower oil, and biodiesel but is not affected by them, etc.
GARCH (1,1) volatility estimation for group 3 (part 1):
Palm oil, Sunflower oil

GARCH (1,1) volatility estimation for group 3 (part 2):
Soybean oil, Biodiesel, Rapeseed oil

Figure 3.5 GARCH (1,1) volatility estimation for group 3: palm oil, rapeseed oil, biodiesel, soybean oil, sunflower oil.
Figure 3.6 Impulse-response functions for group 3 (palm oil, rapeseed oil, biodiesel, soybean oil, sunflower oil).
Figure 3.6 Continued
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. In summary, our results show a very high interconnectedness between the five products in terms of volatility spillovers.

4.4 Group 4: sugar

Sugar: Figure 3.7 shows the estimated volatility for two commodities in the sugar group. The dynamic structure of the resulting VAR model is very simple for the group with sugar and bioethanol. There is persistence in both volatilities and no spillover, neither via lagged volatilities nor via a contemporaneous correlation of the residuals. This observation is fully confirmed by the impulse-response functions as provided in Figure 3.8.

4.5 Group 5: meats

Meat: Figure 3.9 shows the estimated volatility for three commodities in the meat group. Different volatility patterns for prices can be recognized among
Figure 3.7 GARCH (1,1) volatility estimation for group 4: sugar and bioethanol.

Figure 3.8 Impulse–response functions for group 4 (sugar, bioethanol).
Figure 3.8 Continued

Figure 3.9 GARCH (1,1) volatility estimation for group 5: meat (pork), corn, soybean meal.
meat as output and corn and soybean meal as input. 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. This result is confirmed by the impulse-response functions (Figure 3.10). There are spillovers in both directions, from soybean meal to corn and from corn to soybean meal.

Figure 3.10  Impulse-response functions for group 5 (corn, soybean meal, pork).
5 High- and low-frequency components of price volatility

This section focuses on models based on realized volatility with an ex-post analysis perspective in order to investigate alternative methods for questioning what has driven the agricultural price volatility. Section 2 summarized the different estimation methods using GARCH models. In this section, we focus on the GARCH-MIDAS model of Engle et al. (2013), in order to take into consideration high- and low-frequency components of volatility. The mixed data sampling (MIDAS) filtering of Ghysels et al. (2005) is used to model the unconditional variance in this special type of GARCH model, which basically allows for combining the information provided by high-frequency (e.g., daily) prices and low-frequency (e.g., monthly) drivers. The overall interest for using the GARCH-MIDAS model comes from its potential to: (i) reduce the trade-off between the accuracy of the volatility measurement provided by the high-frequency data on prices and the necessity to match it with low-frequency variables and avoid loss of efficiency due to multistep procedures; (ii) analyze the causal relationship between price volatility and its determinants in a dynamic perspective, going beyond the usual contemporary analysis; (iii) enable ranking the importance of the drivers of price volatility, individuating which are the most sensible key drivers to be addressed by the policy makers. In order to utilize and test those benefits, we consider the grains (wheat and corn) and oilseeds (soybean) markets among the markets listed in section 3 over the period 1986–2012.

According to the GARCH-MIDAS model, the unexpected returns can be presented as:
\[ r_{i,t} = \mu + \sqrt{\tau_t g_{i,t}} e_{i,t}, \quad \forall i = 1, \ldots, N_t \]  

where \( r_{i,t} \) is the log return on day \( i \) during month/quarter/year \( t \) \((i = 1, \ldots, N_t; N_t \) is the number of days in period \( t \)); \( \mu \) is the conditional expectation given information at day \((i - 1)\) of any arbitrary period \( t \); and the conditional distribution of the errors is assumed to be normal with zero mean and unit variance. Volatility is decomposed into two separate components as in the tradition of the component GARCH models introduced by Engle and Lee (1999). Namely, \( g_{i,t} \) characterizes daily fluctuations associated with transitory or short-lived effects of volatility, while the secular or low-frequency component \( \tau_t \) represents the unconditional volatility and it is aimed to capture slowly varying deterministic conditions in the economy.

