On the role of financial derivatives for the genesis and analysis of volatility in commodity markets

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Introduction

Agricultural economists often use the term “food price crisis” to describe the period from the end of 2007 till summer 2008 when prices for many agricultural commodities increased sharply. Shortly thereafter, most prices dropped again quickly, but exhibited large fluctuations in the following years,[1] peaking again in 2011.[2] Hence, the term food price crisis does not only refer to a change in price levels, but is perceived as the beginning of a period of higher price volatility as well. Since people suffer from high and unstable prices, especially in least developed countries, this development has been widely recognized as a global problem, and a major impediment to combating hunger and malnutrition. Consequently, governments, non-governmental organizations, and international organizations have expressed serious concerns about food markets’ increasing prices[3] as well as increasing price volatility[4]. The importance of price volatility, even for the highest political levels, was expressed in a meeting of the agricultural ministers of the G20 countries in 2011 when they declared an action plan on food price volatility, saying, among other things, “[w]e agree that managing the risk and mitigating the adverse impact of excessive food price volatility in developed and developing countries would provide an important contribution to longer term agricultural development and strengthen global food security”(G20 Agricultural Ministers (2011, item 42)). Of course, an action plan would not be necessary if managing and mitigating the effects of food price volatility were an easy task. Possible reasons for the difficulty of implementing these intentions are the

[1] See Wright (2011).

[2] See Trostle (2011).

[3] Studies dealing with the increase of food price levels are, for example, Headey and Fan (2008), Mitchell (2008), Trostle (2008).

[4] See, for example, Gilbert and Morgan (2010), Prakash (2011), Tothova (2011) for studies concentrating on the increase in price volatility.

high number of different commodity markets, the heterogeneity of volatility impacts due to different market participants, and also the complexity of capturing the risk itself correctly.

This thesis aims to contribute to the debate on how best to cope with agricultural commodity price volatility. Since different markets with various market participants exist, commodity price risk is a complex issue that requires a deep understanding of the precise occurrences. The vast literature that discusses volatility drivers and the ongoing interplay between political measures and the criticism that often follows underlines this complexity.[5] To gain a comprehensive overview of agricultural price volatility, its causes, and possibilities to help affected market participants in a meaningful way, this thesis will answer three major research questions: (1) How has volatility developed since the food price crisis 2007/2008? (2) What drivers of volatility can be identified? (3) Is it possible to forecast situations that bear risk for market participants?

Chapter 2 deals with volatility measurement and the description of volatility development on agricultural commodity markets. Although many other studies have already analyzed this topic, a robust conclusion about volatility development is hard to draw. An important difference between the price level and price volatility is that the former can easily be observed in the market while the latter is unobservable and has to be estimated. Hence, any description of the volatility development in recent years depends on the method of volatility estimation. Therefore, Chapter 2 has the intention to examine popular statements about the volatility increase since the food price crisis and other relevant issues, such as the change in the volatility persistence and the quantification of the increase, with respect to a robust conclusion. For this purpose, I estimate the volatility for three agricultural commodities—wheat, corn and soybean—since 1972, using a large variety of estimation methods. It can be seen that the measures have different characteristics and sometimes point into different directions for different aspects of volatility development. Nevertheless, all three commodities exhibit a higher volatility since the food price crisis 2007/2008 compared to the thirty years before, regardless of the estimation method. This finding underscores the importance of better understanding what the drivers of the volatility increases are so that market participants or policy makers can react in a better way.

[5]See, for example, FAO (2011).

Detecting the causes of volatility is the focus of Chapter 3, which is a joint work together with Bernhard Brümmer, Olaf Korn and Tinoush Jamali Jaghdani that will be published in the Journal of Agricultural Economics. Popular opinion seems to suggest that the culprits of the problem can easily be identified, as expressed, for example, in this title of an online article: "Financial speculation intensifies agricultural price volatility" (CNCD 11.11.11, SOS Faim, Oxfam-Solidarité, Réseau Financement Alternatif, FAIRFIN (2013)). In general, speculators and index traders became a hotly discussed topic in the media. Scientific investigations, however, show a less clear picture with heterogeneous findings, reaching from a volatility-increasing to a volatility-reducing impact of speculation on volatility.[6] These contradictory results demonstrate at the very least that identifying the one driver is not as obvious as might be expected at a first glance, and so the discussion about speculation and potential other drivers of volatility continues. The literature review by Brümmer, Korn, Schlüßler, Jamali Jaghdani, and Saucedo (2013) points out that many more drivers have been either discussed at a conceptual level or analyzed empirically.[7] Some drivers have been consistently identified, others—such as speculation—remain an open issue. Based on the findings of those studies, I conduct a comprehensive analysis of 16 commodity markets and a broad set of potential drivers in Chapter 3. The application of a vectorautoregressive (VAR) model allows me to simultaneously analyze the explanation potential of variables from outside of commodity markets as well as possible spillover effects between commodity markets for the volatility on a specific market. The most frequently statistically significant impact is found for the exchange rate volatility, measured by the volatility of the strength of the US dollar, whose increases drive up commodity price volatility. Moreover, impulse response functions show strong spillover effects between some markets. However, many volatility drivers found to be important in the literature for other markets have no significant effect in my study, which suggests that volatility drivers are market specific. Consequently, volatility-reducing policies should be designed for each market individually. Since the overall amount of volatility that can be explained by the VAR model is relatively small, it may prove difficult for policy makers to devise

[6] For a review of different findings in the literature, see Brümmer, Korn, Schlüßler, Jamali Jaghdani, and Saucedo (2013) and Will, Prehn, Pies, and Glauben (2013).

[7] A graphical illustration of the results can be found in Brümmer, Korn, Jamali Jaghdani, Saucedo, and Schlüßler (2013).

volatility-reducing measures in the first place. In fact, it seems to be a better approach to focus on how one can cope with this high volatility instead of trying to combat it.

FAO, IFAD, IMF, OECD, UNCTAD, WFP, the World Bank, the WTO, IFPRI, and the UN HLTF (2011, p. 6) state that "not all price variations are problematic, [...] but variations in prices become problematic when they are large and cannot be anticipated and, as a result, create a level of uncertainty which increases risks for producers, traders, consumers and governments and may lead to sub-optimal decisions". This statement highlights that volatility is a too superficial measure to base policy decisions on because a volatility increase can result from price movements during the measurement period that are (slightly) higher over that period, but could also be due to only a few very large price movements in that period with relatively smooth price movements otherwise. Moreover, various market participants act on a market and depending on the price process different economic consequences follow that require different policy measures. Additionally, there is a need to anticipate certain price movements in order to have the chance to react to them in advance. The need for such forward-looking information motivates the analysis in the following chapter.

Chapter 4 is joint work together with Bernhard Brümmer and Olaf Korn and contributes to the two issues that are of major importance if one aims to react appropriately to increased price risk: First, since volatility is a directionless measure of unexpected price movements, one needs to have more precise information about the upcoming risk because (few) large price moves can have severe economic consequences, while a slight general increase of price moves can be better coped with by market participants on their own. Additionally to the amount of a price move, its direction is important for describing the risk, since different scenarios are dangerous for different market participants. Naturally, consumers fear sudden price increases, whereas producers fear price decreases. Second, if governments and other institutions that are interested in price security want to implement measures to mitigate the consequences of certain risks, one needs to have reliable instruments to forecast those risks in order to have time to react. Since especially large price moves are a threat for market participants, Chapter 4 starts with an overall risk measure that is disaggregated into "large" and "normal" price moves and further into "large positive" and "large negative" price moves. The disaggregation allows insights into the fine structure of volatility and leads to new risk measures that are directly connected to the different economic consequences for market participants. The ex post analysis with these new measures shows that a high overall volatility has had different reasons in the past. In order to contribute to the second issue, option implied estimators are developed. While it is possible to use estimates that are based on observations of historical price moves, the major drawback of concentrating only on historical price data is that it does not allow for making any statements about market participants' expectations of future price risks. On the contrary, implied estimators have the advantage that they only use price data of currently traded options and hence capture the expectations of market participants of future price movements. Since market participants are assumed to take all information relevant for future price moves, such as weather shocks, into account, implied estimates are supposed to deliver better forecasts than estimates based on historical price data. In fact, my results show that forward-looking risk estimates are superior to simple historical ones and have especially in combination with fundamental drivers of risk predictive power. Thus, option based implied estimators are a promising starting point for developing a more sophisticated early warning system.

Finally, Chapter 5 summarizes the results from the three main chapters and gives a brief overview of the consequences for policy-makers.

2

Characteristics of agricultural commodity price volatility

Abstract

This article investigates different characteristics of several volatility measures. General differences in volatility level, volatility of volatility, and volatility persistence for a set of realized, GARCH model-based and implied volatilities are noted for three agricultural commodities. Moreover, common statements regarding the increase of volatility since the food price crisis of 2007/2008 and further relevant issues such as changes in volatility persistence and quantification of the increase are checked in terms of a robust conclusion. Some questions can clearly be answered, regardless of the volatility measure, while others are sensitive to the precise implementation of volatility estimation.

2.1 Introduction

Since the food price crisis of 2007/2008, governments, non-governmental organizations, and international organizations have expressed serious concerns about increasing prices and increasing price volatility in agricultural commodity markets. A large stream of literature analyzes price increases during recent years and their causes (e.g., Headey and Fan (2008); Mitchell (2008); Trostle (2008)). Another stream deals with the development of price volatility and potential drivers of volatility (e.g., Gilbert and Morgan (2010); Balcombe (2011); Tothova (2011)). An important difference between price levels and price volatility is that the former can easily be observed in the market, whereas price volatility is unobservable and must be estimated. Since there are several methods of volatility estimation, it is important to ask whether and how much the results of a volatility analysis in agricultural commodity markets depend on the choice of the estimation method.

When describing the development of volatility, two characteristics are important: The first one is the level of volatility. Since higher volatility can lead to problems for producers and consumers (Gilbert and Morgan (2010); Bellemare, Barrett, and Just (2013); Galtier and Vindel (2013)), the question of whether volatility has increased since 2007/2008 has become a relevant topic in recent years. The second issue is the persistence of volatility, because whether volatility shocks are transitory or remain in the market for longer is crucial to the design of appropriate policy measures aimed at dealing with volatility (Cashin, Liang, and McDermott (2000))[1]. Studies so far mainly agree that food price volatility has been higher since 2007/2008 compared to the 1990s and 2000s, but—at least for most commodities—lower compared to the 1970s (Gilbert and Morgan (2010); Huchet-Bourdon (2011)). Although this development of price volatility after 2007/2008 seems to be non-controversial, the magnitude of this increase is seldom precisely defined. A comprehensive understanding of the situation in agricultural commodity markets, though, requires quantifying the volatility increase. Therefore, it is necessary to analyze whether different volatility measures lead to different results or whether a robust statement about

[1] Cashin, Liang, and McDermott (2000) discuss price shocks, but their results can be transferred to volatility shocks.

the magnitude of the effects can be made. Moreover, the similarity of volatility measures is interesting not only for the volatility analysis itself, but also for every analysis that is built on volatility estimates. Studies so far have failed to uniformly identify drivers of volatility.[2] The contradictory results could, of course, have several causes: different methodological approaches, different ways of measuring the respective driver, or different ways of estimating the explained variable, namely, food price volatility.

This article aims to shed light on the role of the estimation method by analyzing its impact on several characteristics of volatility and on statements regarding volatility development. More specifically, this article focuses on two aspects: First, the volatility in three major agricultural markets is estimated with different approaches. A general comparison of the characteristics should identify the main differences between possible volatility estimators so that results based on a specific method can be better analyzed. Second, this article investigates whether robust statements about the volatility development in commodity markets can be made or whether the results are sensitive to the estimation method. The analysis includes not only the most common volatility estimation methods in the food price crisis literature, but also several implied volatility estimators that so far have rarely been applied to these markets. Indeed, some studies use implied volatility estimators in the context of agricultural markets, but their focus is more on the application of the estimators for forecasting and not on the analysis of volatility behavior during the crisis of 2007/2008.[3] Implied volatility estimators are investigated for my analysis because they are useful not only for forecasting but also for the ex post measurement of perceived risk, which might be different than the risk based on historical prices. Since both the risk estimated on the basis of prices as well as the perceived risk can have an impact on decisions, risk perception is, likewise, an important issue. Implied volatility is used as a

[2]The most controversially discussed driver of food price volatility is the trading activity of speculators or index funds. A review of different findings is given by Brümmer, Korn, Schlüßler, Jamali Jaghdani, and Saucedo (2013) and Will, Prehn, Pies, and Glauben (2013).

[3]See the recent study of Triantafyllou, Dotsis, and Sarris (2015) for an application of implied information and an overview of studies working with implied volatility. Exceptions in the food price crisis literature are the works of FAO, IFAD, IMF, OECD, UNCTAD, WFP, the World Bank, the WTO, IFPRI, and the UN HLTF (2011) and Prakash (2011), who calculate implied volatilities. Both use Black–Scholes model-based volatilities. As discussed in the next sections, there exist more possibilities for calculating implied volatilities.

proxy for perceived risk because it is supposed to be influenced by investor sentiment.[4] Sarris (2014), in fact, points out that, for cereals, differences between option implied and spot price realized volatilities exist, which is in line with the literature on financial markets that generally agrees on implied volatilities being a biased estimator of realized volatility. Of course, investor sentiment is only one potential reason for this bias and a further widely accepted cause is the volatility risk premium. Since the effects that cause the bias cannot be disentangled, the implied estimator does not perfectly capture investor sentiment but does so at least partially.[5]

The comparative analysis in this article includes parametric and non-parametric volatility estimators that are based on either historical price data or on information implied in the prices of currently traded options. This results in four different combinations, for which several representatives are chosen: The first group is realized volatilities, which are non-parametric estimators based on historical data. Inside this group, "standard" realized volatility, realized volatility with a correction for the autocorrelation of daily returns, realized volatility based on the adjusted absolute deviation, realized volatility based on adjusted residuals from a regression, and realized volatility based on opening, closing, high, and low prices are calculated. In addition to these estimators that are all based on the interpretation of volatility as the standard deviation of returns, realized absolute deviations will also be included in the analysis. Second, generalized autoregressive conditional heteroskedasticity (GARCH) model-based volatilities are applied to obtain parametric estimators that use historical price data. The standard GARCH(1,1) and Glosten, Jagannathan, and Runkle's (1993) GARCH(1,1) (GJR-GARCH(1,1)) model are therefore used. Finally, option implied volatilities are computed for the last two groups to also compare estimators that are not based on historical price data but use current information and expectations. For the third group, the implied volatilities of at-the-money options based on the inversion of Black's (1976) option pricing formula are used as a representative of a parametric implied estimator. Fourth, the model-free implied volatility

[4] "Investor sentiment, defined broadly, is a belief about future cash flows and investment risks that is not justified by the facts at hand" (Baker and Wurgler (2007, p. 129)). For the influence of sentiment on implied volatility, see, for example, Kaplanski and Levy (2010).

[5] Besides investor sentiment and the volatility risk premium, also other aspects could partially lead to the bias. For further reasons, see, for example, Fleming (1999).

based on the approach of Bakshi, Kapadia, and Madan (2003) is calculated to represent a non-parametric estimator, as well as—equivalent to the realized volatilities—the implied absolute deviation. The two implied measures from the fourth group will also be calculated with a risk adjustment as proposed by Prokopczuk and Wese Simen (2014).[6]

This article is related to different strands of literature. Obviously, there is a close link to the above-mentioned stream of research that analyzes the development of volatility in agricultural commodity markets in recent years. A second stream of related literature compares different volatility estimators. Most of these studies try to evaluate the forecasting power of several measures of, for example, stock return volatility (Blair, Poon, and Taylor (2001)) or agricultural commodity return volatility (Manfredo, Leuthold, and Irwin (2001); Benavides (2009)). Chen, Daigler, and Parhizgari (2006) investigate different persistence patterns depending on several volatility estimation methods with the aim of finding the best measure for identifying persistence. Unlike those studies, my analysis neither primarily focuses on how volatility developed nor tries to find the best estimation method for a specific purpose but, rather, attempts to more generally compare the characteristics of different volatility estimation methods and survey the robustness of statements regarding volatility development by using a broad set of volatility measures. Closely related work is that of Huchet-Bourdon (2011), who also aims to obtain robust assessments of the price volatility development in agricultural markets. Her analysis does not, however, primarily concentrate on the volatility estimation method but, instead, also on other factors, such as the data sources or the currency of the price series. As she only analyzes three different volatility measures—all based on historical data—, my analysis of estimation methods goes beyond Huchet-Bourdon's (2011) comparison because many more measures will be analyzed.

The remainder of this article is structured as follows: The next section deals with previous statements regarding agricultural commodity price volatility. It is not the intention to provide a complete literature overview of this topic but, rather, to demonstrate critical

[6]The adjustment shall correct the bias of implied estimates due to a volatility risk premium. As discussed in the paragraph above, the bias could have other causes, such as sentiment, which cannot be separated. Therefore, the adjustment corrects simultaneously for other sources of bias and not only for the volatility risk premium.

points in former conclusions and the need for further robustness checks. Section 2.3 presents relevant issues that must be considered when measuring volatility to emphasize which decisions are necessary before estimating volatility. The data and design of the analysis are described in Section 2.4. Section 2.5 discusses several volatility measures and presents their precise application in the empirical part of this study. Section 2.6 illustrates and comments on the results of volatility characteristics for different measures and on the robustness of statements regarding volatility development since the food price crisis. Finally, Section 2.7 concludes the article.

2.2 Issues in describing the development of volatility

When reviewing journal articles and especially the gray literature dealing with the development of volatility, common findings are that "[c]ommodity prices have exhibited increased volatility in recent years" (Botman (2011, p. 1)) and "both price spikes and volatility have increased in most recent periods" (Von Braun and Tadesse (2012, p. 4)).[7] Although these sentences seem to be relatively unambiguous statements at first glance, questions arise if one wants to understand them more deeply.

The first crucial point is the concrete definition of *recent years*. Despite often very vague statements in the literature, some declarations can be found that are a bit more detailed. The HLPE (2011, p. 9) name 2007 as an important turning point: "After staying at historic lows for decades, food prices have become significantly higher and more volatile since 2007." For FAO (2008, p. 55), this point is in 2008: "Beginning with 'bulk commodities' [...] it is seen that historic volatility in international wheat prices has been steadily rising over recent years, reaching unprecedented levels in 2008." Overall, the literature indicates that the years 2007/2008 are relevant for the analysis of a change in volatility. This is not surprising, since it is the time typically referred to as the years of the food price crisis, which are also accompanied by large price increases.

The next important issue that is necessary to clarify is the reference period. The meaning of an increase in volatility in recent years can only be assessed if which period the change

[7] These authors also provide more precise information elsewhere in the paper.

is related to is clear. It is also possible that not only the average volatility over a certain period has increased but also the volatility from year to year over the past years. The important point is that statements regarding the development of volatility can only be tested if the periods compared are precisely defined. When looking at studies that define their time windows very clearly, the results regarding the development of volatility are still less straightforward than one might think after reading the rather flat statements, which often suggest that volatility has reached unprecedented levels in 2007/2008. Diaz-Bonilla and Ron (2010, p. 9) claim that "[e]ven though the recent episode of increases in food prices generated higher volatility than in the nineties, it has not reached the magnitude of the food price crisis in the seventies, at least in real terms." A similar comparison is made by Barrett and Bellemare (2011): "Food price levels are at historic highs, but food price volatility, although high these past few years, is not out of line with historical experience and is generally lower than it was in the 1970s." ECLAC, FAO, and IICA (2011, p. 4) even specify that "[i]n fact, 2008 saw greater volatility than any year since the crisis that occurred in the first half of the 1970s." These examples underline that conclusions depend on whether the years 2007 and 2008 are compared to the 1970s or to more recent history and stresses the importance of defining a reference period.

Other studies come to very similar conclusions but demonstrate that volatility development differs across commodities and one should be careful when generalizing results from only a few markets. Gilbert and Morgan (2010, p. 3023) analyze 19 agricultural commodities and conclude that "volatility has generally been lower over the two most recent decades than previously. Variability over the most recent period has been high but, with the important exception of rice, not out of line with historical experiences" and Huchet-Bourdon (2011, p. 6) states that "price volatility in the recent period of 2006–2010 was higher than that in the nineteen nineties, but, in general, not higher than that of the nineteen seventies with the major exception of wheat and rice."

A further salient issue is the amount by which volatility has increased. Especially for this aspect, it is important to be well aware of the periods between which the increase is measured, because this provides important information about how fast volatility has risen. It is obvious that a certain amount of rise in volatility between two successive periods points out a much quicker increase than the same amount between periods that are further apart. The increase is even faster if the periods over which volatility is estimated are relatively short. Therefore, both the length of the two periods over which volatility is measured and compared as well as the length of the period between the two periods that are compared must be clear to draw precise conclusions.

Finally, not only the magnitude of the volatility matters, but also its persistence. The results of Cashin, Liang, and McDermott (2000, p. 182) “highlight the need for policymakers to be cautious when implementing schemes designed to ameliorate the domestic effects of shocks to world commodity prices. In using policies such as national stabilization arrangements [...] international stabilization arrangements [...] or compensatory financing, knowledge of the typical duration of price shocks is crucial. If price shocks are typically short-lived, then scope exists for policy initiatives to smooth national income and consumption. Alternatively, if price shocks are typically long-lived, then adjustment to the new long-run levels of national consumption and income is the preferred policy response.” This statement about shocks in price levels can be transferred to price volatility, because a temporary volatility increase can also have other implications for policymakers and market participants alike in finding the “right” measures to cope with it besides those of a permanent volatility increase. While volatility persistence over the whole period of data used is sometimes analyzed for commodities, a changing pattern over time has not been part of the focus so far.

Motivated by the conclusions in the literature, the robustness of the following characteristics of volatility development are investigated:

(1) Is volatility higher since 2007/2008 compared to the 1990s?

(2) Is volatility lower since 2007/2008 compared to the (early) 1970s?

(3) Is volatility higher in 2008 than in any year after the early 1970s?

Moreover, the following so far rarely debated questions are also investigated:

(4) By how much did volatility increase in 2007 and 2008 compared to the previous year?

(5) Has the persistence of agricultural commodity price volatility changed since 2007/2008 compared to the 1970s and 1990s?

2.3 Issues in estimating volatility

Volatility is a directionless measure for the dispersion of a variable within a certain time horizon. Although it seems quite obvious what a volatility measure should do, the estimation of volatility requires many decisions and is thus exposed to subjectivity. The following points out the ways in which volatility estimators can differ from each other.

The clearest difference is the *general method*: One can broadly distinguish between non-parametric estimators based on historical prices, parametric estimators based on historical prices, and implied volatility estimators.[8] The most widely used representatives of the first two methods are realized volatilities and GARCH model-based volatilities, respectively. Since my later analysis focuses only on several forms of realized and GARCH model-based volatilities, I use these terms in the following instead of *parametric* and *non-parametric*.[9]

The main difference between realized and implied estimators is the information on which the estimator is based. Realized volatility uses only price information within a certain period to estimate the volatility of exactly this period. Unlike this, implied estimators extract market participants' volatility expectations from the prices of currently traded options. These estimators thus include all price information, from the past—theoretically infinitely far back—to the beginning of the period for which volatility is to be estimated, that might be relevant for future price movements, as well as all non-price information that might affect future price movements, such as information about stock levels or weather. Due to the different information with regard to content and to the temporal frame, the implied estimators are often called ex ante estimators because they use information up to a certain point in time to estimate the volatility after that point. The realized estimators are primarily ex post estimators because they can only estimate the volatility of a period

[8] In addition, among implied volatilities, one can distinguish between parametric and non-parametric estimators. I address this point later, in the description of the estimators.

[9] See Andersen, Bollerslev, and Diebold (2009) for other forms of parametric and non-parametric estimators based on historical data.

at the end of that period. This shows that the methods mainly serve different purposes. If one wants to forecast volatility in future periods, the implied methods directly provide an estimator. On the contrary, if one wants to use historical realized volatilities to create a "realized forecast", one needs a model based on assumptions on how historical volatility behavior will be transferred to future periods. However, to analyze volatility in retrospect, realized volatility has the major advantage of using data within the period of interest, which is not incorporated by the implied methods. GARCH volatility is more difficult to classify because the information used in the volatility estimation model depends on the specific method applied. Similar to realized volatility, GARCH volatility is based only on price data and not on other market-relevant information.[10] Unlike realized and implied volatility estimators, GARCH model-based estimators allow for more possibilities regarding the period used for estimation. GARCH volatility for a certain period could contain price information up to that period, ending afterward or much later. Again, different objectives are satisfied. If data up to that period are used, the GARCH model fit to the data allows forecasting the volatility of the next period. If the data of the relevant period are included, it allows for an ex post estimation of volatility. Like the end of the data period, its beginning is also flexible in this approach. One can use either the full available data period for all volatility estimations, a rolling window, or a window that has a fixed beginning and end after the period for which the volatility is to be estimated. After deciding on a general concept of volatility estimation, more issues—partially depending on the general concept—must be taken into account, as discussed below.

The *time horizon* is the period over which the volatility is estimated. Which horizon is relevant depends on the purpose of the analysis. In the food price volatility literature, typical time horizons are a week or a month. For realized estimators, the time horizon directly defines the length of the period from which data are used. For GARCH model-based estimators, the volatility of a time horizon can be estimated either directly or based on volatilities estimated for smaller horizons. The precise application depends on the data frequency, discussed in the next paragraph. Implied estimators are based on currently

[10] An exception is the GARCH-X models, which are an extension of the standard GARCH model and allow for additional variables in the variance equation (see, e.g., the model of Brenner, Harjes, and Kroner (1996)).

traded options and reflect the expected average volatility from that time until the maturity of the option. Therefore, time to maturity must be equivalent to the time horizon to extract the appropriate implied information. Volatilities are often annualized with the square root of time rule; for example, the monthly volatility is multiplied by $\sqrt{12}$. This makes volatilities more comparable but these must not be confused with the time horizon on which they are based. Although the square root of time rule is often applied, it is only appropriate if returns are independent and identically distributed (Diebold, Hickman, Inoue, and Schuermann (1997)). Several studies indicate that this assumption is invalid for the stock market and also for commodity futures.[11]

Depending on the estimation method, the *data frequency* must be chosen. This is especially important for realized volatility, since the frequency must be higher than the time horizon. Often daily price data are used if the time horizon is a week or a month. If the horizon is longer, for example, one year, data at a weekly or monthly frequency could be used instead of daily data. Lower frequencies are often necessary due to data limitations. In addition, different data frequencies are possible for GARCH models. The frequency does not necessarily have to be higher than the horizon but could also be equal. The frequency does not matter for implied volatilities because those volatilities only use the information at one point in time.

A more general question is how volatility is exactly *defined*. Almost all papers dealing with the volatility of returns define it as the standard deviation of relative price changes (log-returns). While this is a well-known *statistical* measure, the experiment of Goldstein and Taleb (2007) shows that even financial professionals misinterpret the standard deviation as the average absolute deviation from the mean. Although the average absolute deviation is hardly considered in the literature for describing volatility in financial or commodity markets, it nevertheless seems to be a more *intuitive* measure of volatility. While standard GARCH models are only designed to estimate the standard deviation, realized and implied volatility estimation methods can easily contribute to both definitions.

[11] See, for example, Lo and MacKinlay (1988) for the stock market and Gordon (1985) for several agricultural futures markets.

2.4 Data and study design

For the analysis of volatility estimators, I use price data for wheat, corn, and soybean futures and options traded on the Chicago Mercantile Exchange. These markets are appropriate for my robustness analysis because many market participants are interested in these commodities, since they are an output highly demanded by consumers as well as an important input factor for animal feed and biofuel production. Moreover, due to their importance, these commodities have highly developed futures and options markets with a relatively long history, which allows for a more comprehensive volatility analysis than for less developed markets. The data used in this article start in January 1972 for all futures and in March, October, and May 1987 for wheat, corn, and soybean options, respectively, ending in June 2012. Until May 1998, options on wheat and corn futures expired on five dates each year (March, May, July, September, and December) and those on soybean futures expired on seven dates (January, March, May, July, August, September, and November). Since June 1998, expiring options for every month are available for all three commodities.

The study implies a general comparison of volatility characteristics as well as an analysis of volatility development. The purpose of the latter is to determine whether answers to the questions identified as relevant in Section 2.2 can be obtained that are robust to different measures of volatility. This analysis will be twofold: First, I take a closer look at the development in more recent history. Most of the literature refers to periods instead of certain years. As the representative examples in Section 2.2 pointed out, the starting point for higher volatility is supposed to be in 2007 or 2008. To investigate the potential increase since these years, I form five-year periods for the analysis. I can thus compare the average monthly volatility and volatility persistence between 2007 and 2011 with the respective values in the previous five-year periods since 1987. This analysis is very comprehensive because it includes several implied measures of volatility that cannot be calculated before 1987 due to the lack of data availability. However, this comparison ignores the supposedly interesting period of the 1970s. Therefore, the time horizon is extended to 1972 as the starting year in a second part of the analysis to capture the highly unstable years of the 1970s and the analysis will be conducted with several estimators based on historical data. This investigation allows the comparison of agricultural commodity price volatility since 2007 with the 1970s as well as with the 1990s as reference periods. In addition to the investigation of certain periods, the averages of single years are also considered to contribute to the questions related to specific years.

The next section presents some specific volatility estimation methods that will be applied for the robustness analysis. However, before introducing the measures, I briefly address how the issues mentioned in the previous section are dealt with in my analysis to better understand the precise description of the different volatility measures:

The time horizon considered later is one month for all estimators. Data at a daily frequency are used for the calculation of realized estimates and data at a daily as well as monthly frequency are used for the GARCH model-based estimates. No decision has to be made for implied estimators. The monthly volatilities are then annualized with the square root of time rule. The scaling of monthly to annualized values is not problematic for my comparison, since I apply this rule similarly to all measures. However, for the measures based on daily data, I must convert average daily to monthly values by the square root of time rule, which might be inappropriate because the returns are not independent and identically distributed. Nevertheless, I use this method because the intention is to compare the measures in the way they are often applied and the square root of time rule is normally used because of the lack of easily applicable alternatives. Moreover, Diebold, Hickman, Inoue, and Schuermann (1997) show that problems occur particularly if one-day volatility is converted to longer horizons. Therefore the conversion to a monthly horizon may be less problematic.

2.5 Volatility estimation methods

2.5.1 Realized volatility measures

The *standard realized volatility (SRV)* over a certain time horizon T with N observations within T is defined according to the sample standard deviation as the square root of the sample variance:[12]

$$\mathrm{SRV(T)} = \sqrt{\frac{N}{N-1}\sum_{t=1}^{N}\left[r_t - \bar{r}\right]^2}, \tag{2.1}$$

where r_t is the logarithmic return at time t and $\bar{r}$ is the mean return within the time horizon T (see, for example, Poon and Granger (2003)). Despite being a very popular volatility estimator, the SRV has several shortcomings that motivate the use of other realized measures.

Marquering and Verbeek (2004) argue that the true variance will be underestimated if returns are positively correlated. They use a realized measure that has a correction term, assuming that the daily return series within a month is appropriately described by an autoregressive process of order one. I use the square root of this variance estimator for the volatility analysis, calling it *realized volatility with autocorrelation correction (RVAC)*. This measure is defined by[13]

$$\mathrm{RVAC(T)} = \sqrt{\sum_{t=1}^{N}\left[r_t - \bar{r}\right]^2 \left[1 + 2N^{-1}\sum_{t=1}^{N-1}\left[N-t\right]\hat{\phi}_T^t\right]}, \tag{2.2}$$

where $\hat{\phi}_T$ is the autocorrelation coefficient from an AR(1) model fitted to the N returns within the time horizon T.

If the sample variance is an unbiased estimator of the true variance, the SRV and RVAC are biased estimators of the true standard deviation due to Jensen's inequality and a correction factor that depends on the return distribution would be necessary to eliminate the bias (Fleming (1998)). However, Fleming (1998) shows that the impact of the correction is very small. Therefore, no bias-corrected SRV will be considered in the following. Instead, I use another approach that is a direct and unbiased volatility estimator and thus serves as an appropriate extension of the robustness analysis. At the same time, it has a further

[12]This formula is usually written without N in the numerator at the beginning and thus estimates the average standard deviation for the returns at the given data frequency. To obtain the standard deviation for the whole time horizon T (one month here) the square root of time rule is applied by multiplying by $\sqrt{N}$. This is also the case in some of the following formulas, which are usually defined without $\sqrt{N}$.

[13]See Marquering and Verbeek (2004) for the underlying variance estimator. Given this definition, the RVAC is not identical to the SRV for an autocorrelation coefficient of zero because $N-1$ is in the divisor of the SRV and not N.

advantage compared to the SRV. Another drawback of the SRV estimator is its sensitivity to outliers caused by the squaring of returns. To circumvent this problem, Ederington and Guan (2006) propose taking the average absolute deviation of returns from the mean return. Since they also define volatility as the standard deviation of returns, they make a further adjustment, assuming the returns to be normally distributed. Under this assumption, the approach further delivers an unbiased volatility estimator. The *realized volatility based on the adjusted absolute deviation (RVAAD)* is defined as

$$\text{RVAAD(T)} = \frac{1}{N}\sum_{t=1}^{N} |\, r_t - \bar{r}\,| \sqrt{\frac{\pi}{2}N}. \tag{2.3}$$

As discussed in Section 2.3, the mean absolute deviation seems to be a more intuitive measure of volatility. Therefore, I also want to consider the mean absolute deviation, refusing the adjustment necessary for the standard deviation. The disadvantage of measures based on this volatility definition compared to the standard deviation is the lack of general scaling rules. However, under the assumption of log-returns being not only independent and identically distributed but also normally distributed, the scaling with the square root of time rule leads to an appropriate estimator for the annualized mean absolute deviation. Therefore, the square root of time rule is also applied here and allows for results that can be compared to the other measures. The *realized absolute deviation (RAD)* is thus given by

$$\text{RAD(T)} = \frac{1}{N}\sum_{t=1}^{N} |\, r_t - \bar{r}\,| \sqrt{N}. \tag{2.4}$$

A method similar to the RVAAD was introduced by Schwert (1990), whose volatility definition is again the standard deviation. Instead of adjusting the average absolute deviations from the mean, the author uses the residuals $\hat{u}_t$ from a regression that regressed the daily log-returns within a month on 22 lagged returns, which cover approximately one month, and a dummy variable D representing the day of the week to capture differences in mean returns:[14]

$$r_t = \sum_{i=1}^{5} \hat{\alpha}_i D_{it} + \sum_{j=1}^{22} \hat{\beta}_i r_{t-j} + \hat{u}_t. \tag{2.5}$$

The *realized volatility based on adjusted residuals (RVAR)* is than adjusted like the RVAAD:

$$\mathrm{RVAR(T)} = \frac{1}{N} \sum_{t=1}^{N} \mid \hat{u}_t \mid \sqrt{\frac{\pi}{2} N}. \tag{2.6}$$

The last specification of realized volatilities that I use differs from the others in the amount of information used. Indeed, like all realized volatility estimators, it uses only price information from the relevant time horizon, but like many other estimators[15]—and in contrast to the SRV estimator—it takes also additional price information into account. I use a relatively new estimator, which includes daily opening, closing, high, and low price information. The *realized volatility developed by Yang and Zhang (2000) (RVYZ)* is given by[16]

$$\begin{aligned} \mathrm{RVYZ(T)} = & \sqrt{\frac{N}{N-1} \sum_{t=1}^{N} [o_t - \bar{o}]^2 + k \frac{N}{N-1} \sum_{t=1}^{N} [c_t - \bar{c}]^2} \\ & \overline{+ [1-k] \sum_{t=1}^{N} [u_t [u_t - c_t] + d_t [d_t - c_t]],} \end{aligned} \tag{2.7}$$

with $o = \ln O_1 - \ln C_0$, $c = \ln C_1 - \ln O_1$, $u = \ln H_1 - \ln O_1$, and $d = \ln L_1 - \ln O_1$, where O_t, C_t, H_t, and L_t are the opening, closing, high, and low price on day t, respectively. Moreover, $\bar{o}$ and $\bar{c}$ are the average o and c, respectively, within the time horizon T and $k = \frac{\alpha - 1}{\alpha + \frac{N+1}{N-1}}$. I follow the suggestion of Yang and Zhang (2000) and set $\alpha = 1.34$.

[14]The only difference is that I use only five dummy variables for the day of the week because no trading on Saturday takes place in my sample.

[15]See, for example, Garman and Klass (1980), Parkinson (1980) and Rogers and Satchell (1991).

[16]Yang and Zhang (2000) suggest a method for an unbiased variance estimation. To be in line with the other approaches, I use the square root of their estimator as a volatility estimator. Again, this leads to the problem of a biased volatility estimator, since the variance estimator is unbiased.

2.5.2 GARCH model-based volatility measures

Since GARCH model-based volatility estimators belong to the group of parametric estimators, they make certain assumptions regarding the return process. Consequently, many different GARCH models exist with (slightly) different assumptions. I focus on the easiest and first developed form, the GARCH(1,1) model. This form is widely used in the analysis of food price volatility. Moreover, I look at one extension, the GJR-GARCH.

The starting point for the GARCH group is the simple GARCH(1,1) model as developed by Bollerslev (1986). The GARCH(1,1) process is given by

$$r_t = E_{t-1}\left[r_t\right] + \epsilon_t \quad \text{with} \quad \epsilon_t \sim N\left(0, \sigma_t^2\right), \tag{2.8}$$

$$\sigma_t{}^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}{}^2 + \beta_1 \sigma_{t-1}{}^2, \tag{2.9}$$

where $E_{t-1}\left[r_t\right]$ denotes the return that is expected for time t at $t-1$. Hence, the *GARCH* volatility estimator is GARCH(T) $= \sqrt{\sigma_t{}^2}$, with $\sigma_t{}^2$ resulting from the GARCH(1,1) variance process with estimated parameters, as described in equation 2.9. Since a specific GARCH model explains the variance with past variance and past return innovations, the "measurement of return volatility requires determination of the component of a given price increment that represents a return innovation as opposed to an expected price movement" (Andersen, Bollerslev, and Diebold (2009, p. 69)). Therefore, volatility estimation requires the modeling of an adequate price process. Especially in commodity markets, cyclical components or seasonality may play a big role in the determination of the expected return. It should be stressed that seasonality in futures returns is not as obvious as in spot price returns. For the latter it is quite intuitive that returns differ in harvest and non-harvest months due to changes in supply. However, since futures reflect the expectations of the spot price at maturity plus a potential risk premium, all these seasonal price movements should be captured in advance and should not appear in futures returns. According to the theory of Keynes (1930) and Hicks (1946), futures prices are not an unbiased forecast of future spot prices because speculators require compensation for bearing risk.[17] The

[17]The Keynes–Hicks theory assumes that mainly producers want to hedge their price risk and therefore speculators, as holders of the long position, require a risk premium. This leads to futures prices that

literature is not unambiguous regarding whether risk premia exist.[18] However, if there exist such risk premia and their magnitude is seasonally different, the futures price can also exhibit such a seasonal pattern. For grain commodities, spot prices are more volatile during growing periods because more information that is relevant to the expected yield enters the market (Tomek and Peterson (2001)). Thus, it is possible for futures contracts, which expire in the harvest period or shortly thereafter, to include a higher risk premium than others, which could explain higher futures returns in certain months.

The distinction between expected and unexpected returns for volatility estimation is also relevant to the realized estimators. However, the different realized estimators make implicit assumptions about the expected price movement by definition, such as the mean return over the relevant horizon in the case of the SRV or an AR(1) process for the RVAC. For GARCH estimators, this issue is generally held to be more flexible and more relevant. Unlike the GARCH models, which are normally fit to a relatively long time series, the realized volatilities are measured over only a month. Hence, using, for example, a constant expected daily return within a month that changes from month to month directly captures seasonal differences between months, unlike a constant expected return over several years.

Another issue for the implementation of the GARCH model in agricultural (and financial) markets is the conditional distribution of the error term. While the original version of Bollerslev (1986) assumes the error to be normally distributed, other distributions are conceivable. Onour and Sergi (2011) find the student t-distribution to be more appropriate than the normal distribution for the innovation of several commodity spot price returns, which is in line with the research on financial asset returns (see, for example, Bollerslev (1987)).