In the GARCH-MIDAS model, the \( g_{i,t} \) component is assumed to be a (daily) GARCH (1,1) process, namely:

\[ g_{i,t} = (1 - \alpha - \beta) + \alpha \frac{(r_{i-1,t} - \mu)^2}{\tau_t} + \beta g_{i-1,t} \]

where \( \alpha > 0, \beta > 0 \) and \( \alpha + \beta < 1 \).

The MIDAS regression is facilitated to model the low-frequency \( \tau_t \) component in (1). It is the key element for the analysis as it allows for using data sampled at different frequencies:

\[ \tau_t = m + \theta \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2) RV_{t-k} \]

where \( RV_t \) is the fixed time span realized volatility at time \( t \) calculated by the square sum over high-frequency index \( i \) of log returns and \( \varphi_k() \) is the function defining the weighting scheme of MIDAS filters. Engle et al. (2013) proposed two different functions for the weighting scheme: the Beta and the exponentially weighted lag structures. Following Joyeux and Girardin (2013) and Engle et al. (2013), who showed that they yield similar results, we decided to use the Beta lag structure due to its flexibility to accommodate various lag structures:

\[ \varphi_k(\omega_1, \omega_2) = \frac{(k / K)^{\omega_1-1} (1 - k / K)^{\omega_2-1}}{\sum_{j=0}^{K} (j / K)^{\omega_1-1} (1 - j / K)^{\omega_2-1}} \]

Different combinations of \( \omega_1 \) and \( \omega_2 \) values in (4) can accommodate monotonically increasing, monotonically decreasing, and also unimodal hump-shaped weighting schemes with nonnegative weights resulting in positive estimates of volatility. In this study, we use \( \omega_1 = 1 \) and \( \omega_2 > 1 \) in order to have a monotonically decreasing pattern over the lags, which is typical of volatility filters.
It is worth emphasizing that the GARCH-MIDAS model presented in (1)–(4) has a fixed parameter space, which makes it more parsimonious compared to other component volatility models. This feature is exploited to compare different models with various time spans \( t \) (e.g., month, quarter, annual) and different number of lags \( K \). In particular, we choose the time period \( t \) by comparing the values of log-likelihood functions and, subsequently, define the optimum number of lags \( K \) through the minimization of the Bayesian information criteria (BIC). For estimating the parameters, we use the conventional quasi-maximum likelihood estimation (QMLE) method.

In order to calculate realized volatility, we use daily settlement prices of the first nearby futures contracts traded at the Chicago Board of Trade (CBOT) from 1 January 1986 to 31 December 2012 for calculating the returns. We are interested in using futures prices instead of spot prices since: (i) they are standardized and promote accuracy; (ii) they perform as a risk-transfer tool for hedgers and speculators; (iii) they provide information to the market over the price formation; and (iv) they are sampled at high frequency (Hernandez and Torero, 2010). In order to build a unique series for the futures prices and combine different contracts with a limited life span, we conduct some data processing. First of all, we take the nearest contract up to the first day of its maturity month and then we roll over to the next contract (e.g., Gilbert and Morgan, 2010; Gutierrez, 2012) in order to avoid the Samuelson effect supporting that the price volatility increases as the contract approaches its delivery date (Samuelson, 1965). Moreover, as suggested by Ghysels et al. (2006), we take into consideration the effect of seasonality induced by the harvest cycles during a calendar year\(^{11}\) by seasonally adjusting the monthly and quarterly \( \text{RV} \) (realized volatility) series before fitting MIDAS regression. We remove the periodic pattern using a multiplicative-type of adjustment via regression on monthly/quarterly dummies.