Finally, GARCH models allow for more flexibility regarding the data period and the data frequency. While only the data from the period for which the volatility is estimated are used for realized estimators, this relation does not exist for GARCH models. For my analysis, I use all the available data for the model fit. This approach is, of course,

are lower than the expected spot price at maturity. Hence the theory is often called the theory of normal backwardation (e.g., Gorton and Rouwenhorst (2006)). Hamilton and Wu (2014) suppose that the situation reversed in recent years due to index investments such that the risk premium shifted from the long to the short side, which would result in a contagion situation.

[18] See Garcia and Leuthold (2004, p. 247) for a brief overview.

inappropriate if one wants to use the GARCH model to predicting volatilities, because the model fit uses information for the volatility estimation that is not available at the point in time for which the forecast should be made. However, since I carry out an ex post analysis, I prefer to use as much information as possible. In GARCH models, the frequency can be equal to the time horizon over which volatility is estimated, contrary to realized estimators.

To reduce the complexity of the comparison of volatility measures, I conduct a pre-analysis of GARCH models to contribute to the alternatives discussed above. First, I take advantage of the possibility of using data at different frequencies and base the estimation on both monthly and daily log-returns. Second, for each frequency, I run variations of the return process regarding the determination of the expected return, as well as the distribution of the error term. This means that the following different processes for the model with a monthly data frequency are tested: (1) a constant return, (2) the return as an AR(1) process, (3) a constant return with additional monthly dummy variables to consider potential seasonality in futures returns, and (4) the return as an AR(1) process with additional monthly dummy variables. For the model based on data at a daily frequency, I additionally run an (5) AR(22) return process to capture lagged effects of approximately one month. In addition to the different specifications for the expected return, I further test each of the models with normally and student t-distributed errors. Afterward, only the model with the highest goodness of fit according to the Akaike information criterion (AIC) is used for the further analysis of volatility estimators.

The models that fit best according to the AIC, using monthly returns, are model (1) for wheat and soybean futures, that is, a constant expected return without monthly dummy variables, and model (3) for corn futures, that is, a constant expected return with monthly dummy variables, all with student t-distributed errors.

For daily data, the model with an AR(1) return process and without (with) seasonal dummies works best for wheat and soybeans (corn). However, all models for daily data that would be chosen according to the AIC face the problem of highly significant residual autocorrelation[19]. Therefore, I use an AR(22) return process for the volatility estimation

[19]This has been tested with a Ljung–Box test with lags 10, 15, and 20.

with daily data to capture the high autocorrelation of returns. The best model out of this subset is the AR(22) return process with no seasonal dummies for wheat and soybeans and with seasonal dummies for corn, again all with a student t error distribution.[20] To distinguish between the frequencies, I use the terms *GARCHm* and *GARCHd* for measures with monthly and daily data, respectively.

The GARCH model described above implicitly assumes that return innovations affect future volatility symmetrically. However, especially in financial markets, changes in volatility could differ depending on the direction of previous unexpected price moves.[21] To consider potentially asymmetric effects in agricultural markets, I apply the model extension developed by Glosten, Jagannathan, and Runkle (1993). The difference of the GJR-GARCH(1,1) model compared to the standard GARCH model as described above is that there is not one coefficient for the lagged return innovation, but an additional coefficient, so that the effect of return innovations can be split into effects from positive and negative innovations. While the return process is described as in equation 2.8, it follows for the variance

$$\sigma_t{}^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}{}^2 + \gamma_1 S_{t-1} \epsilon_{t-1}{}^2 + \beta_1 \sigma_{t-1}{}^2 \text{ with } S_{t-1} = \begin{cases} 1 & \text{if } \epsilon_{t-1} < 0 \\ 0 & \text{if } \epsilon_{t-1} \geq 0. \end{cases} \tag{2.10}$$

Accordingly, the *GJRGARCH* volatility estimator is GJR-GARCH(T) $= \sqrt{\sigma_t{}^2}$, with $\sigma_t{}^2$ resulting from the GJR-GARCH(1,1) variance process with estimated parameters, as described in equation 2.10.

The same pre-analysis as in the standard GARCH case is carried out for the GJRGARCH. The GJRGARCH model with the lowest AIC value is nearly always the same model as in the standard GARCH case. The only exception is corn with monthly data, where the seasonal dummies disappear for the GJRGARCH model, all else equal to the GARCH case.

[20]The AIC for the best models with an AR(22) return process is only a little higher compared to the overall best model, that is, AIC=-5.5216 instead of AIC=-5.5226 for wheat, AIC=-5.8979 instead of AIC=-5.8992 for corn, and AIC=-5.7664 instead of AIC=-5.7683 for soybeans.

[21]See the review of Poon and Granger (2003, p. 495), who find that “in general, models that allow for volatility asymmetry came out well in the forecasting contest because of the strong negative relationship between volatility and shock”.

As in the case of the standard GARCH model I use *GJRGARCHm* and *GJRGARCHd*, depending on the data frequency used.

A brief overview of the selected GARCH and GJRGARCH models after the pre-analysis is provided in Table 2.1.

Table 2.1: Overview of selected GARCH and GJRGARCH models

	Wheat	Corn	Soybean
GARCHm	constant mean, student t-distr.	constant mean, seasonal dummies, student t-distr.	constant mean, student t-distr.
GARCHd	AR(22) mean process, student t-distr.	AR(22) mean process, seasonal dummies, student t-distr.	AR(22) mean process, student t-distr.
GJRGARCHm	constant mean, student t-distr.	constant mean, student t-distr.	constant mean, student t-distr.
GJRGARCHd	AR(22) mean process, student t-distr.	AR(22) mean process, seasonal dummies, student t-distr.	AR(22) mean process, student t-distr.

Note: This table provides an overview of the return process and the distribution of the error term for the (GJR)GARCH(1,1) models selected for the main analysis after a pre-analysis with several variations. The selection criterion is the AIC. In the case of daily data, only models with an AR(22) return process are considered due to highly significant residual autocorrelation from models with a constant or AR(1) return process.

2.5.3 Implied volatility measures

Finally, several ways of calculating implied volatility measures are presented. The starting point is *IVBlack*, which is the implied volatility that can be gained from inverting the Black

(1976)-formula for the valuation of futures options.[22] Although the underlying assumption of Black (1976)'s model is a constant volatility over time, which implies the same implied volatility for options with different moneyness levels, empirical evidence has shown that implied volatilities differ with the moneyness of options. The question therefore arises as to which implied volatility best represents the perceived volatility of the underlying futures contract. Most often, the volatility of at-the-money options is used because they have the greatest liquidity (Poon and Granger (2003)). I therefore also use the implied volatility of the option with a strike price nearest to that of the underlying.[23] Indeed, Black's formula allows pricing options of the European type but the options used here are of the American type. Hence, implied volatilities are calculated with the approximation of Barone-Adesi and Whaley (1987), which allows for early exercise. To calculate the implied volatility for a specific month, I extract the implied volatility of options traded on the last trading day of the previous month with a time to maturity of 30 calendar days. Since the required time to maturity is not exactly available, I linearly interpolate the implied volatility of options that are nearest to being less than and more than 30 calendar days from maturity. This procedure is also carried out for each of the following implied measures.

The main disadvantage of the IVBlack is its model dependence. This could lead to biased estimators if, for example, the model's assumed price process differs from the true one. The observable non-constant volatility in the moneyness dimension—often referred to as the volatility smile—is clear evidence against the assumed price process.[24] A solution of the model dependence problem is model-free implied volatilities, which only assume complete markets but make no assumptions about the price process. The principle of model-free implied volatility estimation approaches is then based on the implications of complete markets: The fair price of any derivative can be calculated by discounting the expected payoff under risk-neutral probabilities with the risk-free interest rate (risk-neutral valuation).[25] I follow the approach of Bakshi, Kapadia, and Madan (2003) (BKM) for calculating model-free implied volatilities, *IVBKM*. Unlike the IVBlack, which is obtained

[22]The formula is a variation of the option valuation equation of Black and Scholes (1973), which considers that entering a futures position does not require a capital investment. For the formula, this means that the dividend yield is set equal to the risk-free interest rate.

[23]If both a call and a put option are the nearest options, the call option is chosen.

[24]For an elaborate discussion on volatility smiles, see, for example, Hull (2009, p. 389-406).

[25]For the theoretical foundation of risk-neutral valuation, see Cox and Ross (1976).

by using the information of only one option, the implied volatility resulting from the method of BKM uses the information of all at- and out-of-the-money options available at a certain point of time with the required time to maturity. Since the BKM model requires a continuum of strike prices but only a discrete number of prices is available, I use an interpolation method based on all available strikes. Following the procedure of Jiang and Tian (2005), I apply a cubic spline with a smoothing parameter of 0.3 to the Black implied volatilities of all traded options[26] at a specific date with the same specific time to maturity and a flat extrapolation outside the strike range to obtain a volatility curve as a continuous function of moneyness. I then use Black's formula to translate this curve back into a continuum of option prices. I do not assume the Black model to hold for this procedure. The formula is only used as a data transformation that makes the interpolation numerically more stable (Chang, Christoffersen, Jacobs, and Vainberg (2012)). I also apply the data filters as described by Jiang and Tian (2005).

Although the IVBKM is model independent, it could still lead to biased estimators. One possible reason is that the volatility is calculated under the risk-neutral measure. Since the probability distribution under the real-world (physical) measure can differ from this if market participants are not risk neutral, an adjustment is necessary to obtain the "real" expected volatility.[27] If market participants are risk averse, they require compensation for the volatility risk.[28] To consider market participants' risk preferences in the volatility estimation, I follow the method of Prokopczuk and Wese Simen (2014) and calculate the risk-adjusted model-free implied BKM volatility, *IVBKMRA*. The IVBKMRA is calculated by dividing the IVBKM by the average relative volatility risk premium, which is the square root of the average ratio of the implied BKM variance and the standard realized variance

[26]I mainly use settlement prices from the electronic market. If no electronic trading data is available (as it is the case for the earlier years), I use settlement prices from floor trading. If no settlement price is available, I use the closing price.

[27]The volatility under the risk-neutral measure equals the volatility under the physical under certain assumptions, for example, if the price process is assumed to follow a geometric Brownian motion. Since no assumption about the price process is made for the IVBKM estimator, differences between the measures are probable.

[28]For studies investigating the volatility risk premium, see, for example, Carr and Wu (2009).

of the previous 18 months:[29]

$$\text{IVBKMRA(T)} = \frac{IVBKM_T}{\sqrt{RA_T}}, \tag{2.11}$$

whereby RA_T is the risk adjustment for the horizon T, which is defined as

$$RA_T = \frac{1}{18} \sum_{i=T-19}^{T-1} \frac{IVBKM_i^2}{SRV_i^2}. \tag{2.12}$$

The idea is that the IVBKM represents the forecast variance under the risk-neutral measure, while the ex post SRV is a proxy for the physical measure.

As already described in Section 2.5.1 , the absolute deviation is a more intuitive measure of volatility. While standard GARCH models are not designed to capture this volatility definition, implied estimates of the absolute deviation are straightforward. Contrary to the RAD, it is not possible to determine the implied monthly average return. Instead, I directly model the expected return over a month with an AR(1) process fitted to the 60 previous monthly returns and then calculate the implied absolute deviation from this return. The concept of the implied absolute deviation estimator, *IAD*, is based on the same idea as the IVBKM. Starting from the assumption of complete markets, portfolios are built at the beginning of a month with a payoff at the end of the month that reflects the expected deviation from the expected return. Therefore, European put and call options with a strike price equal to the expected price are necessary. Formally,

$$\text{IAD(T)} = e^{r\tau} \left[\, C_t \,(\tau, \, K) + P_t \,(\tau, \, K) \, \right], \tag{2.13}$$

where τ is the options' time to maturity, K equals the expected price at the end of the horizon T ($T = t + \tau$) at time t, r denotes the risk-free interest rate for the horizon T, and $C_t\,(\tau,\, K)$ and $P_t\,(\tau,\, K)$ are the prices of a call and a put option with time to maturity τ and strike price K at time t, respectively.

[29]Prokopczuk and Wese Simen (2014) use a shorter period but explain that an 18-month estimation window leads to similar results. Before June 1998, the IVBKM could not be calculated for every month; therefore I use the 18-month window to obtain more observations and, thereby, more robust estimates.

Corresponding to the implied volatility estimator based on the method of Bakshi, Kapadia, and Madan (2003), I again use a risk adjustment to obtain implied absolute deviations under the physical measure, $IADRA$:

$$IADRA(T) = \frac{IAD_T}{\sqrt{RA_T}}, \tag{2.14}$$

where RA_T is the risk adjustment for the horizon T, which is defined as

$$RA_T = \frac{1}{18} \sum_{i=T-19}^{T-1} \frac{IAD_i^2}{RAD_i^2}. \tag{2.15}$$

Table 2.2 summarizes the volatility measures described above.

Table 2.2: Overview of volatility estimators

Panel A: Realized volatility (RV) estimators

	Estimator
Based on SD	• Standard RV (SRV) • RV with autocorrelation correction (RVAC) • RV based on the adjusted absolute deviation (RVAAD) • RV based on adjusted residuals (RVAR) • RV developed by Yang and Zhang (RVYZ)
Based on AD	• Realized absolute deviation (RAD)

Panel B: GARCH model-based volatility estimators

	Estimator
Based on SD	• GARCH(1,1), monthly data (GARCHm) • GARCH(1,1), daily data (GARCHd) • GJR-GARCH(1,1), monthly data (GJRGARCHm) • GJR-GARCH(1,1), daily data (GJRGARCHd)

Panel C: Implied volatility (IV) estimators

	Estimator
Based on SD	• IV based on inversion of Black's pricing formula (IVBlack) • IV based on approach of BKM (IVBKM) • IV based on approach of BKM, adjusted for risk aversion (IVBKMRA)
Based on AD	• Implied absolute deviation (IAD) • Implied absolute deviation, adjusted for risk aversion (IADRA)

Note: This table provides an overview of the different volatility measures used. Each panel distinguishes between measures that define volatility as the standard deviation (SD) or the absolute deviation (AD) of returns.

2.6 Empirical results

2.6.1 Characteristics of volatility estimates

This chapter provides an overview of the main properties of the different volatility measures by comparing the levels of estimated volatilities, their variation, and their persistence, as well as the co-movement of different estimates.

Table 2.3 shows the mean volatilities based on the different estimation methods for wheat, corn, and soybean futures. Due to the dissimilar interpretations of standard and absolute deviations, the mean volatilities are not comparable among each other but must be investigated separately for both volatility definitions. The comparison of the average estimates of the years 1987–2011 demonstrates that, among the volatilities defined as the standard deviation of returns, those for the realized group tend to be the smallest, followed by GARCH model-based and implied volatilities without risk adjustment. While risk-adjusted implied volatilities for wheat are lower than the unadjusted ones but still larger than any of the realized or GARCH model-based volatilities, the IVBKMRAs for corn and soybeans are—with a level about five percentage points lower compared to the unadjusted measure—at least lower than the GARCH volatilities. If the volatility is defined as the absolute deviation, the implied estimators again lead to higher values than the realized, even if they are risk adjusted. There is no clear ranking within the group of realized volatilities, but the comparisons of the periods 1972–2011 and 1987–2011 show that RVAR mostly yields the highest volatilities, while RVAC and RVYZ lead to the lowest volatilities. However, the differences are with less than one percentage point in most of the cases, relatively small. For the GARCH group, the discrepancy between estimates based on daily data is always extremely small, 0.04 percentage points at most. For wheat and soybeans, the standard GARCH model leads to slightly higher volatilities in the periods 1972–2011 and 1987–2011 compared to the GJRGARCH models. Since, for corn, the relation is the opposite, there is no clear order of the two GARCH specifications with regard to the level of volatility. Moreover, the order of the volatility level depending on the data frequency differs between the commodities. The (GJR)GARCHm volatilities are normally higher than their daily equivalents. The only exceptions in the 1972–2011 and 1987–2011 samples are wheat in the latter period. For wheat, the differences between both frequencies are relatively small, less than one percentage point. In contrast, the volatilities based on monthly data are at least 2.04 (3.4) percentage points higher than those based on daily data for corn and soybeans in 1987–2011 (1972–2011). Such large differences between estimates within one of the three main groups are found in the group of implied volatilities as well, where the estimates indicate the strong impact of the risk adjustment. For all three commodities, the IVBKM is higher than the IVBlack and the IVBKMRA is the lowest, while the difference between the IVBKM and IVBKMRA lies between 3.02 percentage points (wheat) and 5.65 percentage points (corn). The picture is the same if volatility is defined as the absolute deviation, because a similarly large difference exists between the IAD and IADRA. The realized measures are lower than the implied measures, whereas the risk-adjusted implied measures are very close to the realized ones, always less than one percentage point higher, which indicates that the risk adjustment partially removes the bias from the unadjusted estimators.

Table 2.3: Mean volatilities

Panel A: Wheat

year(s)	SRV	RVAC	RVAAD	RVAR	RVYZ	RAD
1972	19.66%	22.21%	19.24%	19.84%	18.80%	15.35%
1973	40.87%	42.88%	43.52%	45.59%	42.41%	34.73%
1974	37.83%	35.23%	38.59%	39.17%	42.13%	30.79%
1975	33.78%	30.17%	32.84%	33.70%	30.90%	26.20%
1976	26.40%	22.21%	25.54%	26.53%	25.18%	20.38%
1977	17.88%	16.95%	17.46%	18.28%	16.69%	13.93%
1978	21.71%	21.77%	21.55%	22.38%	19.85%	17.20%
1979	24.65%	23.58%	24.13%	24.44%	23.38%	19.25%
1980	25.01%	23.61%	24.19%	24.22%	24.08%	19.30%
1981	18.79%	17.63%	18.31%	18.59%	19.36%	14.61%
1982	17.72%	19.20%	17.82%	18.16%	17.74%	14.22%
1983	18.45%	17.58%	17.31%	17.79%	18.47%	13.81%
1984	15.19%	16.11%	15.93%	15.81%	14.60%	12.71%
1985	15.26%	15.88%	14.99%	15.46%	14.70%	11.96%
1986	24.06%	22.70%	23.58%	23.80%	21.09%	18.82%
1987	19.91%	20.11%	19.12%	19.40%	18.95%	15.25%
1988	24.73%	22.35%	24.87%	24.94%	24.99%	19.85%
1989	14.39%	14.98%	13.94%	14.03%	13.60%	11.12%
1990	16.04%	16.59%	15.96%	16.42%	15.84%	12.73%
1991	20.54%	20.63%	19.56%	20.43%	20.29%	15.61%
1992	18.86%	21.07%	18.61%	18.82%	18.60%	14.84%
1993	17.95%	18.10%	18.37%	18.44%	18.62%	14.66%
1994	18.26%	18.37%	18.20%	18.37%	18.00%	14.52%
1995	21.18%	19.78%	20.91%	21.02%	20.88%	16.68%
1996	27.06%	27.11%	26.42%	27.47%	26.39%	21.08%
1997	21.38%	19.75%	21.95%	22.43%	22.79%	17.51%
1998	21.14%	20.47%	21.08%	21.64%	21.22%	16.82%
1999	24.37%	22.70%	23.78%	24.42%	24.07%	18.97%
2000	21.34%	21.30%	21.04%	20.92%	22.77%	16.79%
2001	21.76%	20.20%	21.03%	21.44%	21.53%	16.78%
2002	25.62%	23.74%	25.19%	25.84%	26.50%	20.10%
2003	28.37%	27.00%	28.27%	28.72%	27.03%	22.56%
2004	28.88%	25.08%	27.78%	28.01%	26.12%	22.17%
2005	23.46%	23.36%	23.14%	23.85%	23.91%	18.46%
2006	28.21%	28.17%	27.97%	28.18%	27.19%	22.31%
2007	32.43%	31.89%	32.39%	33.03%	33.26%	25.85%
2008	49.95%	47.22%	49.51%	50.13%	48.42%	39.50%
2009	37.09%	30.64%	35.49%	37.37%	33.29%	28.31%
2010	35.04%	31.17%	33.28%	34.17%	31.84%	26.55%
2011	39.17%	37.01%	37.22%	38.52%	34.31%	29.70%
2012	34.02%	34.75%	32.52%	33.22%	25.18%	25.95%

year(s)	SRV	RVAC	RVAAD	RVAR	RVYZ	RAD
1972- 2011	24.86%	23.91%	24.50%	25.06%	24.24%	19.55%
1987-2011	25.49%	24.35%	25.00%	25.52%	24.82%	19.95%
1972-1976	31.71%	30.54%	31.95%	33.19%	31.88%	25.49%
1977-1981	21.61%	20.71%	21.13%	21.58%	20.67%	16.86%
1982-1986	18.14%	18.30%	17.92%	18.20%	17.32%	14.30%
1987-1991	19.12%	18.93%	18.69%	19.04%	18.73%	14.91%
1992-1996	20.66%	20.89%	20.50%	20.83%	20.50%	16.36%
1997-2001	21.99%	20.88%	21.77%	22.17%	22.47%	17.37%
2002-2006	26.91%	25.47%	26.47%	26.92%	26.15%	21.12%
2007-2011	38.74%	35.58%	37.58%	38.65%	36.22%	29.98%

year(s)	GARCHm	GARCHd	GJR GARCHm	GJR GARCHd
1972	26.49%	21.81%	27.99%	22.50%
1973	35.24%	39.94%	40.08%	40.37%
1974	43.99%	38.38%	47.59%	38.13%
1975	39.52%	33.99%	40.45%	33.63%
1976	34.27%	27.48%	34.32%	27.09%
1977	27.48%	19.07%	26.98%	18.93%
1978	25.76%	22.88%	27.43%	23.10%
1979	24.81%	25.26%	27.66%	25.55%
1980	24.39%	24.91%	25.59%	24.95%
1981	22.79%	20.55%	22.23%	20.23%
1982	21.88%	19.31%	19.40%	18.95%
1983	22.50%	20.15%	20.37%	20.10%
1984	22.47%	17.13%	21.39%	17.13%
1985	19.86%	16.75%	20.01%	16.89%
1986	22.31%	24.68%	21.64%	24.79%
1987	20.60%	20.57%	20.81%	20.75%
1988	21.02%	26.04%	22.03%	26.33%
1989	19.89%	16.49%	21.14%	16.41%
1990	20.44%	17.53%	19.58%	17.13%
1991	21.15%	21.46%	19.59%	21.65%
1992	22.95%	20.35%	23.08%	20.31%
1993	20.88%	19.24%	21.92%	19.48%
1994	20.35%	19.38%	21.64%	19.43%
1995	22.54%	22.14%	24.20%	22.41%
1996	27.17%	27.33%	29.69%	27.03%
1997	29.28%	22.71%	28.30%	22.55%
1998	27.27%	22.10%	24.41%	21.75%
1999	26.77%	24.99%	23.86%	24.62%
2000	23.33%	21.74%	21.15%	21.51%
2001	21.64%	22.25%	20.23%	22.27%
2002	22.16%	25.91%	21.92%	26.11%
2003	25.87%	28.37%	24.91%	28.39%
2004	24.29%	29.33%	23.95%	29.35%
2005	23.88%	24.05%	23.72%	24.21%
2006	23.43%	27.91%	23.93%	28.16%
2007	27.13%	32.12%	28.61%	32.62%
2008	35.48%	48.15%	35.00%	47.28%
2009	36.95%	37.92%	32.30%	37.64%
2010	38.23%	35.68%	36.38%	35.89%
2011	39.27%	38.80%	37.92%	38.19%
2012	36.80%	31.68%	32.87%	31.75%

year(s)	GARCHm	GARCHd	GJR GARCHm	GJR GARCHd
1972-2011	26.39%	25.62%	26.33%	25.60%
1987-2011	25.68%	26.10%	25.21%	26.06%
1972-1976	36.06%	32.32%	38.26%	32.34%
1977-1981	25.04%	22.53%	25.98%	22.55%
1982-1986	21.80%	19.60%	20.56%	19.57%
1987-1991	20.62%	20.42%	20.63%	20.45%
1992-1996	22.78%	21.69%	24.11%	21.73%
1997-2001	25.66%	22.76%	23.59%	22.54%
2002-2006	23.92%	27.12%	23.69%	27.24%
2007-2011	35.41%	38.53%	34.04%	38.32%

year(s)	IVBlack	IVBKM	IVBKMRA	IAD	IADRA
1987	20.26%	24.49%	NA	18.82%	NA
1988	29.95%	29.29%	26.00%	24.30%	18.97%
1989	19.33%	20.21%	14.11%	16.02%	11.00%
1990	20.00%	16.92%	11.37%	13.87%	9.63%
1991	20.74%	21.90%	20.02%	16.57%	15.10%
1992	20.96%	21.91%	22.63%	16.66%	16.77%
1993	20.09%	20.59%	18.59%	16.61%	15.26%
1994	20.33%	21.63%	19.28%	16.39%	14.73%
1995	21.70%	22.95%	19.34%	18.08%	15.99%
1996	22.87%	24.00%	22.82%	18.88%	18.21%
1997	24.05%	25.29%	26.11%	19.45%	20.41%
1998	23.22%	24.78%	20.61%	19.02%	16.75%
1999	26.94%	28.82%	21.67%	22.12%	17.40%
2000	27.01%	26.65%	21.62%	20.97%	17.09%
2001	23.42%	23.77%	20.06%	19.71%	16.03%
2002	24.53%	25.00%	22.67%	21.10%	17.51%
2003	26.60%	26.72%	26.08%	21.07%	19.55%
2004	27.73%	28.31%	28.96%	22.14%	22.64%
2005	27.47%	27.91%	26.19%	21.94%	20.19%
2006	31.21%	31.19%	25.55%	24.69%	20.33%
2007	33.27%	33.50%	29.60%	26.44%	23.32%
2008	46.63%	46.23%	42.77%	36.42%	33.92%
2009	40.82%	41.90%	37.86%	32.57%	28.93%
2010	34.78%	36.40%	31.51%	28.21%	23.76%
2011	37.71%	39.04%	36.01%	30.41%	27.43%
2012	33.77%	34.40%	32.34%	26.76%	24.53%
1987-2011	28.55%	29.45%	26.43%	23.30%	20.60%
1987-1991	22.06%	22.72%	17.30%	18.05%	14.13%
1992-1996	21.19%	22.21%	20.53%	17.35%	16.23%
1997-2001	25.11%	25.67%	21.55%	20.31%	17.21%
2002-2006	27.52%	27.84%	25.89%	22.21%	20.05%
2007-2011	38.64%	39.30%	35.43%	30.71%	27.36%

Panel B: Corn

year(s)	SRV	RVAC	RVAAD	RVAR	RVYZ	RAD
1972	14.03%	13.24%	13.62%	14.59%	12.58%	10.87%
1973	36.66%	40.71%	38.28%	39.58%	37.70%	30.54%
1974	30.84%	29.53%	31.95%	32.95%	31.03%	25.49%
1975	25.11%	22.77%	25.33%	26.35%	23.53%	20.21%
1976	17.83%	15.92%	17.12%	17.33%	15.54%	13.66%
1977	15.63%	15.56%	15.54%	16.01%	14.61%	12.40%
1978	14.17%	13.68%	14.16%	14.91%	13.89%	11.30%
1979	17.59%	15.82%	17.71%	18.13%	15.84%	14.13%
1980	16.92%	14.92%	16.81%	17.82%	17.16%	13.41%
1981	16.49%	16.26%	16.12%	16.99%	15.74%	12.87%
1982	12.89%	12.83%	12.56%	13.16%	13.06%	10.03%
1983	17.52%	16.81%	17.86%	18.40%	17.01%	14.25%
1984	13.49%	13.11%	12.89%	13.30%	12.28%	10.29%
1985	10.65%	10.43%	10.43%	10.73%	9.97%	8.33%
1986	17.38%	18.32%	17.29%	17.25%	16.96%	13.80%
1987	22.11%	20.45%	21.63%	22.22%	20.75%	17.26%
1988	25.48%	26.86%	25.94%	27.03%	25.21%	20.69%
1989	18.97%	18.51%	17.92%	17.98%	17.09%	14.29%
1990	14.79%	15.25%	14.74%	15.03%	14.67%	11.76%
1991	16.60%	16.59%	16.24%	16.74%	16.67%	12.96%
1992	15.11%	13.95%	14.83%	15.37%	13.92%	11.83%
1993	14.24%	13.48%	13.95%	14.10%	14.94%	11.13%
1994	17.01%	15.80%	16.24%	16.37%	16.66%	12.96%
1995	13.26%	13.17%	12.98%	12.98%	14.66%	10.36%
1996	23.16%	26.22%	22.81%	23.22%	21.71%	18.20%
1997	21.54%	19.19%	21.07%	21.87%	19.82%	16.82%
1998	19.75%	19.40%	18.83%	19.55%	19.26%	15.03%
1999	20.32%	21.02%	19.87%	20.01%	19.49%	15.86%
2000	20.54%	19.04%	20.37%	20.34%	19.31%	16.25%
2001	19.89%	20.14%	19.65%	20.18%	19.71%	15.68%
2002	19.70%	20.72%	19.69%	20.08%	19.86%	15.71%
2003	20.10%	20.33%	18.38%	18.54%	19.73%	14.67%
2004	22.62%	20.78%	21.94%	23.41%	23.87%	17.50%
2005	22.03%	21.55%	20.78%	21.52%	21.81%	16.58%
2006	27.25%	26.99%	27.23%	27.44%	26.46%	21.72%
2007	31.08%	30.90%	31.14%	32.09%	31.17%	24.85%
2008	41.00%	40.35%	40.62%	41.06%	41.22%	32.41%
2009	35.73%	35.21%	34.13%	34.54%	34.59%	27.23%
2010	30.05%	27.52%	28.45%	28.72%	29.28%	22.70%
2011	33.65%	32.74%	32.34%	32.50%	32.54%	25.81%
2012	29.84%	30.20%	27.60%	27.79%	26.20%	22.02%

year(s)	SRV	RVAC	RVAAD	RVAR	RVYZ	RAD
1972-2011	21.08%	20.65%	20.74%	21.27%	20.53%	16.55%
1987-2011	22.64%	22.25%	22.07%	22.52%	22.18%	17.61%
1972-1976	24.89%	24.44%	25.26%	26.36%	24.08%	20.15%
1977-1981	16.16%	15.25%	16.07%	16.77%	15.45%	12.82%
1982-1986	14.39%	14.30%	14.21%	14.57%	13.86%	11.34%
1987-1991	19.59%	19.53%	19.29%	19.80%	18.88%	15.39%
1992-1996	16.56%	16.52%	16.16%	16.41%	16.38%	12.90%
1997-2001	20.41%	19.76%	19.96%	20.39%	19.52%	15.93%
2002-2006	22.34%	22.07%	21.61%	22.20%	22.35%	17.24%
2007-2011	34.30%	33.34%	33.34%	33.78%	33.76%	26.60%

year(s)	GARCHm	GARCHd	GJR GARCHm	GJR GARCHd
1972	21.37%	16.38%	21.45%	16.47%
1973	39.56%	37.51%	44.58%	37.88%
1974	42.70%	31.49%	44.13%	31.73%
1975	36.38%	26.35%	33.82%	26.32%
1976	22.30%	18.88%	21.37%	18.84%
1977	20.93%	16.76%	20.12%	16.62%
1978	21.70%	15.73%	24.49%	15.71%
1979	19.87%	18.17%	21.29%	18.24%
1980	24.57%	18.27%	23.81%	18.42%
1981	24.38%	17.68%	21.96%	17.41%
1982	20.90%	14.74%	19.14%	14.66%
1983	24.66%	18.62%	27.19%	18.91%
1984	19.33%	14.71%	20.71%	14.70%
1985	16.98%	12.28%	18.43%	12.34%
1986	19.33%	17.85%	20.29%	17.68%
1987	22.97%	22.67%	23.60%	22.62%
1988	35.38%	26.55%	39.18%	26.69%
1989	26.21%	19.96%	26.78%	19.86%
1990	20.23%	15.61%	21.42%	15.58%
1991	17.91%	17.79%	18.57%	17.79%
1992	19.10%	16.27%	19.28%	16.12%
1993	18.53%	15.39%	19.16%	15.59%
1994	21.59%	18.07%	21.79%	17.80%
1995	19.01%	14.33%	20.33%	14.56%
1996	26.74%	23.80%	28.91%	23.85%
1997	27.05%	22.40%	26.49%	22.47%
1998	24.74%	20.65%	22.62%	20.54%
1999	20.80%	20.95%	20.49%	20.78%
2000	21.92%	21.13%	21.85%	21.11%
2001	25.53%	20.92%	22.51%	20.77%
2002	22.85%	20.64%	21.37%	20.76%
2003	21.51%	20.47%	23.09%	20.59%
2004	28.34%	23.87%	28.92%	23.79%
2005	26.01%	22.33%	23.27%	22.36%
2006	23.64%	27.42%	24.81%	27.69%
2007	30.85%	31.62%	31.80%	31.62%
2008	35.32%	39.95%	35.72%	39.80%
2009	35.79%	37.01%	32.30%	37.16%
2010	32.31%	30.63%	30.33%	30.77%
2011	36.48%	34.03%	36.67%	33.98%
2012	31.58%	28.01%	28.20%	27.88%

year(s)	GARCHm	GARCHd	GJR GARCHm	GJR GARCHd
1972-2011	25.40%	22.00%	25.61%	22.01%
1987-2011	25.63%	23.38%	25.65%	23.38%
1972-1976	32.65%	26.12%	33.27%	26.25%
1977-1981	22.29%	17.32%	22.33%	17.28%
1982-1986	20.24%	15.64%	21.15%	15.66%
1987-1991	24.54%	20.51%	25.91%	20.51%
1992-1996	20.99%	17.57%	21.89%	17.58%
1997-2001	24.01%	21.21%	22.79%	21.13%
2002-2006	24.47%	22.95%	24.29%	23.03%
2007-2011	34.15%	34.65%	33.37%	34.66%

year(s)	IVBlack	IVBKM	IVBKMRA	IAD	IADRA
1987	23.80%	24.49%	NA	17.91%	NA
1988	34.27%	35.98%	19.13%	28.54%	15.78%
1989	21.03%	22.36%	15.33%	17.52%	11.84%
1990	18.06%	18.73%	13.76%	15.32%	11.93%
1991	23.12%	28.04%	23.97%	20.38%	17.15%
1992	19.23%	22.84%	17.60%	18.47%	14.75%
1993	16.38%	19.38%	12.69%	13.44%	9.17%
1994	21.88%	25.71%	14.46%	19.29%	11.99%
1995	17.83%	22.07%	18.33%	16.91%	14.51%
1996	24.37%	25.01%	19.30%	20.20%	16.42%
1997	24.08%	25.49%	21.10%	20.31%	16.52%
1998	24.19%	25.84%	20.38%	20.76%	15.99%
1999	24.97%	26.70%	20.34%	21.17%	15.83%
2000	23.48%	24.39%	18.13%	18.95%	13.95%
2001	23.75%	24.18%	18.39%	19.07%	14.61%
2002	23.31%	23.66%	17.96%	19.47%	14.49%
2003	22.26%	22.34%	17.79%	17.97%	14.07%
2004	27.55%	28.06%	23.14%	22.06%	17.80%
2005	23.56%	24.16%	19.39%	19.06%	14.67%
2006	27.86%	28.45%	23.71%	22.23%	18.21%
2007	31.54%	34.27%	30.67%	26.55%	23.73%
2008	38.69%	40.44%	34.64%	31.17%	27.00%
2009	39.52%	41.73%	35.61%	31.75%	27.15%
2010	31.96%	33.41%	27.85%	25.67%	21.30%
2011	37.33%	38.71%	32.85%	30.30%	25.70%
2012	29.15%	30.26%	24.38%	23.27%	18.40%
1987-2011	27.10%	28.80%	23.15%	22.73%	18.19%
1987-1991	24.30%	25.84%	17.51%	20.62%	14.12%
1992-1996	19.94%	23.44%	17.10%	18.24%	14.01%
1997-2001	24.10%	25.20%	19.38%	19.90%	15.12%
2002-2006	24.95%	25.33%	20.40%	20.23%	15.90%
2007-2011	35.81%	37.66%	32.28%	29.05%	24.94%

Panel C: Soybeans

year(s)	SRV	RVAC	RVAAD	RVAR	RVYZ	RAD
1972	15.39%	14.08%	15.11%	15.46%	13.98%	12.05%
1973	41.76%	55.76%	43.09%	47.42%	43.97%	34.38%
1974	31.39%	31.63%	32.93%	35.16%	30.81%	26.27%
1975	30.66%	27.61%	31.20%	32.19%	29.76%	24.89%
1976	25.44%	23.07%	25.92%	26.95%	24.13%	20.68%
1977	31.40%	30.86%	32.77%	33.92%	30.45%	26.14%
1978	24.19%	22.19%	24.02%	24.47%	22.84%	19.16%
1979	21.61%	18.46%	21.34%	22.01%	19.81%	17.03%
1980	24.08%	22.94%	24.01%	24.84%	22.48%	19.16%
1981	20.43%	18.35%	19.79%	20.55%	20.05%	15.79%
1982	15.14%	13.39%	15.20%	15.58%	14.95%	12.13%
1983	24.62%	24.73%	24.51%	25.56%	23.25%	19.56%
1984	24.36%	22.51%	24.22%	24.93%	22.87%	19.33%
1985	15.91%	13.18%	15.75%	16.18%	14.77%	12.57%
1986	12.97%	12.09%	12.31%	12.57%	12.56%	9.82%
1987	17.07%	14.31%	16.65%	17.29%	16.30%	13.28%
1988	27.52%	27.82%	27.29%	27.99%	26.82%	21.78%
1989	20.58%	18.90%	20.06%	20.41%	18.21%	16.01%
1990	16.85%	15.81%	16.59%	16.79%	15.85%	13.24%
1991	20.12%	19.26%	19.00%	19.35%	19.59%	15.16%
1992	14.09%	12.68%	13.53%	14.04%	13.89%	10.79%
1993	15.46%	14.88%	14.60%	14.74%	15.50%	11.65%
1994	17.11%	16.64%	16.17%	16.24%	15.89%	12.90%
1995	15.23%	13.43%	13.96%	14.29%	15.39%	11.14%
1996	18.91%	18.55%	18.75%	19.22%	17.36%	14.96%
1997	22.77%	20.80%	21.98%	22.41%	21.08%	17.54%
1998	16.10%	14.98%	15.81%	16.55%	16.35%	12.61%
1999	21.58%	21.27%	20.66%	21.36%	20.32%	16.48%
2000	18.14%	15.29%	17.68%	18.47%	18.95%	14.11%
2001	18.29%	15.67%	18.03%	18.76%	18.99%	14.39%
2002	19.34%	18.82%	19.42%	19.94%	20.28%	15.49%
2003	20.64%	18.11%	20.18%	21.02%	20.84%	16.10%
2004	30.84%	27.09%	30.04%	30.73%	30.74%	23.97%
2005	25.98%	24.28%	25.18%	25.55%	26.15%	20.09%
2006	18.20%	17.13%	18.53%	18.86%	20.28%	14.78%
2007	22.03%	20.12%	20.99%	21.38%	22.33%	16.74%
2008	38.34%	37.38%	38.56%	39.60%	40.13%	30.76%
2009	31.13%	31.61%	29.26%	30.22%	29.43%	23.34%
2010	20.48%	18.50%	19.44%	19.73%	19.78%	15.51%
2011	21.08%	20.64%	19.85%	20.42%	20.59%	15.84%
2012	18.71%	17.45%	18.57%	18.95%	18.79%	14.82%

year(s)	SRV	RVAC	RVAAD	RVAR	RVYZ	RAD
1972-2011	22.18%	21.12%	21.86%	22.59%	21.69%	17.44%
1987-2011	21.12%	19.76%	20.49%	21.01%	20.84%	16.35%
1972-1976	28.93%	30.43%	29.65%	31.71%	28.53%	23.66%
1977-1981	24.34%	22.56%	24.39%	25.16%	23.13%	19.46%
1982-1986	18.60%	17.18%	18.40%	18.97%	17.68%	14.68%
1987-1991	20.43%	19.22%	19.92%	20.37%	19.36%	15.89%
1992-1996	16.16%	15.24%	15.40%	15.71%	15.60%	12.29%
1997-2001	19.38%	17.60%	18.83%	19.51%	19.14%	15.03%
2002-2006	23.00%	21.09%	22.67%	23.22%	23.66%	18.09%
2007-2011	26.61%	25.65%	25.62%	26.27%	26.45%	20.44%