As mentioned before, building a GARCH-MIDAS model requires finding the optimum time span \( t \) and the MIDAS lag years \( K \) that are used in the specification of the low-frequency component \( \tau \). Our estimations lead us to monthly specification, since it always outperforms the quarterly and annual representations of \( \tau \). Following to the time span selection, we use the BIC criteria to define the lag number. Figure 3.11 displays the estimated lag weights of the GARCH-MIDAS model with monthly \( \text{RV} \) for one (\( k = 12 \)) to three (\( k = 36 \)) MIDAS lag years. Figure 3.11 shows that the optimal weights decay to zero around 20 months of lags for wheat and soybean, regardless if we select two or three years of MIDAS lags. The model with a one-year MIDAS lag is not proper for exploiting all the information provided by the past values of \( \text{RV} \), since the weights do not converge to zero. Corn shows a different pattern, where the optimal weights decay to zero with both one and two years of MIDAS lags while the model with three years of MIDAS lags does not converge to zero. Nevertheless, the BIC criteria for the three crops suggest
that two years of MIDAS lags achieves the best fit, implying that the best representation is given by the model with $t = \text{month}$ and $k = 24$.

After defining $t$ and $k$, we use the QMLE method to estimate parameters. For an overall view, the annualized volatility components of the GARCH-MIDAS models are displayed for all crops in Figure 3.12. It is observed that the MIDAS

![Figure 3.11 Optimal lag structures.](image-url)
Figure 3.11 Continued

Figure 3.12 Conditional volatility and its low-frequency component for wheat, corn, and soybean.
Figure 3.12 Continued
filter applied to the realized volatility allows for extracting a $\tau$ component, which is smoother than the total price volatility as it was expected. Nevertheless, the $\tau$ component still follows the path of the total volatility and increases substantially in the last decade, especially for wheat and corn.

The parameter estimates of the GARCH-MIDAS model with realized volatility are presented in Table 3.2. For each crop, the first row of the parameters indicates the estimates and the second row shows the robust t-statistics computed by Bollerslev and Wooldridge (1992) standard errors. All of the statistically significant estimates respect the expected sign. Especially, the estimates of $\theta$ for all crops are significant and positive, indicating that the information contained in the last two years of RV contributes to explain the low-frequency component of the price volatility. Not surprisingly, the higher the level of past RV, the higher the level of $\tau$. We also estimate a restricted specification of equation (4) with $\theta = 0$ which reduces the GARCH-MIDAS model to a GARCH (1,1) model with constant unconditional variance (Conrad et al., 2012). The GARCH (1,1) model is nested in the GARCH-MIDAS specification, therefore the comparison of the two models is straightforward. The seventh column of Table 3.2 gives the value of the log likelihood function (LLF) and below the BIC while the last column presents the value of the LLF of the GARCH (1,1) and below the chi-square test statistic of the log likelihood ratio test with respect to the GARCH-MIDAS model. According to this test statistic, the GARCH-MIDAS models outperform the standard GARCH (1,1) model. This result supports that a time-varying unconditional variance model accommodates better the analysis of historical agricultural price volatility. It is also worth noting that while the sum of $\alpha$ and $\beta$ is always close to one in the GARCH model, in the GARCH-MIDAS model the sum is significantly lower, indicating a lower persistence in the low-frequency volatility component. This result is in line with other works based on component models such as Engle and Rangel (2008) and Engle et al. (2013). It can be concluded that modeling the agricultural price volatility as the product of high- and low-frequency components could be further explored. In this respect, an additional effort has already been made by Donmez and Magrini (2013), who studied the