year(s)	GARCHm	GARCHd	GJR GARCHm	GJR GARCHd
1972	20.56%	17.29%	22.65%	17.63%
1973	61.95%	44.50%	70.79%	45.27%
1974	51.32%	32.29%	60.81%	32.61%
1975	45.43%	31.61%	48.56%	30.94%
1976	31.37%	26.30%	34.26%	26.63%
1977	37.18%	31.61%	32.42%	31.87%
1978	28.19%	25.03%	28.37%	24.86%
1979	20.17%	22.23%	20.13%	22.00%
1980	24.98%	24.08%	21.93%	24.01%
1981	28.83%	22.31%	22.10%	21.71%
1982	20.63%	16.74%	16.79%	16.42%
1983	29.59%	24.69%	30.25%	25.05%
1984	32.34%	25.63%	28.93%	25.07%
1985	21.97%	17.04%	18.86%	16.76%
1986	17.40%	14.84%	16.39%	14.58%
1987	18.01%	18.14%	17.88%	18.05%
1988	33.67%	27.98%	33.84%	28.14%
1989	24.35%	21.54%	24.00%	20.98%
1990	18.78%	17.74%	17.05%	17.48%
1991	19.68%	21.09%	17.19%	20.86%
1992	17.85%	15.67%	16.82%	15.51%
1993	17.31%	16.79%	17.01%	16.84%
1994	20.20%	18.44%	17.85%	17.95%
1995	16.37%	16.32%	15.26%	16.48%
1996	19.66%	20.01%	19.48%	19.90%
1997	25.98%	23.06%	25.15%	23.45%
1998	21.66%	17.57%	20.43%	17.26%
1999	25.08%	22.15%	20.92%	21.72%
2000	23.47%	19.59%	22.98%	19.68%
2001	23.85%	19.21%	21.96%	18.83%
2002	21.38%	20.09%	22.48%	20.44%
2003	25.69%	21.21%	26.63%	21.57%
2004	41.88%	31.75%	36.86%	31.45%
2005	31.21%	26.00%	30.61%	26.17%
2006	22.22%	19.29%	22.16%	19.31%
2007	23.70%	22.62%	26.98%	22.93%
2008	43.21%	37.97%	38.65%	37.56%
2009	32.71%	31.80%	33.24%	32.59%
2010	26.76%	21.74%	27.66%	21.95%
2011	26.68%	22.07%	26.90%	21.89%
2012	29.00%	19.91%	26.03%	20.38%

year(s)	GARCHm	GARCHd	GJR GARCHm	GJR GARCHd
1972-2011	27.35%	23.15%	26.84%	23.11%
1987-2011	24.85%	21.99%	24.00%	21.96%
1972-1976	42.49%	30.40%	47.83%	30.62%
1977-1981	27.87%	25.05%	24.99%	24.89%
1982-1986	24.39%	19.79%	22.25%	19.58%
1987-1991	22.90%	21.30%	21.99%	21.10%
1992-1996	18.28%	17.45%	17.29%	17.34%
1997-2001	24.01%	20.32%	22.29%	20.19%
2002-2006	28.48%	23.67%	27.75%	23.79%
2007-2011	30.61%	27.24%	30.69%	27.38%

year(s)	IVBlack	IVBKM	IVBKMRA	IAD	IADRA
1987	18.32%	24.61%	NA	17.96%	NA
1988	35.29%	36.16%	28.73%	28.61%	23.70%
1989	22.52%	24.82%	20.50%	19.25%	16.47%
1990	17.76%	20.47%	18.16%	15.78%	14.13%
1991	20.02%	22.21%	20.84%	17.60%	16.03%
1992	19.31%	21.47%	19.27%	16.82%	14.62%
1993	19.29%	22.93%	14.96%	17.45%	11.26%
1994	20.78%	23.61%	16.00%	18.33%	12.33%
1995	17.53%	21.55%	15.44%	15.60%	11.65%
1996	19.02%	19.93%	15.76%	14.92%	12.47%
1997	24.06%	25.36%	23.68%	19.45%	19.09%
1998	19.61%	20.46%	17.46%	15.55%	13.78%
1999	25.13%	26.94%	20.11%	20.62%	15.80%
2000	23.68%	24.30%	17.58%	18.73%	13.74%
2001	20.91%	21.48%	15.38%	16.52%	12.08%
2002	20.41%	21.02%	17.36%	16.38%	13.87%
2003	22.24%	22.04%	19.33%	17.98%	15.91%
2004	32.41%	33.25%	30.19%	26.52%	23.33%
2005	27.67%	28.46%	24.65%	23.01%	19.00%
2006	22.78%	23.55%	19.06%	18.65%	14.90%
2007	24.42%	24.89%	19.30%	19.67%	15.27%
2008	39.97%	41.21%	33.77%	32.94%	26.69%
2009	36.93%	38.17%	30.45%	29.65%	23.24%
2010	23.41%	24.56%	18.26%	19.09%	13.79%
2011	24.51%	26.25%	19.82%	20.48%	15.20%
2012	22.01%	23.33%	17.22%	18.22%	13.25%
1987-2011	24.50%	26.08%	21.02%	20.43%	16.49%
1987-1991	22.78%	26.04%	21.91%	20.29%	17.53%
1992-1996	19.18%	21.85%	16.29%	16.53%	12.42%
1997-2001	22.65%	23.61%	18.41%	18.14%	14.54%
2002-2006	25.15%	25.66%	22.12%	20.51%	17.43%
2007-2011	29.68%	30.84%	24.16%	24.22%	18.70%

Note: This table provides an overview of the mean annualized volatility based on a monthly time horizon for wheat (panel A), corn (panel B), and soybeans (panel C). The values for IVBKMRA and IVRAD begin in 1988 due to the 18-month rolling window required for the estimation of the risk adjustment. The average values for 2012 base on only six observations because my option data end in June 2012.

Beside the differences in volatility levels, it can be also important to know whether a measure is relatively smooth or varies much over time. To investigate this issue, the standard deviations of the volatility in each of the five-year periods and the one (for the implied volatilities) or two (for the realized and GARCH model-based volatilities) longer periods are calculated first. Since the mean comparison has shown large differences, it is not useful to look at the standard deviations of the measures for a comparison of variation. Hence, the coefficient of variation (CV), which is defined as $\frac{\text{standard deviation}}{\text{mean}}$, is calculated for all periods and allows one to check all measures against each other, including those based on the absolute deviation. The CVs of the volatilities between 1972–2011 and 1987–2011 are highest for the realized estimates, whereby the RVAC has the highest of all measures, as can be seen in Table 2.4. The use of more information than just closing prices seems to smooth the estimates, since the RVYZ has the lowest CV in the realized group for both of the longer periods. The CVs of the GARCH and implied volatilities are mostly lower than the CV of the realized volatilities. This shows that the estimation method matters for the volatility of volatility. Moreover, the data frequency impacts the GARCH-based volatilities, with monthly data leading to much smoother volatility estimates. The implied volatilities tend to lie between the (GJR)GARCH volatilities at the monthly and daily frequencies. The implied volatilities show that, for the IVBKM as well as for the IAD, the risk adjustment leads to estimates with greater variation. Finally, one cannot see a regular difference between the standard deviation and absolute deviation measures within their realized or implied groups, so this differentiation has obviously no general impact on the smoothness of the volatility estimates.

Table 2.4: Coefficient of variation of volatilities

Panel A: Wheat

year(s)	SRV	RVAC	RVAAD	RVAR	RVYZ	RAD
1972-2011	0.417	0.461	0.420	0.424	0.403	0.420
1987-2011	0.414	0.451	0.407	0.409	0.375	0.407
1972-1976	0.343	0.439	0.378	0.382	0.384	0.378
1977-1981	0.317	0.382	0.309	0.306	0.305	0.309
1982-1986	0.339	0.379	0.314	0.324	0.281	0.314
1987-1991	0.456	0.384	0.450	0.444	0.442	0.450
1992-1996	0.322	0.390	0.299	0.321	0.308	0.299
1997-2001	0.212	0.295	0.201	0.199	0.162	0.201
2002-2006	0.249	0.298	0.243	0.231	0.208	0.243
2007-2011	0.281	0.408	0.294	0.288	0.264	0.294

year(s)	GARCHm	GARCHd	GJR GARCHm	GJR GARCHd
1972-2011	0.252	0.340	0.272	0.339
1987-2011	0.235	0.341	0.222	0.338
1972-1976	0.195	0.269	0.213	0.271
1977-1981	0.078	0.219	0.095	0.222
1982-1986	0.068	0.237	0.060	0.239
1987-1991	0.061	0.330	0.073	0.332
1992-1996	0.139	0.244	0.153	0.240
1997-2001	0.116	0.149	0.127	0.152
2002-2006	0.062	0.189	0.074	0.199
2007-2011	0.151	0.214	0.144	0.205

year(s)	IVBlack	IVBKM	IVBKMRA	IAD	IADRA
1987-2011	0.292	0.285	0.312	0.283	0.308
1987-1991	0.342	0.287	0.408	0.309	0.368
1992-1996	0.143	0.141	0.167	0.149	0.161
1997-2001	0.155	0.146	0.160	0.149	0.169
2002-2006	0.158	0.154	0.167	0.152	0.172
2007-2011	0.177	0.177	0.199	0.179	0.207

Panel B: Corn

year(s)	SRV	RVAC	RVAAD	RVAR	RVYZ	RAD
1972-2011	0.487	0.567	0.501	0.501	0.486	0.501
1987-2011	0.462	0.524	0.467	0.467	0.442	0.467
1972-1976	0.469	0.649	0.513	0.515	0.533	0.513
1977-1981	0.374	0.404	0.388	0.389	0.364	0.388
1982-1986	0.393	0.430	0.420	0.409	0.381	0.420
1987-1991	0.512	0.639	0.525	0.548	0.491	0.525
1992-1996	0.453	0.541	0.449	0.442	0.405	0.449
1997-2001	0.338	0.429	0.351	0.351	0.318	0.351
2002-2006	0.344	0.402	0.362	0.362	0.317	0.362
2007-2011	0.292	0.343	0.293	0.287	0.263	0.293

year(s)	GARCHm	GARCHd	GJR GARCHm	GJR GARCHd
1972-2011	0.321	0.425	0.337	0.426
1987-2011	0.285	0.406	0.293	0.406
1972-1976	0.387	0.408	0.431	0.413
1977-1981	0.161	0.288	0.164	0.289
1982-1986	0.152	0.305	0.167	0.308
1987-1991	0.388	0.446	0.425	0.448
1992-1996	0.177	0.375	0.191	0.375
1997-2001	0.144	0.265	0.115	0.267
2002-2006	0.191	0.299	0.230	0.307
2007-2011	0.161	0.250	0.148	0.242

year(s)	IVBlack	IVBKM	IVBKMRA	IAD	IADRA
1987-2011	0.337	0.310	0.355	0.303	0.347
1987-1991	0.471	0.413	0.381	0.458	0.409
1992-1996	0.317	0.258	0.271	0.273	0.296
1997-2001	0.241	0.235	0.254	0.236	0.252
2002-2006	0.247	0.251	0.272	0.231	0.252
2007-2011	0.217	0.187	0.194	0.191	0.202

Panel C: Soybeans

year(s)	SRV	RVAC	RVAAD	RVAR	RVYZ	RAD
1972-2011	0.464	0.648	0.486	0.482	0.460	0.486
1987-2011	0.432	0.522	0.431	0.428	0.417	0.431
1972-1976	0.507	0.838	0.535	0.497	0.530	0.535
1977-1981	0.391	0.500	0.427	0.428	0.376	0.427
1982-1986	0.423	0.551	0.451	0.457	0.414	0.451
1987-1991	0.482	0.643	0.483	0.492	0.491	0.483
1992-1996	0.405	0.480	0.386	0.378	0.370	0.386
1997-2001	0.350	0.476	0.324	0.312	0.277	0.324
2002-2006	0.339	0.366	0.333	0.323	0.311	0.333
2007-2011	0.399	0.461	0.413	0.413	0.384	0.413

year(s)	GARCHm	GARCHd	GJR GARCHm	GJR GARCHd
1972-2011	0.434	0.390	0.490	0.391
1987-2011	0.346	0.358	0.319	0.356
1972-1976	0.456	0.425	0.466	0.420
1977-1981	0.293	0.311	0.247	0.309
1982-1986	0.315	0.345	0.383	0.352
1987-1991	0.380	0.407	0.388	0.408
1992-1996	0.165	0.287	0.126	0.286
1997-2001	0.122	0.273	0.123	0.284
2002-2006	0.359	0.296	0.289	0.287
2007-2011	0.296	0.326	0.192	0.312

year(s)	IVBlack	IVBKM	IVBKMRA	IAD	IADRA
1987-2011	0.342	0.317	0.348	0.326	0.352
1987-1991	0.499	0.417	0.407	0.451	0.456
1992-1996	0.323	0.290	0.307	0.275	0.282
1997-2001	0.217	0.220	0.252	0.217	0.252
2002-2006	0.276	0.285	0.322	0.284	0.307
2007-2011	0.285	0.281	0.320	0.286	0.327

Note: This table provides an overview of the coefficient of variation ($\frac{\text{standard deviation}}{\text{mean}}$) of the annualized volatility based on a monthly time horizon for the several periods for wheat (panel A), corn (panel B), and soybeans (panel C).

Table 2.5 indicates the persistence of volatility. Therefore, the optimal lag length for an autoregressive process is determined by the AIC. The table shows the sum of autocorrelation coefficients (SAC) of this optimal AR(p) model.[30] The GARCH model-based estimates mostly show the highest volatility persistence of all the estimators. Moreover, consistent with prior results in the literature, the SAC decreases with the data frequency (see, for example, Poon and Taylor (1992)). The implied estimates usually have higher coefficients than the realized estimates for both periods in which estimates are available. Between the different periods analyzed, the coefficients vary much more for the realized volatilities than for the GARCH estimates. This is also no surprise, because I estimated the latter using all the available data and thus have the same model parameters for every month or day. Within the realized group, the RVYZ has the highest SAC in most of the periods, while the RVAC, which accounts, by definition, for autocorrelation of daily returns, often has the lowest.

[30]Several other possibilities exist for measuring persistence. Andrews and Chen (1994, p. 190) argue that the sum of coefficients is "a fairly reliable measure of the persistence of a series." However, they also discuss that it is an unbiased estimator for AR(1) processes, but not for higher-order processes. Since most of the time the AR(1) model is the optimal model and the simple sum of coefficients is an easily understandable measure, I rely on this measure without using any correction.

Table 2.5: AR(p) coefficients of volatilities

Panel A: Wheat

year(s)	SRV	RVAC	RVAAD	RVAR	RVYZ	RAD
1972-2011	0.838	0.722	0.842	0.848	0.825	0.842
1987-2011	0.777	0.672	0.771	0.831	0.767	0.771
1972-1976	0.701	0.499	0.727	0.726	0.864	0.727
1977-1981	0.354	0.000	0.369	0.356	0.338	0.369
1982-1986	0.471	0.321	0.487	0.461	0.577	0.487
1987-1991	0.522	0.413	0.557	0.555	0.599	0.557
1992-1996	0.442	0.273	0.426	0.412	0.557	0.426
1997-2001	0.000	0.000	0.000	0.308	0.284	0.000
2002-2006	0.392	0.219	0.331	0.344	0.430	0.331
2007-2011	0.333	0.383	0.351	0.324	0.525	0.351

year(s)	GARCHm	GARCHd	GJR GARCHm	GJR GARCHd
1972-2011	0.982	0.863	0.977	0.862
1987-2011	0.982	0.857	0.971	0.854
1972-1976	0.944	0.846	0.947	0.846
1977-1981	0.925	0.670	0.931	0.693
1982-1986	0.838	0.664	0.815	0.665
1987-1991	0.829	0.729	0.893	0.743
1992-1996	0.903	0.647	0.893	0.640
1997-2001	0.966	0.477	0.986	0.444
2002-2006	0.840	0.648	0.835	0.630
2007-2011	0.942	0.659	0.903	0.648

year(s)	IVBlack	IVBKM	IVBKMRA	IAD	IADRA
2002-2006	0.633	0.617	0.658	0.585	0.651
2007-2011	0.684	0.742	0.784	0.719	0.782

Panel B: Corn

year(s)	SRV	RVAC	RVAAD	RVAR	RVYZ	RAD
1972-2011	0.753	0.673	0.748	0.747	0.778	0.748
1987-2011	0.716	0.625	0.680	0.679	0.736	0.680
1972-1976	0.767	0.717	0.799	0.776	0.810	0.799
1977-1981	0.444	0.277	0.444	0.438	0.292	0.444
1982-1986	0.593	0.527	0.616	0.609	0.632	0.616
1987-1991	0.537	0.456	0.547	0.529	0.547	0.547
1992-1996	0.615	0.615	0.624	0.646	0.604	0.624
1997-2001	0.239	0.000	0.315	0.330	0.346	0.315
2002-2006	0.466	0.392	0.491	0.470	0.452	0.491
2007-2011	0.462	0.391	0.439	0.578	0.440	0.439

year(s)	GARCHm	GARCHd	GJR GARCHm	GJR GARCHd
1972-2011	0.898	0.807	0.887	0.807
1987-2011	0.884	0.801	0.867	0.782
1972-1976	0.871	0.827	0.868	0.830
1977-1981	0.748	0.548	0.756	0.549
1982-1986	0.896	0.665	0.865	0.674
1987-1991	0.818	0.596	0.811	0.599
1992-1996	0.932	0.699	0.924	0.692
1997-2001	0.744	0.391	0.717	0.379
2002-2006	0.727	0.666	0.780	0.659
2007-2011	0.746	0.653	0.744	0.664

year(s)	IVBlack	IVBKM	IVBKMRA	IAD	IADRA
2002-2006	0.678	0.662	0.703	0.625	0.688
2007-2011	0.399	0.619	0.497	0.508	0.506

Panel C: Soybeans

year(s)	SRV	RVAC	RVAAD	RVAR	RVYZ	RAD
1972-2011	0.679	0.614	0.676	0.712	0.702	0.676
1987-2011	0.655	0.533	0.661	0.670	0.690	0.661
1972-1976	0.593	0.630	0.643	0.744	0.695	0.643
1977-1981	0.464	0.377	0.486	0.497	0.486	0.486
1982-1986	0.739	0.649	0.731	0.720	0.752	0.731
1987-1991	0.522	0.560	0.515	0.500	0.629	0.515
1992-1996	0.518	0.356	0.539	0.547	0.405	0.539
1997-2001	0.324	0.332	0.364	0.450	0.407	0.364
2002-2006	0.692	0.511	0.661	0.671	0.714	0.661
2007-2011	0.601	0.461	0.677	0.623	0.653	0.677

year(s)	GARCHm	GARCHd	GJR GARCHm	GJR GARCHd
1972-2011	0.895	0.805	0.930	0.813
1987-2011	0.896	0.768	0.923	0.775
1972-1976	0.860	0.777	0.883	0.784
1977-1981	0.819	0.651	0.894	0.718
1982-1986	0.858	0.797	0.881	0.795
1987-1991	0.843	0.588	0.892	0.606
1992-1996	0.810	0.606	0.814	0.593
1997-2001	0.613	0.427	0.652	0.431
2002-2006	0.868	0.772	0.873	0.739
2007-2011	0.828	0.788	0.840	0.815

year(s)	IVBlack	IVBKM	IVBKMRA	IAD	IADRA
2002-2006	0.712	0.700	0.741	0.723	0.742
2007-2011	0.887	0.878	0.888	0.883	0.867

Note: This table provides an overview of the sum of coefficients gained from an AR(p) model fit on the returns in the specific periods for wheat (panel A), corn (panel B), and soybeans (panel C). The optimal lag length p is determined by the AR(p) model with the lowest AIC. Since implied volatilities could not be estimated every month before 1999, only the coefficients of the periods 2002–2006 and 2007–2011 are presented.

Table 2.6 allows for a closer look on the co-movement of the volatility estimates by providing an overview of their correlations. All commodities taken together, some clear patterns can be identified:[31] The realized volatility with a correction for autocorrelation (RVAC) has the lowest correlation among the realized group with all the other volatility measures. This finding stresses that the autocorrelation adjustment is an important extension to the SRV, since it leads to different estimates. Within the realized group, the lowest correlations are between RVAC and RVYZ, but they are still at least 0.835. Naturally, the correlation between RAD and RVAAD equals one because the only difference is the constant adjustment factor of the RVAAD. Within the GARCH group, the correlations between GARCH and GJRGARCH based on the same frequency are very high, whereby the correlations for the daily frequencies are the highest, with values close to one. The relatively small correlations of the same measurement methods with different frequencies underline the importance of the frequency that influences the estimated volatilities. Furthermore, it can be seen that GARCHd and GJRGARCHd volatilities show a much higher correlation with all realized and implied estimates compared to their monthly equivalents. This is in line with the finding of Andersen and Bollerslev (1998), that an increase in the data frequency leads to higher correlations due to reduced measurement errors.[32] The implied estimates show high correlations within their group. With only two exceptions overall, the correlations are above 0.9. The lowest correlations are found between IVBlack and IVBKMRA for wheat and corn and between IVBKM and IADRA for soybeans. Generally, the implied estimates are more highly correlated with the (GJR)GARCHd volatilities than with the realized volatilities. Interestingly, the risk adjustments for the IVBKM and the IAD mostly lead to lower correlations of the implied measures with the realized volatilities compared to the unadjusted measures.

[31] The results presented are based on pairwise complete observations. Overall complete observations are used for the calculation of correlations as a robustness check, but the main findings do not change.

[32] Specifically, Andersen and Bollerslev (1998, p. 900) find that the predictions of a GARCH(1,1) model with daily data is correlated more highly with the cumulative five-minute squared returns than with the squared daily return.

Table 2.6: Correlation between volatility estimates

Panel A: Wheat

	SRV	RVAC	RVAAD	RVAR	RVYZ	RAD	...
SRV	1.000	0.881	0.985	0.980	0.932	0.985	
RVAC	-	1.000	0.877	0.874	0.835	0.877	
RVAAD	-	-	1.000	0.993	0.932	1.000	
RVAR	-	-	-	1.000	0.930	0.993	
RVYZ	-	-	-	-	1.000	0.932	
RAD	-	-	-	-	-	1.000	
GARCHm	-	-	-	-	-	-	
GARCHd	-	-	-	-	-	-	
GJRGARCHm	-	-	-	-	-	-	
GJRGARCHd	-	-	-	-	-	-	
IVBlack	-	-	-	-	-	-	
IVBKM	-	-	-	-	-	-	
IVBKMRA	-	-	-	-	-	-	
IAD	-	-	-	-	-	-	
IADRA	-	-	-	-	-	-	

	...	GARCHm	GARCHd	GJR GARCHm	GJR GARCHd	...
SRV		0.618	0.885	0.623	0.887	
RVAC		0.482	0.725	0.512	0.733	
RVAAD		0.617	0.879	0.635	0.882	
RVAR		0.621	0.878	0.639	0.882	
RVYZ		0.620	0.879	0.647	0.883	
RAD		0.617	0.879	0.635	0.882	
GARCHm		1.000	0.718	0.948	0.709	
GARCHd		-	1.000	0.714	0.997	
GJRGARCHm		-	-	1.000	0.712	
GJRGARCHd		-	-	-	1.000	
IVBlack		-	-	-	-	
IVBKM		-	-	-	-	
IVBKMRA		-	-	-	-	
IAD		-	-	-	-	
IADRA		-	-	-	-	

	...	IVBlack	IVBKM	IVBKMRA	IAD	IADRA
SRV		0.726	0.728	0.713	0.731	0.720
RVAC		0.556	0.558	0.550	0.566	0.563
RVAAD		0.715	0.713	0.700	0.717	0.708
RVAR		0.716	0.714	0.700	0.716	0.706
RVYZ		0.746	0.742	0.720	0.750	0.735
RAD		0.715	0.713	0.700	0.717	0.708
GARCHm		0.710	0.749	0.750	0.722	0.728
GARCHd		0.885	0.901	0.892	0.899	0.894
GJRGARCHm		0.730	0.761	0.766	0.740	0.750
GJRGARCHd		0.881	0.897	0.886	0.896	0.889
IVBlack		1.000	0.987	0.942	0.989	0.986
IVBKM		-	1.000	0.962	0.991	0.964
IVBKMRA		-	-	1.000	0.949	0.992
IAD		-	-	-	1.000	0.964
IADRA		-	-	-	-	1.000

Panel B: Corn

	SRV	RVAC	RVAAD	RVAR	RVYZ	RAD	...
SRV	1.000	0.923	0.988	0.982	0.955	0.988	
RVAC	-	1.000	0.922	0.908	0.908	0.922	
RVAAD	-	-	1.000	0.991	0.950	1.000	
RVAR	-	-	-	1.000	0.947	0.991	
RVYZ	-	-	-	-	1.000	0.950	
RAD	-	-	-	-	-	1.000	
GARCHm	-	-	-	-	-	-	
GARCHd	-	-	-	-	-	-	
GJRGARCHm	-	-	-	-	-	-	
GJRGARCHd	-	-	-	-	-	-	
IVBlack	-	-	-	-	-	-	
IVBKM	-	-	-	-	-	-	
IVBKMRA	-	-	-	-	-	-	
IAD	-	-	-	-	-	-	
IADRA	-	-	-	-	-	-	

	...	GARCHm	GARCHd	GJR GARCHm	GJR GARCHd	...
SRV		0.572	0.930	0.564	0.930	
RVAC		0.541	0.858	0.555	0.860	
RVAAD		0.587	0.928	0.589	0.928	
RVAR		0.579	0.927	0.582	0.928	
RVYZ		0.610	0.924	0.601	0.925	
RAD		0.587	0.928	0.589	0.928	
GARCHm		1.000	0.669	0.941	0.666	
GARCHd		-	1.000	0.647	0.999	
GJRGARCHm		-	-	1.000	0.647	
GJRGARCHd		-	-	-	1.000	
IVBlack		-	-	-	-	
IVBKM		-	-	-	-	
IVBKMRA		-	-	-	-	
IAD		-	-	-	-	
IADRA		-	-	-	-	

	...	IVBlack	IVBKM	IVBKMRA	IAD	IADRA
SRV		0.727	0.738	0.708	0.726	0.704
RVAC		0.648	0.654	0.615	0.637	0.606
RVAAD		0.733	0.746	0.711	0.734	0.708
RVAR		0.729	0.738	0.701	0.727	0.696
RVYZ		0.740	0.770	0.747	0.756	0.741
RAD		0.733	0.746	0.711	0.734	0.708
GARCHm		0.640	0.644	0.636	0.645	0.649
GARCHd		0.829	0.869	0.843	0.856	0.840
GJRGARCHm		0.644	0.627	0.603	0.633	0.623
GJRGARCHd		0.832	0.868	0.841	0.855	0.838
IVBlack		1.000	0.948	0.891	0.947	0.897
IVBKM		-	1.000	0.962	0.992	0.963
IVBKMRA		-	-	1.000	0.947	0.992
IAD		-	-	-	1.000	0.963
IADRA		-	-	-	-	1.000

Panel C: Soybeans

	SRV	RVAC	RVAAD	RVAR	RVYZ	RAD	...
SRV	1.000	0.892	0.986	0.976	0.943	0.986	
RVAC	-	1.000	0.899	0.883	0.877	0.899	
RVAAD	-	-	1.000	0.986	0.935	1.000	
RVAR	-	-	-	1.000	0.944	0.986	
RVYZ	-	-	-	-	1.000	0.935	
RAD	-	-	-	-	-	1.000	
GARCHm	-	-	-	-	-	-	
GARCHd	-	-	-	-	-	-	
GJRGARCHm	-	-	-	-	-	-	
GJRGARCHd	-	-	-	-	-	-	
IVBlack	-	-	-	-	-	-	
IVBKM	-	-	-	-	-	-	
IVBKMRA	-	-	-	-	-	-	
IAD	-	-	-	-	-	-	
IADRA	-	-	-	-	-	-	

	...	GARCHm	GARCHd	GJR GARCHm	GJR GARCHd	...
SRV		0.647	0.913	0.655	0.908	
RVAC		0.618	0.843	0.649	0.839	
RVAAD		0.666	0.913	0.682	0.906	
RVAR		0.681	0.915	0.698	0.913	
RVYZ		0.685	0.914	0.686	0.916	
RAD		0.666	0.913	0.682	0.906	
GARCHm		1.000	0.756	0.921	0.758	
GARCHd		-	1.000	0.739	0.994	
GJRGARCHm		-	-	1.000	0.749	
GJRGARCHd		-	-	-	1.000	
IVBlack		-	-	-	-	
IVBKM		-	-	-	-	
IVBKMRA		-	-	-	-	
IAD		-	-	-	-	
IADRA		-	-	-	-	

...	IVBlack	IVBKM	IVBKMRA	IAD	IADRA
SRV	0.783	0.754	0.745	0.765	0.758
RVAC	0.716	0.690	0.673	0.693	0.680
RVAAD	0.789	0.759	0.752	0.777	0.771
RVAR	0.790	0.760	0.754	0.779	0.775
RVYZ	0.830	0.803	0.800	0.818	0.810
RAD	0.789	0.759	0.752	0.777	0.771
GARCHm	0.696	0.663	0.684	0.696	0.700
GARCHd	0.884	0.875	0.868	0.881	0.878
GJRGARCHm	0.737	0.685	0.692	0.720	0.710
GJRGARCHd	0.887	0.875	0.866	0.880	0.873
IVBlack	1.000	0.993	0.961	0.990	0.956
IVBKM	-	1.000	0.965	0.991	0.954
IVBKMRA	-	-	1.000	0.960	0.989
IAD	-	-	-	1.000	0.966
IADRA	-	-	-	-	1.000

Note: This table provides an overview of the correlations between the different volatility measures for wheat (panel A), corn (panel B), and soybeans (panel C). The correlations are calculated by pairwise complete observations, which means that the observations of all dates when the two analyzed estimators have a calculated volatility are taken into account for the correlation of these two estimates, irrespective of any of the other estimates not having a value on these dates.

2.6.2 Implications for the development of volatility

The previous section has shown that some general characteristics of volatility estimates depend on the specific decisions one makes for the calculation. Against the background of the most important questions regarding the volatility development around the food price crisis of 2007/2008, as identified in Section 2.2, the different characteristics are of minor importance if each one indicates the same development. In the following, I have a closer look at the individual answers from the different estimates to these questions.

The question whether volatility is higher since 2007/2008 compared to the 1990s and also compared to the early 2000s can easily be answered. All realized, GARCH model-based, and implied measures indicate that, for the commodities investigated, the mean volatility in the period 2007–2011 is higher compared to all five-year periods since 1992. The statement that volatility is exceptionally high since the food price crisis compared to those years is therefore robust to a variety of volatility measures.

It is not as easy to neglect or underline this statement if it refers to the 1970s. Since no implied estimates are available for these years, the historical estimates need to shed light on it. The results show that no unambiguous conclusion can be drawn because it depends on the commodity as well as the specific method used. For soybeans, there is clear evidence that volatility is not higher compared to the 1970s. Specifically, the period 1972–1976 shows the highest volatility for all methods. On the other hand, while the picture is also very clear for corn, it goes in the other direction. The years 2007–2011 have the highest volatility, even compared to the 1970s. Only for wheat are the results a bit more mixed. Most of the estimates indicate that volatility is higher since the food price crisis compared to the early 1970s. The exceptions are the (GJR)GARCH estimates based on monthly data. This result again stresses that the data frequency is an important issue for the volatility analysis and that conclusions must be drawn carefully. Overall, to answer the question of whether volatility is exceptionally high since 2007/2008, which commodity is analyzed seems to matter much more than the specific method used for the estimation.

A look at the mean volatility of single years allows one to answer the question of whether volatility in 2008 was higher than in any previous year. A comparison starting in 1987 would indicate a clear yes, so it is more interesting to look at the historical measures that capture the early 1970s. Again, it depends on the commodity and—more so than in the period comparison—on the specific method. The clearest case is soybeans, which has by far the highest volatility in 1973, especially notable for the (GJR)GARCH monthly data estimations. Although comparison of the five-year periods leads to clear conclusions for corn, the examination of single years is more puzzling because the answers differ even within the realized group. Albeit the differences between 1973 and 2008 are small, the RVAC is the only measure that negates the volatility from being highest in 2008. In addition, in the GARCH group, the results are different for daily and monthly data, with the former exhibiting the highest volatility in 2008 and the latter in 1973 or 1974. Interestingly, for the models with monthly data, the highest volatility since the food price crisis was not in 2008, but in 2011. The results for wheat are similar to the comparison of the periods above. GJR(GARCH) volatilities based on monthly data constitute the exceptions, with the highest volatility in 1974 and not 2008, as for the other measures. Similar to the corn case, for these two measures, 2011 is the most volatile year in recent history. Taken all together, the clear answer for soybeans would be no, while it would only be a tentative yes for corn and wheat. However, the latter conclusion is not very robust, because even within the realized group different directions exist for corn. Generally, the expression *exceptionally high* seems to be exaggerated, since differences between 2008 and the early 1970s are not that big, at least for corn.

The quantification of the volatility increase differs strongly between the measures and commodities. Since volatility changes from 2006 to 2007 are mostly less than five percentage points, the focus will be on the change of volatility between 2007 and 2008. To contribute to the fact that the mean level differs between the measures and an absolute change of percentage points is not helpful, the relative changes based on the volatility of 2007 are examined. Therefore, the following numbers result from $\frac{\text{volatility in 2008}-\text{volatility in 2007}}{\text{volatility in 2007}}$. For wheat, the implied estimates exhibit a lower increase than the realized estimates. For the latter, the volatility increase in 2008 is between 45.6% (RVYZ) and 54.02% (SRV), while the implied estimates' increases range between 37.71% (IAD) and 44.48% (IVBKMRA). The GARCH model-based estimates show large differences in their group. The generally smoother estimates from the monthly data show increases of only 30.77% and 22.33% and those from the daily data show increases of 49.94% and 44.92%. The daily estimates thus show a higher increase than the implied estimates and are nearly in the same range as the realized estimates. Corn behaves similarly regarding the relation of the estimates of the main groups but generally exhibits a lower volatility increase. The highest increase in the realized group is obtained by RVYZ—with the lowest in the case of wheat—with 32.28%. The daily (GJR)GARCH volatility changes are around 26%, followed by the lower implied estimates and even lower (GJR)GARCH monthly estimates. Interestingly, the differences in the implied group are quite large, demonstrating an increase of 22.66% for the IVBlack and only 12.94% for the IVBKMRA. For corn, the risk adjustments lead to a lower increase than the non-adjusted counterpart and vice versa for wheat and soybeans. Soybeans show by far the highest relative increase in 2008, with realized volatilities rising between 74.02%

(SRV) and 85.76% (RVAC). The range of the implied estimates is approximately 10% lower, with increases between 63.71% (IVBlack) and 74.95% (IVBKMRA). The increases of the GARCH group deviate from the usual picture because GARCHm (82.31%) indicates a higher increase than GARCHd (67.85%). Finally, the amount of the volatility increase can be stated to differ substantially between the three commodities and it can be robustly found that, for the comparison of 2007 and 2008, soybeans experienced the highest increase, followed by wheat and corn. The specific amount of the increase varies largely not only between the three main groups but even within. The GARCH measures seem to be especially sensitive to the precise application.

Against the background of the food price crisis, it is interesting to see that the persistence of volatility in the former crisis, in 1972–1976, was much higher for wheat and corn, indicating that the recent crisis is not connected to volatility being of higher persistence. For soybeans, there is much variation between the estimates. Although the years 1972–1976 do not always have the highest SAC, there is also no evidence that persistence increased in 2007–2011 compared to the past.

2.7 Conclusions

The comparison of several volatility measures helps draw some robust ex post conclusions regarding volatility development in three important agricultural commodity markets. Moreover, it is helpful to gain a more general feeling of the characteristics of volatility measures. It was not my intention to evaluate the different measures but, rather, to illustrate issues to consider when interpreting or analyzing volatility.

The analysis has shown that the level of volatility not only depends on the broad group but also varies inside the three main groups between the several specific estimators. The data frequency matters especially, as the GARCH examples demonstrate. Hence, one should never base a conclusion about the development of the volatility level on a comparison of two volatility estimates that result from different methods. Furthermore, the CV and the persistence analysis have shown that the variation over time and the durability of a volatility level depend on which measure has been used. This is also a relevant aspect for volatility analysis because a certain increase might be more worrisome if measured with a normally relatively smooth estimator than with a rather volatile one.

In spite of the differences, the measures often point in the same direction when analyzing concrete aspects of the food price crisis, at least when the question is narrowed down to a specific tendency such as an increase or decrease. However, it can be seen that the three commodities do not always behave similarly. As former studies have shown as well, the conclusions should always refer only to the commodity analyzed. It can be concluded that volatility is higher in the years of and after the food price crisis compared to the 1990s for all the commodities investigated, but only for corn and, with less robust results, wheat is it also higher compared to the early 1970s. Moreover, it cannot be definitely said that the year 2007 or 2008 exhibits exceptionally high volatility. The precise answer to the extent to which volatility has increased is very sensitive to the specific method and one can at best mention only a broad bandwidth.

My investigation has contributed to most of the issues discussed in Section 2.3: The estimation method has been varied by using several specific realized, GARCH model-based, and implied measures, with different data frequencies in the GARCH case and different definitions of volatility considered, including the usual standard deviation as well as the seldom used but more intuitive absolute deviation.

The only issue mentioned without closer analysis is the time horizon. Since I always estimated the volatility over one month and annualized it with the square root of time rule, it might be interesting for further research to look at the influence of different time horizons. Additionally, the decision of the specific application of the (GJR)GARCH models with regard to the time window might be another aspect worth a closer look.

3

Volatility in oilseeds and vegetable oils markets: drivers and spillovers

together with Bernhard Brümmer, Olaf Korn and Tinoush Jamali Jagdhani[1]

published in Journal of Agricultural Economics,[2] forthcoming

Abstract

Food price volatility has re-emerged as an important topic of political discussion since the food price crisis of 2007/08. Different volatility drivers have been identified for different markets in the theoretical and empirical literature. However, there is no comprehensive analysis that considers a large number of potential drivers and investigates their joint effects in a dynamic model of interrelated markets. Our study provides such a volatility analysis for the oilseeds and vegetable oils markets. We use a common GARCH approach and a VAR model to identify volatility drivers and spillover effects. Our results show that exchange rate volatility is very important. However, the hotly debated financialisation of commodity markets is not found to be volatility increasing in our monthly data. Impulse response functions show strong spillover effects. Because many volatility drivers found to be important in other markets have no significant effect in our study, our results suggest that volatility drivers are market specific. This implies that any volatility-reducing policies need to be designed for the market in question.