<table>
<thead>
<tr>
<th>Crop</th>
<th>$\mu$</th>
<th>$\alpha$</th>
<th>$\beta$</th>
<th>$m$</th>
<th>$\theta$</th>
<th>$\omega_2$</th>
<th>LLF/BIC</th>
<th>GARCH (1,1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wheat</td>
<td>-0.0004</td>
<td>0.0667</td>
<td>0.8779</td>
<td>0.0000</td>
<td>0.0002</td>
<td>4.9853</td>
<td>17055.58</td>
<td>17038.1888</td>
</tr>
<tr>
<td></td>
<td>-2.19</td>
<td>7.37</td>
<td>38.53</td>
<td>2.29</td>
<td>9.85</td>
<td>1.82</td>
<td>-5.42</td>
<td>34.77</td>
</tr>
<tr>
<td>Corn</td>
<td>-0.0002</td>
<td>0.0858</td>
<td>0.8857</td>
<td>0.0000</td>
<td>0.0002</td>
<td>2.1433</td>
<td>17935.83</td>
<td>17916.9234</td>
</tr>
<tr>
<td></td>
<td>-1.39</td>
<td>8.44</td>
<td>57.69</td>
<td>1.08</td>
<td>5.68</td>
<td>2.91</td>
<td>-5.69</td>
<td>37.82</td>
</tr>
<tr>
<td>Soybean</td>
<td>0.0000</td>
<td>0.0722</td>
<td>0.9027</td>
<td>0.0001</td>
<td>0.0001</td>
<td>4.0278</td>
<td>18228.01</td>
<td>18224.6246</td>
</tr>
<tr>
<td></td>
<td>0.07</td>
<td>8.70</td>
<td>66.21</td>
<td>2.36</td>
<td>2.98</td>
<td>8.67</td>
<td>-5.79</td>
<td>6.76</td>
</tr>
</tbody>
</table>

Note: The 5% critical value for the chi-square with two degrees of freedom is equal to 5.99.
effect of potential drivers on the low-frequency component of volatility and found that the global business cycle, weather shocks, and the degree of market financialization are the most important determinants.

6 Discussion

The after-crisis period (starting from the second quarter of 2008) is generally characterized by high price volatility for many agricultural commodities. However, in comparison to the 1970s, recent volatility spikes remain well below their historical peaks for most of the commodities. Gilbert and Morgan (2010) conclude that the volatility for agricultural products, with the exception of rice, is lower over the past two decades than in the 1970s and 1980s, and although volatility is high over the 2007–2009 period for many foodstuffs, in the case of groundnut oil, soybeans, and soybean oil, their conditional variances increase significantly. Despite no increasing tendency toward food volatility during recent years, volatility of the main grains does increase. Gilbert and Prakash in Prakash (2011) argue that the periods of extreme volatility in agricultural markets are seldom. They distinguish the 1973–1974 episode as a “crisis” with extreme high price levels and volatility on commodity markets, whereas the recent 2006–2007 episode – despite showing relative high price levels and volatility – is not comparable in size and effects (about five million malnutrition–related deaths) to the former one. Huchet-Bourdon (2011) finds from the analysis of ten products (1957–2010) that agricultural price volatility is on average low for beef and sugar. She also arrives at the conclusion that volatility is higher in the last decade than in the 1990s but not higher than in the 1970s. However, same as Gilbert and Morgan (2010), she finds that recent volatility is higher than in the 1970s only for cereals. The recent literature on the analysis of the volatility of major crops (maize, rice, wheat, and soybean) shows that the distinction between the period of lower volatility before 2006–2007 and higher volatility after that until today is still recognizable (for instance, Geman and Ott, 2014, p. 37). However, the latest OECD-FAO agricultural outlook for the period 2014–2023 forecasts a reduction in the risk of volatility because of the recovery in the stock levels (OECD-FAO, 2014).

Notes

1 The only alternative concept that is used in some papers is the coefficient of variation; however, this measure contains the standard deviation in the numerator.
2 The approach dates back to the seminal work by Engle (1982) and Bollerslev (1986). A comprehensive review of the most important ARCH and GARCH variants can be found in Bollerslev et al. (1994).
3 An early example of a model that treats volatility itself as stochastic is Clark (1973). A very popular stochastic volatility model is the one by Heston (1993). For a review paper that covers both GARCH models and stochastic volatility models see Andersen et al. (2010).
Has price volatility increased?

4 This approach was first introduced and applied by French et al. (1987), Schwert (1989, 1990a, 1990b), and Schwert and Seguin (1990). It was later formalized by Andersen and Bollerslev (1998).


6 German pork prices have a leading role in European pig price formation, in particular for EU export prices (Serra et al., 2006).