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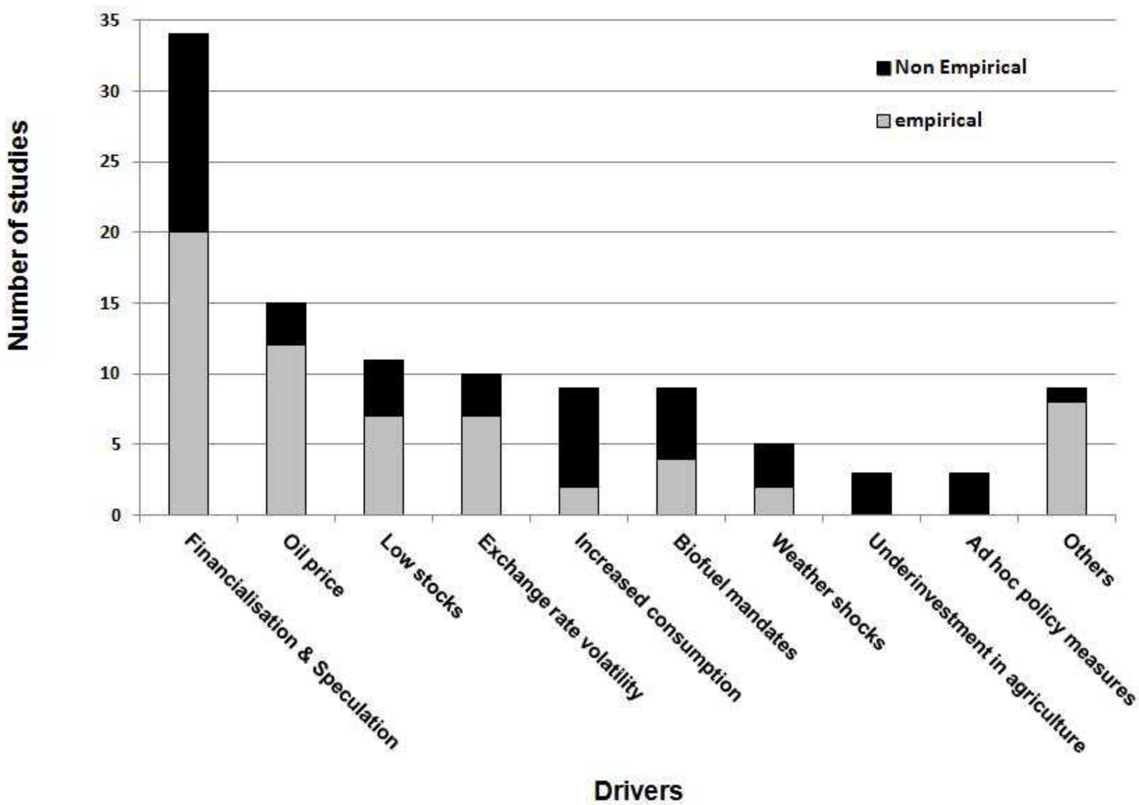
3.1 Introduction

Price volatility in agricultural markets is still an important topic 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 apparent 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, while 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, no consensus has yet been reached about the drivers of price volatility in agricultural markets over the past years. In an overview of the existing literature Brümmer, Korn, Schlüßler, Jamali Jaghdani, and Saucedo (2013), a number of broader categories is identified which were often mentioned in the studies contained in the review. Figure 3.1 (Brümmer, Korn, Jamali Jaghdani, Saucedo, and Schlüßler (2013)) gives an overall impression of the frequency at which a given category was addressed in the existing literature (separated by whether or not the study contained any empirical assessment).

Figure 3.1: Drivers of food price volatility



Source: Brümmer, Korn, Jamali Jaghdani, Saucedo, and Schlüßler (2013).

Financialisation and speculation are by far the most important in numerical terms, followed by a set of macro-economic variables (oil prices, exchange rate volatility, and increasing consumption) and then biofuel mandates, as an important policy factor, followed by weather shocks. Underinvestment in agriculture and the impact of ad hoc policy measures, perhaps being difficult to quantify, were not examined empirically. 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 market(s). To restrict a single study to a narrowly defined subset of agricultural markets, on the one hand, 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 also missed. As Roache (2010) and Zheng, Kinnucan, and Thompson (2008) point out, it is difficult to shed light on the spillover effects between commodities markets. On the other hand, by an exclusive focus on spillover effects among commodities markets (e.g., Kristoufek, Janda, and Zilberman (2012) or Serra, Zilberman, and Gil (2011)), the general perspective on volatility drivers might be lost. For instance, Kristoufek et al. (2012) analyse the volatility spillover between biofuel and agricultural commodity prices (corn, wheat, sugar cane, soybeans and sugar beets) in the US and Germany. They conclude that even though biofuel is affected by food and fuel prices, biofuel prices have a limited role in the determination of food prices. Serra, Zilberman, and Gil (2011) test the volatility spillover between Brazilian sugar, ethanol, and oil prices. They find that an increase in crude oil/sugar prices have been associated with higher ethanol prices and, in the short run, higher price volatility.

Our study addresses this research gap. We provide a thorough analysis of agricultural price volatility for seven different markets of global importance, grouped into two commodity groups, 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 the broader 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 two groups. In each VAR model, we use the same set of variables as potential exogenous drivers of price volatility. These candidate variables are chosen to represent the most important categories from Figure 3.1: 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 biodiesel is included in the set of markets analysed.

In the next section (Section 3.2), we briefly delineate how we selected the agricultural products (including biodiesel) in each commodity group, for which we model the estimated volatilities as an interdependent system. Section 3.3 explains the estimation procedure for price volatility. Section 3.4 explains which variables were used to capture the categories of drivers outlined above. Given that the number of potential candidate variables is large, we explain in Section 3.5 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. Section 3.6 presents the parameter estimates by commodity groups, and discusses the results on two aspects of major relevance: the estimated impact of the drivers; the identified spillovers among the price volatilities of the commodities included in each group. Section 3.7 concludes by pointing out the policy implications of our analysis.

3.2 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 identify influential factors affecting food price volatility and to quantify the effects of these drivers on volatility we select two groups of commodities. Table 3.1 shows the commodities considered in each group. We focus on spot prices because the physical trade takes mainly place at spot markets, and the impact of spot prices on the real economy is much stronger than the impact of futures prices.[3] The descriptive summary of the price data series and the data sources are given in the Appendix. Each group consists of commodities which are considered likely to be affected by a changing volatility of the other members of the group. For the commodities of the two groups, prices that are representative of the international markets are selected. For being appropriate representative, it is important that the prices are affected as little as possible by price distorting interventions. As import restrictions were made by several countries especially during the years of the food price crisis, export prices tend to be better representatives.[4] Accordingly, we focus on the biggest exporter / producer for our price selection. An exception is the sunflower oil market, where no consistent exporter price series is available for our period of study, hence the CIF-price of Rotterdam is used.[5]

[3]Futures markets are of high importance for market participants to hedge risks. Moreover, since futures prices contain expectations of future spot prices, they are also important for the price formation in the spot market. But since the focus of our analysis is more on the actual trading than on hedging activities, spot prices seem to be more appropriate in this case.

[4]Tothova (2011) points out that FOB prices generally better reflect world market prices since they are less affected by changes in transportation costs.

[5]The focus on large producer / exporter markets explains why we do not consider the Chinese market for the soybean price. The Chinese market is clearly important, but especially because China is a major importer of soybeans. Furthermore, most traders view China as being far from fully integrated in price

Table 3.1: Groups and commodities

	Groups	
	Oilseeds	Vegetable oils
Commodities	Soybean (US) Rapeseed (EU)	Palm oil (Malaysia) Soybean oil (Argentina) Rapeseed oil (EU) Sunflower oil (Netherlands) Biodiesel (Germany)

Group one 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[6] are at the core of the composition of our second group, "vegetable oils". It contains palm oil from Malaysia, soybean oil from Argentina, rapeseed oil from North West Europe, and sunflower oil from the Netherlands. These agricultural markets are considered jointly with the market for biodiesel (in Germany) as a major use of vegetable oils in the EU. Moreover, this group captures possible volatility spillovers between different geographical regions.

3.3 Estimating volatility

While food prices are easily observable, price volatilities cannot be observed, but have to be estimated. For our investigation, we choose continuously compounded returns with a monthly data frequency because it is supposed to be a relevant horizon for decision

formation on international agricultural markets, in particular during the 2008 food price crisis (Yang, Qiu, Huang, and Rozelle (2008)). Additionally, the time horizon of our analysis starts in 1990 but the Chinese market became important much later around 2000.

[6]Since the groups are formed to analyse volatility spillovers, we expect that linkages in consumption are more important than in production as adjustments in production processes of agricultural products are generally more difficult than substitution in consumption, at least in the short run.

makers in commodity markets. For the volatility estimation a model is preferred that on the one hand considers the volatility clustering of returns, but is on the other hand not too complex, so that the same model can be used for all commodities analysed in our study to make results comparable. Therefore, the GARCH (1,1) model[7] is chosen as the most appropriate model for our study.

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 as an autoregressive process. Since volatility patterns for the chosen commodities might be different across years, a different lag length for the autoregressive process might be optimal. For those commodities that we were sure about having a clear 12-month-seasonal-pattern we have selected an AR(12) model for the mean process of the returns and for those, for which we were not sure we decided for an AR(1) mean process. There might be other lag lengths optimal for several commodities, but we want to avoid too many different approaches for better comparability.[8] 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 3.5 without consideration of non-stationarity and co-integration. Finally, the monthly volatility estimates resulting from the GARCH are annualised by multiplying them by $\sqrt{12}$. Table 3.2 summarizes the GARCH estimates for the different commodities and provides some descriptive statistics for the resulting volatilities.

As table 3.2 shows, the agricultural commodities have an average volatility of about 18% to 26%. Compared to the agricultural commodities, biodiesel has a relatively low volatility,

[7] See Bollerslev (1986).

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

Table 3.2: Description of annualised GARCH (1,1) volatility estimations

Commod.	Region	Start	End	Mean process	Mean	SD	Min.	Max.
Soybean	US	Feb. 1990	Dec. 2012	AR(1)	26.22%	9.43%	14.96%	70.95%
Rapeseed	Europe	Feb. 1990	Dec. 2012	AR(1)	18.18%	2.97%	14.34%	30.62%
Palm oil	Malaysia	Feb. 1990	Dec. 2012	AR(1)	23.48%	6.11%	17.11%	54.91%
Soybean oil	Argentina	Dec. 1995	Dec. 2012	AR(1)	28.34%	3.70%	22.10%	42.51%
Rapeseed oil	Northwest Europe	Oct. 1995	Dec. 2012	AR(12)	22.58%	9.15%	15.63%	67.73%
Sunflower oil	Netherlands	Feb. 1990	Dec. 2012	AR(12)	22.04%	4.73%	18.71%	64.44%
Biodiesel	Germany	Aug. 2002	Dec. 2012	AR(1)	11.59%	2.19%	7.67%	15.62%

Source: Own estimates.

while soy oil has the greatest. This might be explained by subsidization of biodiesel in the European Union, and biodiesel is not substitutable for food consumption.

3.4 Incorporating exogenous drivers of volatility

In the following, we present our measurement of the potential volatility drivers used in the VAR model, following the categories identified in Brümmer, Korn, Schlüßler, Jamali Jaghdani, and Saucedo (2013) as noted above.

3.4.1 Crude oil price level and volatility

Oil prices affect agricultural markets from both the input and the output sides. From the input side, the energy utilization of crops according to Rathke, Wienhold, Wilhelm, and Diepenbrock (2007) depends on tillage approaches, fertilizer and pesticide usages, and rotation practices. Since soybean and rapeseed cultivation need fertilizer whose production costs are affected by oil prices.[9] 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 major use of agricultural products. Today, bioenergy, in particular biofuel policies, strengthen the link between energy and food. For instance, soybean and rapeseed oils are two important biofuel feedstocks.

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 exhibit 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. The volatility spillover effect from oil market to biofuel and agricultural commodity markets such as soybean, sugar, corn, etc. has been recognised by different researchers (e.g. Kristoufek, Janda, and Zilberman (2012) and Serra, Zilberman, and Gil (2011)) especially for the period after the financial crisis of 2008. Our main focus lies on 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.[10]

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.[11] The calculation of the implied volatility is based on the model-free approach of Bakshi,

[9] Soybeans are less affected by high energy prices from the input side compared to other crops such as corn. As it is shown by Rathke, Wienhold, Wilhelm, and Diepenbrock (2007), the energy input that is required for corn systems with mouldboard plow tillage is almost twice that for soybean with no-tillage.

[10] Source: Thomson Reuters Datastream, Code = "CRUDWTC".

[11] See Poon and Granger (2005), Poon and Granger (2003) and Christoffersen, Jacobs, and Chang (2012) for a documentation of the predominance of implied volatilities for many different markets.

Kapadia, and Madan (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.

3.4.2 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 exporter side (Krugman (1986) and Knetter (1993)). In any case, if exchange rate changes are at least partially transmitted to domestic prices, volatilities in exchange rates might be also 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.[12] 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. Contrary to the estimation of crude oil price volatility, we used the realised volatility because no options are traded on this index.[13] In order to circumvent

[12]For details on the construction of the index weights see Loretan (2005).

[13]Indeed, the ICE Futures U.S. lists a Dollar index (USDX) for which options are available but this index has constant weights for the currencies included in the basket. Contrary to this, the FED Dollar index that we use weights each of the seven currencies included based on their trade relations with the US and is revised annually. Therefore, it might be more appropriate to capture the strength of the US dollar.

underestimation of the true volatility if the returns are positively autocorrelated, our formula corrects for autocorrelation:[14]

$$Variance_t = \sum_{i=1}^{N_t} (r_{i,t} - \overline{r})^2 \cdot \left[1 + \frac{2}{N_t} \cdot \sum_{j=1}^{N_{t-1}} (N_t - j) \hat{\Phi}_t^j \right]$$

with

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

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

$\hat{\Phi}_t^j$ = 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 $\sqrt{12}$.

3.4.3 Speculation and financialisation

It is theoretically accepted 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 and 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:[15]

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

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

where

S_S = speculators' short positions and S_L = speculators' long positions and

H_S = hedgers' short positions and H_L = hedgers' long positions.

[14] See Marquering and Verbeek (2004).

[15] See Working (1960).

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 probable that this noise has increased in the last decade due to commodity index funds. A large part of index investors consists 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 into 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. Similar to the speculation measure, our suggested measure for total index investments might be affected by some noise for several reasons. For example, the CFTC does not disentangle the (possibly different) trading activities of a trader. If a trader is identified as an index trader, all his positions are classified as index trader positions, regardless of the actual nature of the positions. Moreover, the CFTC data does not capture all swap dealer activities because swap dealers internally net customers' positions and hedge only a part of all index-trading activities in the futures market.[16] Despite these inaccuracies, Irwin and Sanders (2012) conclude that this variable is a useful measure for index investment at least on agricultural markets. 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.[17] As the

[16]For more discussion of the problems with CFTC data, see e.g. Grosche (2014) and Sanders and Irwin (2013).

[17]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.

reports with CIT information are available since 2006[18], 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.

Trading activities of hedge funds could be another possible candidate as a volatility driver. But hedge funds likely follow different strategies which makes it difficult to hypothesise how a general measure for hedge fund activities might influence price volatility. Despite the discussed problems with the CFTC data, there might still be a relatively close relation between the market participants' strategy and the measure of speculation and financialisation that we use. Therefore, we concentrated only on speculative and index trading activities for our analysis.

The speculation and financialisation measures are calculated separately for each group and can be interpreted as a benchmark speculation / financialisation measure for the group. Since each group contains only one commodity for which the required data is available, soybeans and soybean oil are the representatives for the two groups.

3.4.4 Stock data

Stock levels changes and the stocks-to-use ratios 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 serve as a buffer for growing demand and mitigate shortages (Bobenrieth, Wright, and Zeng (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. We name the positive monthly stock projection change "good news" and the negative change of that "bad news". Moreover, we calculate 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. These variables are calculated for US stocks as well as for world stocks

[18]The data for index investment activities is published by the CFTC since 2007. The data for 2006 has been published retrospectively.

and are based on the reports published by the World Agricultural Outlook Board (WAOB) of the United States Department of Agriculture.[19]

3.4.5 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 (McPhail, Du, and Muhammad (2012); Gilbert and Morgan (2010)). The relative change of the sum of the quarterly GDP of the BRICS[20] 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.

3.4.6 Weather shocks

Several authors emphasize the importance of the climate change on food price volatility (Algieri (2014); Roache (2010)). One of the major climatic phenomena is 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 an 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). A strong El Niño event typically results in drought in the Western Pacific region, which in turn reduces the production of palm and palm kernel oil. Therefore, these price shocks will eventually impact the demands for close substitutes such as soybean oil or sunflower oil. Ubilava and Holt (2013) and Liao, Chen, and Chen (2010) found that El Niño has a negative effect on soybean futures prices while La Niña has the opposite effect.

[19] As mentioned by Greenfield and Abbassian (2011), there are many doubts on the results of the forecasting methods which are used for estimating the production level, consumption level and stock level of agricultural commodities. However, the WAOB stock data can be valuable for analysing volatility in spite of their unreliability (Bobenrieth, Wright, and Zeng (2013)).

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

3.5 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 econometric 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.

Our choice of a set of potentially interrelated commodities or products, as outlined in Section 3.2 above, is oilseeds (2 products) and vegetable oils (5 products). The estimated GARCH return volatilities of these products constitute the set of endogenous variables of the two VAR models that we use. Our potential volatility drivers are also outlined above (Section 3.4), and our approach enables us to quantify the additional impact of a specific driver on volatility.

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 our VAR model requires 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. Starting with a general unrestricted model, this approach reduces the complexity of the model step by step. The concept 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 reflect the true data structure.

Several studies have documented the good performance of automatic model selection procedures (see, e.g., Hoover and Perez (1999); Hendry and Krolzig (1999); Hendry and Krolzig (2005)). This is attractive here, to minimize the bias of subjective choices, "letting the data speak" as to which volatility drivers are important.

We use the autometrics algorithm developed by Doornik (2009), which is a further improvement over previous procedures. The algorithm allows for the specification of some parameters (p-values) that govern how easily a variable is excluded from the model. We choose rather high p-values (10%), to avoid excluding significant drivers, which lead to relatively large models. Our results (next section) are for the final model outcome of this specification process.

3.6 Results and interpretation

3.6.1 Parameter estimates and price volatility drivers

We focus first on the exogenous drivers of volatility, and then examine volatility spillovers among the commodities in each group.

Selected oilseeds: For the oilseeds group we have chosen soybeans and rapeseed from the biggest producer markets, US and Europe respectively. Our monthly data period is May 1990 to July 2012.[21]

As Table 3.3 shows, we find the expected strong impacts of the own lagged volatilities, with statistically significant cross effects for both commodities, which we discuss in the next section. Among all the potential exogenous drivers tested, the volatility of the US dollar exchange rate against a basket of other important currencies proved to have a statistically significant positive impact on rapeseed price volatility, but not on soybeans. However, more of the exogenous drivers are found to be statistically significant in the soybean equation. The "La Niña" effect reduces soybean volatilities, consistent with Liao, Chen, and Chen (2010). The stocks-to-use ratio (as a projection) also reduces this volatility.

[21]The financialisation variable is extrapolated between May 1990 and January 2006.

Table 3.3: Results group "oilseeds"

Variable	Soybean	Rapeseed
Soybean (US) volatility$_{t-1}$	**0.84**	-0.02
	(0.05)	(0.02)
Soybean (US) volatility$_{t-3}$	-0.02	**0.05**
	(0.05)	(0.02)
Rapeseed (EU) volatility$_{t-1}$	0.06	**0.77**
	(0.14)	(0.06)
Rapeseed (EU) volatility$_{t-2}$	**0.81**	0.08
	(0.18)	(0.08)
Rapeseed (EU) volatility$_{t-3}$	**-0.65**	-0.06
	(0.14)	(0.06)
Constant	-0.00	**0.03**
	(0.02)	(0.01)
Trend	**0.00**	0.00
	(0.00)	(0.00)
Dollar strength volatility	0.11	**0.09**
	(0.11)	(0.09)
SOI positive (La Niña)	**-0.01**	0.00
	(0.00)	(0.00)
Soybean US - STU	**-0.06**	-0.02
	(0.03)	(0.01)
Soybean World "good News"	**0.30**	0.03
	(0.07)	(0.03)

Source: Own estimates.

The positive influence of positive changes in the projection of the end of year stock level might look surprising at a first glance. An increase in expected stocks should generally lead to lower prices, and typically also lower price volatilities. Changes in projections might bring new information on the market but with positive changes in the world stock projections, some ambiguity about the release of these stocks and their price effects might also be introduced. This could explain the positive parameter estimate.

Selected vegetable oils: Table 3.4 shows the results for the group of vegetable oils, including biodiesel, for August 2002 to July 2012.[22] This group shows substantial 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 are discussed further below.

Only two exogenous drivers 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

[22] The relatively late start of the analysis is due to the late availability of Biodiesel data. Again, the financialisation measure is extrapolated between August 2002 and January 2006.