7 See Bollerslev (1986).

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

9 The mixtures of different frequencies were provided by the other models, such as Roache (2010) and Karali and Power (2013), which exploit the Spline-GARCH model by Engle and Rangel (2008). Their estimation uses a two-step procedure averaging daily/monthly data at monthly/annual level, generally leading to information loss, and the unconditional variance is modelled in a deterministic and nonparametric manner, preventing the possibility to incorporate directly the potential drivers (Ghysels and Wang, 2011). Moreover, not taking into consideration the impact of the lags of the drivers on price volatility imposes exclusively a contemporary relationship which is hardly the case in the agricultural commodity markets.

10 See Ghysels et al. (2007) for a broad discussion on the different patterns that can be obtained through Beta lags.

11 The presence of seasonality in the agricultural commodity price volatility has been largely acknowledged by the literature. For example, see Piot-Lepetit and M’Barek (2011) and Karali and Power (2013).

References


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## Appendix: The data source of the selected commodities prices and their units

<table>
<thead>
<tr>
<th>Commodity</th>
<th>Group</th>
<th>Data source</th>
<th>Datastream Code</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wheat (soft)</td>
<td>1</td>
<td>Datastream</td>
<td>WHEATSF</td>
<td>US cent/bu</td>
</tr>
<tr>
<td>Corn</td>
<td>1</td>
<td>Datastream</td>
<td>CORNUS2</td>
<td>US cent/bu</td>
</tr>
<tr>
<td>Bioethanol</td>
<td>1</td>
<td>Datastream</td>
<td>USNEETHP</td>
<td>US$/gallon</td>
</tr>
<tr>
<td>Ammonia</td>
<td>1</td>
<td>Datastream</td>
<td>AMMUSGO</td>
<td>US$/Ton</td>
</tr>
<tr>
<td>Soybean – No 1 Yellow</td>
<td>2</td>
<td>Datastream</td>
<td>SOYBEAN</td>
<td>US cent/bu</td>
</tr>
<tr>
<td>Rapeseed</td>
<td>2</td>
<td>Alfred C. Toepfer International</td>
<td>-</td>
<td>US$/Ton</td>
</tr>
<tr>
<td>Palm oil</td>
<td>3</td>
<td>Datastream</td>
<td>HWWIPO$</td>
<td>US$/Ton</td>
</tr>
<tr>
<td>Rapeseed oil</td>
<td>3</td>
<td>Datastream</td>
<td>RPOLDNE</td>
<td>Euro/Ton</td>
</tr>
<tr>
<td>Soybean oil</td>
<td>3</td>
<td>Datastream</td>
<td>ARGSBOI</td>
<td>US$/Ton</td>
</tr>
<tr>
<td>Sunflower seed oil</td>
<td>3</td>
<td>Datastream</td>
<td>HWWISO$</td>
<td>US$/Ton</td>
</tr>
<tr>
<td>Biodiesel</td>
<td>3</td>
<td>Agrarmarkt Informations-Gesellschaft mbH</td>
<td>-</td>
<td>Euro cent/lit</td>
</tr>
<tr>
<td>Sugar (raw)</td>
<td>4</td>
<td>Datastream</td>
<td>WSUGDLY</td>
<td>US cent/lb</td>
</tr>
<tr>
<td>Bioethanol</td>
<td>4</td>
<td>Centro de Estudios Avanzados en Economia Aplicada (CEPEA)</td>
<td>-</td>
<td>US$/lit</td>
</tr>
<tr>
<td>Pork</td>
<td>5</td>
<td>Marktbericht der Agrar Markt Austria</td>
<td>-</td>
<td>Euro/100 kg</td>
</tr>
<tr>
<td>Soybean meal</td>
<td>5</td>
<td>Alfred C. Toepfer International</td>
<td>-</td>
<td>US$/Ton</td>
</tr>
<tr>
<td>Corn</td>
<td>5</td>
<td>Alfred C. Toepfer International</td>
<td>-</td>
<td>US$/Ton</td>
</tr>
</tbody>
</table>