Table 3.4: Results group "vegetable oils"

Variable	Palm Oil	Sunflower Oil	Soybean Oil	Biodiesel	Rapeseed Oil
Soybean (US) volatility$_{t-1}$	**0.55**	-0.30	-0.09	**0.24**	1.01
	(0.13)	(0.29)	(0.17)	(0.09)	(0.96)
Soybean (US) volatility$_{t-2}$	**0.60**	**0.83**	0.19	**-0.29**	0.42
	(0.15)	(0.34)	(0.19)	(0.10)	(1.12)
Soybean (US) volatility$_{t-3}$	**-0.28**	**-0.49**	-0.21	0.11	**-1.81**
	(0.10)	(0.24)	(0.14)	(0.07)	(0.80)
Sunflower oil (Netherlands) volatility$_{t-1}$	**0.11**	**0.50**	0.04	**-0.07**	0.38
	(0.06)	(0.14)	(0.08)	(0.04)	(0.46)
Sunflower oil (Netherlands) volatility$_{t-2}$	**-0.11**	-0.11	0.05	**0.12**	0.62
	(0.05)	(0.12)	(0.07)	(0.04)	(0.41)
Soybean oil (Argentina) volatility$_{t-1}$	**0.25**	**0.50**	**0.88**	-0.07	-0.92
	(0.08)	(0.17)	(0.10)	(0.05)	(0.57)
Soybean oil (Argentina) volatility$_{t-2}$	**-0.20**	**-0.38**	-0.09	0.02	**1.05**
	(0.07)	(0.17)	(0.10)	(0.05)	(0.57)
Biodiesel (Germany) volatility$_{t-1}$	0.04	-0.04	**0.18**	**0.81**	**1.23**
	(0.08)	(0.18)	(0.10)	(0.05)	(0.58)
Dollar strength volatility	**0.11**	**0.18**	**0.17**	0.03	-0.30
	(0.05)	(0.11)	(0.06)	(0.03)	(0.35)
SOI positive (La Niña)	-0.00	0.01	-0.00	**0.00**	0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Constant	-0.00	**0.08**	**0.04**	0.01	-0.02
	(0.01)	(0.02)	(0.01)	(0.01)	(0.08)
Trend	0.00	0.00	0.00	0.00	**-0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Source: Own estimates.

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 positive (though very small) is the "La Niña" effect. Since the impacts of "La Niña" are dry summers in the Northern hemisphere, negative impacts on the harvest in Northern Europe and thus on the input for biodiesel are expected. We also find a (very small) negative and statistically significant trend effect in the rapeseed oil equation - possibly a consequence of the policy framework driven by the EU renewable energy directive.

Table 3.5 summarises the impact of all our potential drivers on price volatility across both commodity groups.

Table 3.5: Identified drivers

	commodities tested	increasing effect	not significant	decreasing effect
Financialisation & Speculation	7	0	7	0
Oil	7	0	7	0
Low stocks	7	1	6	0
Revision of stock projection (“good news” / “bad news”)	7	1	6	0
Exchange rate	7	4	3	0
Increased consumption	7	0	7	0
Weather shocks	7	1	5	1

Source: Own estimates.

Our estimated price volatilities are based on the residuals of a GARCH model, where, besides the temporal dynamics of the conditional heteroscedasticity, the residuals are supposed to be white noise. It is not surprising, therefore, that the conditional standard deviations are then hard to explain by adding additional information about potential drivers. Our additional information is based on publicly available data, which might not accurately reflect the investigated driver, at least in some cases.

Nevertheless, we find that exchange rates (volatility of the strength of the US dollar) to be significant in most of the markets analysed, reflecting both a direct $ effect, and possibly also an indirect indication of more general macro-economic volatility as reflected in the $ volatility.

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 possibly yield more significant results.

A low stock level is only once found to have a statistical significant volatility increasing effect, although we only have data for soybeans and soybean oil and not for the other commodities.

The revision of stock levels as a measure for new information on the market is significant in one market. Because the significance occurred for “good news”, i.e. an increase in the amount of the year-end stock level projection, it seems that a huge amount of new information affects volatility regardless of the goodness of the news. Like for the low stock level we do not have enough precise measures for each commodity to make robust statements.

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. Even extending the period of the GDP change measure does not generate a volatility effect.[23] Oil is also not found to be a statistically significant volatility driver. We only found biodiesel to drive the volatility of soybean oil and rapeseed oil.

Finally, we do not find any hint that financialisation or speculation acts as volatility increasing factors for our monthly data horizon, as was discussed in the public over the past years. This is in line with the majority of the recent literature (Brümmer, Korn, Schlüßler, Jamali Jaghdani, and Saucedo (2013)). However, we have to be careful with the interpretation of this result. We could not use market specific measures of the variables for all commodities due to data limitations, but had to use a representative market for each group. Market specific measures would have been more appropriate to draw a robust conclusion. Given that we find rich dynamics through lagged own and cross effects, we cannot rule out that financialisation is part of the underlying mechanism of the lagged spillovers. Hence, we should not overly interpret the result that financialisation or speculation have no significant contemporaneous effects on price volatility.

3.6.2 Volatility spillovers

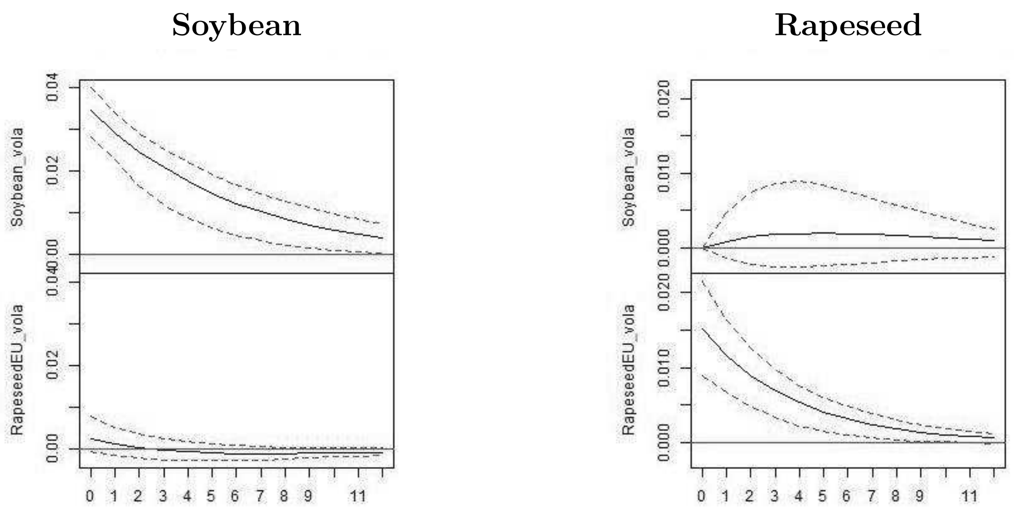
The VAR model allows us to detect and quantify volatility spillovers between different commodities by means of lagged volatilities of all products within a product group. There are two main issues that we address in our analysis of volatility spillovers. The first is the statistical significance of lagged volatilities referring to other products within the VAR model, reflected in the t-stats. The second is the economic significance of spillovers, which

[23] The "normal" measure of GDP change that we use captures the change in the previous quarter. As robustness checks we tested the change over the previous half year, three-fourth year and full year.

is particularly strong if the initial effect on volatility is large and persists over long periods, and can be examined via impulse-response functions, illustrated below (dashed lines in Figures 3.2 and 3.3 indicate 95% bootstrapped confidence intervals).

Oilseeds: The dynamic effects of volatility shocks in this group are rather straightforward (see Table 3.3 and Figure 3.2). 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 (residual correlation of 0.17). Since the economic functioning of the soybean and rapeseed markets leads us to expect the former to lead, we attribute the contemporaneous effects to a shock in the soybean market. As the impulse-response functions show, there are significant spillover effects in both directions. This statement also holds if the order is changed, i.e. the contemporaneous effect is attributed to a shock in the rapeseed market.

Figure 3.2: Impulse response functions for group "oilseeds" (soybean, rapeseed)

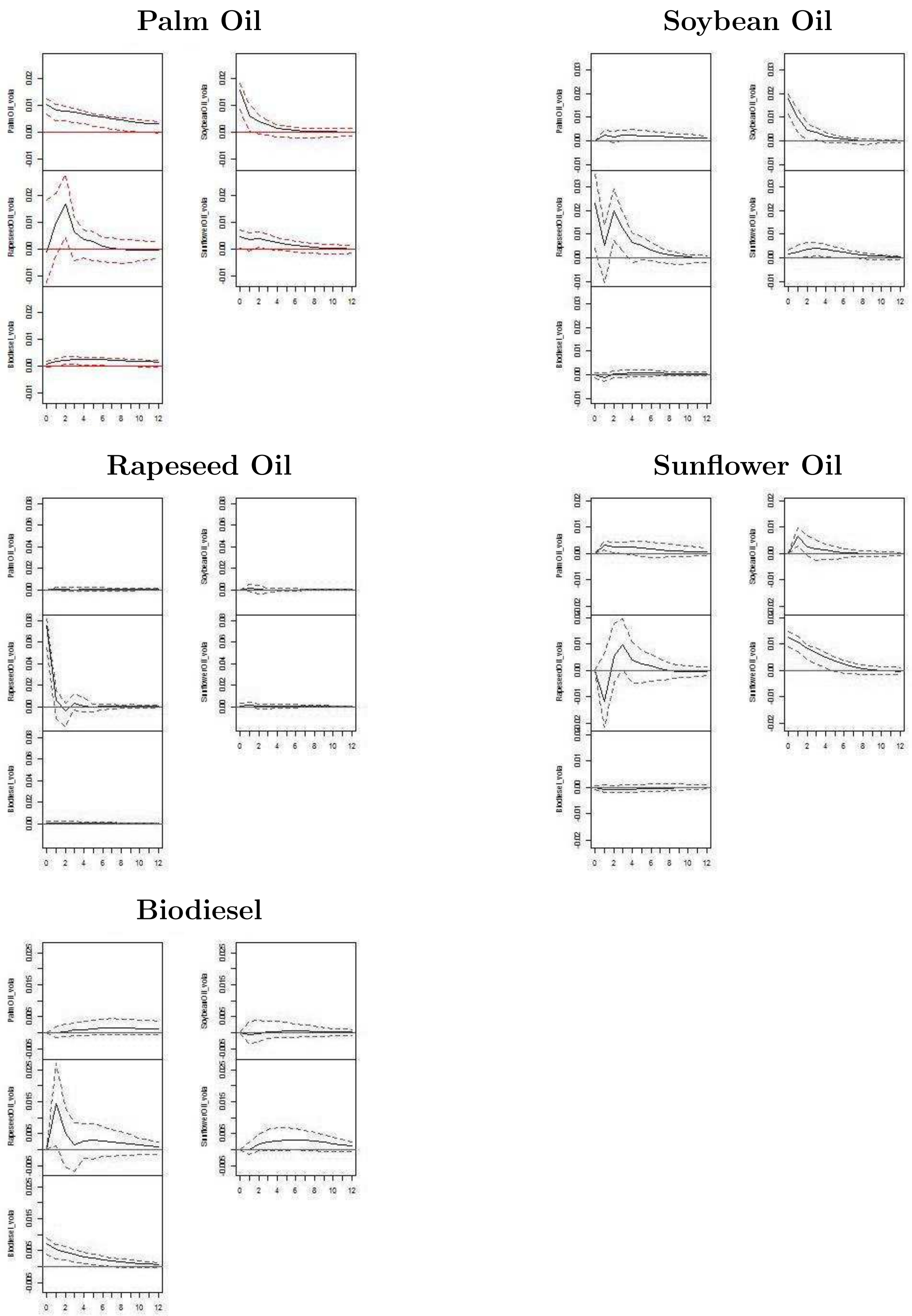


Vegetable oils: The group that contains the vegetable oils has a complicated dynamic structure. For each of the five products, there is at least one lagged volatility of another product that shows a statistically significant impact (see Table 3.4). The impulse-response functions are shown in Figure 3.3. 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 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. This ordering reflects the size of the markets, which we suppose determines the direction of effects. We tested several different orderings of the commodities as additional robustness checks. Given the number of possible orderings, we focused on those orderings that are most likely to lead to different conclusions. Although the impulse response functions are sensitive to ordering, our main conclusions remain unchanged.[24]

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 very considerable volatility spillovers between these markets, with palm oil and soybean oil taking a lead and the markets for rapeseed oil and biodiesel mainly reacting.

[24]The only bigger difference is found, if biodiesel is put at the first position. But at the same time, this is the least reasonably ordering from an economic point of view because biodiesel is a product that needs all other group members as an input and should be affected by those prices instead of the other way round.

Figure 3.3: Impulse response functions for "vegetable oils" (palm oil, rapeseed oil, biodiesel, soybean oil, sunflower oil)



3.7 Conclusions

We conducted a comprehensive price volatility assessment for two agricultural commodity groups (oilseeds and vegetable oils). Estimating price volatility on each market in a standardised GARCH framework sheds light on the dynamics in each group by analysing the estimated price volatilities in a VAR system. In particular, we identify the role played by a number of 'suspect' volatility drivers discussed in the literature.

Our findings indicate that price volatility patterns are not homogenous across these markets. Furthermore, many of the potential drivers do not show any statistically significant impact on agricultural price volatility, at least with our monthly data.

The most frequently identified impact is found for the exchange rate volatility, measured by the volatility in the strength of the US dollar. In the cases where a statistically significant impact is found, exchange rate volatility drives up price volatility of these commodities.

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 remarkable. We do not find any significant effects for our financialisation and speculation variables, although we note that both our data and the periodicity of our analysis could shroud these effects.[25]

We find varying degrees of dynamics in the price volatility spillovers between the markets. A complex picture emerges in the vegetable oils group. One explanation is the strong 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 these two markets.

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 patterns of price volatility over time are highly variable, as is the impact of the

[25] An overview of studies applying Granger Causality tests with different index trading data frequencies is given by Grosche (2014). Gilbert and Pfuderer (2014) find stronger evidence for an impact of index traders on price returns when looking on the contemporaneous instead of the lagged impact.

potential drivers. We find no evidence for financialisation and speculation effects on volatility in our data, but noting the caveats on this finding, suggest that more work needs to be done to support the introduction of position limits, a key element of the MIFID reform, as a curb on agricultural commodity price volatility.

One common pattern in both groups of markets 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 mostly takes place on a global scale, this is a major barrier for effective policy. Perhaps a more promising approach might rely on policies which help producers and consumers *cope* with price volatility, instead of trying to *curb* price volatility.

Appendix

Table 3.6: The descriptive summary of the selected commodities prices and the data sources

Commodity	Source	Datatstream Code	Price	Mean	SD	Max	Min
Palm oil	Datastream	HWWIPO$	US$/Ton	575.92	250.30	1291.75	225.10
Rapeseed oil	Datastream	RPOLDNE	Euro/Ton	608.89	193.82	1090.00	348.00
Soybean oil	Datastream	ARGSBOI	US$/Ton	653.05	298.20	1485.00	266.00
Sunflower seed oil	Datastream	HWWISO$	US$/Ton	735.51	315.70	1870.80	337.60
Soybean No 1 Yellow	Datastream	SOYBEAN	US cent/bu	735.33	292.98	1778.00	407.50
Biodiesel	Agrarmarkt Informations GmbH		Euro cent/lit	94.16	14.16	122.76	72.56
Rapeseed	Alfred C. Toepfer International		US$/Ton	325.60	142.43	754.00	169.00

4

Forward-looking risk measures for agricultural commodity markets

together with Bernhard Brümmer and Olaf Korn[1]

Abstract

This article introduces a set of related risk measures to characterize the detailed structure of volatility in agricultural commodity markets. These measures allow for a decomposition of overall price moves into “large” changes with potentially severe economic consequences and “normal” changes. We derive forward-looking estimators of the risk measures that extract market expectations about future commodity price moves from current option prices. In an empirical study on major grain markets, we show that our measures indeed capture different aspects of price volatility, shedding new light on the food price crisis of 2007–2008. Another key finding is that option-implied estimators show much higher information content for future price moves than historical estimators do.

[1]Earlier versions of this article have been presented at the Center for Financial Risk at Macquarie University, Sydney, 2014, at the Ph.D. workshop of the 2014 Meeting of the German Finance Association, Karlsruhe and at the research colloquium of Georg-August-Universität Göttingen. We are grateful to the participants of each seminar for their helpful comments. The research has been funded under the ULYSSES project, EU 7th Framework Programme, Project 312182KBBE.2012.1.4-05. This article has also been presented at ULYSSES seminars. We particularly thank seminar participants and the members of the consortium for helpful comments.

4.1 Introduction

Volatility in agricultural commodity markets is not constant over time and exhibits marked differences even between individual commodities. The food price crisis of 2007–2008 is a prominent example. In comparison to the decade before, not only did price levels increase substantially, but also price volatility, most notably in wheat, corn, and rice.[2] High volatilities can be difficult for different groups of producers and consumers to cope with (Gilbert and Morgan (2010); Bellemare, Barrett, and Just (2013); Galtier and Vindel (2013)) and may have adverse effects on food security (Naylor and Falcon (2010); FAO (2011); HLPE (2011)). Therefore, a better understanding of volatility is crucial for market participants and policy makers alike.

The perceived need for immediate action to reduce food price volatility, or at least to mitigate potentially negative effects of increased volatility in critical market situations, led to a number of initiatives at various policy levels. However, at least in some cases, prescriptions were discussed and decided before the diagnosis was complete. In this context, two methodological issues about price volatility measurement or risk measurement in general are important. First, it is not enough to realize that volatility has increased if we are already in the midst of a crisis and several large price moves have already occurred. Instead, we need forward-looking risk measures that are able to detect volatile periods (or potentially volatile periods) as early as possible and that contain useful information for the construction of early warning systems. Second, since volatility is a complex phenomenon, it is not enough to rely on a single volatility measure, even if it is forward looking. Instead, we need several risk measures that are linked to the economic consequences of increased volatility. For example, a generally higher volatility may be acceptable if the probability and magnitude of very large price moves are unchanged.[3]

[2]Wright (2011) notes, however, that from a historical perspective, the recently observed price spikes were not of unprecedented magnitude when compared to the mid 1990s and early 1970s.

[3]Von Braun and Tadesse (2012) stress that it is important to distinguish between (standard) volatility and price spikes in terms of economic consequences and whether the spike starts with an upward or downward price move.

This article addresses both issues. It analyzes risk measures implied from current option prices. Option prices contain forward-looking information because they reflect the market participants' expectations about price movements until the expiration date of the options. Moreover, calculation of option-implied risk measures requires just a single cross section of prices, that is, only the latest information available. Our analysis does not stop with simple implied volatility, though. We introduce a whole set of related risk measures that provide insights into the fine structure of volatility. In particular, these distinguish between "normal" price moves and "large" price moves[4] with specific economic and social relevance[5] and between positive and negative moves. The derivation of the implied estimators of these risk measures is this article's first major contribution. The second major contribution is the application of these estimators in an empirical study on grain markets. These markets are often viewed as the cornerstones of price relations between agricultural commodities, since grains are used directly for human consumption, as major feedstock in the livestock industries, and increasingly as a major feedstock for bioenergy, particularly biofuels. Hence, the price volatility of grains is often of specific interest to policy makers and scientists.

Our empirical results show that it is indeed fruitful for the understanding of volatility to distinguish between normal and large price moves. During the food price crisis of 2007–2008, the magnitude of neither normal nor large price moves was extraordinary compared to historical averages. A specific feature of this period is the higher probability of large price moves, particularly price drops. A second important insight from our empirical study is evidence on the predictive power of implied risk measures for future price moves. Implied estimates clearly dominate estimates based on historical time series and remain the most important predictors, even if supplemented with fundamental volatility drivers such as stocks, oil price volatility, and exchange rate volatility.

Our article is related to different strands of literature. At the conceptual level, there is a close link to the work on risk measurement and implied volatilities in financial economics. A first related idea is to measure risk in terms of price movements that exceed a certain threshold, because of the severe economic consequences of large adverse price moves.

[4]Large price jumps are characteristic of many commodity markets. For example, Hilliard and Reis (1999) provide evidence for the soybean market and Koekebakker and Lien (2004) for the wheat market.

[5]Bellemare (2015) shows that large food price increases have led to increases in social unrest.

Corresponding risk measures are the value-at-risk or the conditional value-at-risk.[6] In contrast to our study, however, these risk measures are usually estimated from historical time series data and not from option prices. A second important concept related to our work is implied volatility. The vast literature on implied volatility currently extends to higher-order implied moments and implied correlations and the concept has been extensively applied in asset pricing, portfolio management, and risk management (Poon and Granger (2003); Christoffersen, Jacobs, and Chang (2012); Giamouridis and Skiadopoulos (2012)). However, we do not rely on standard estimators of implied moments but derive new model-free implied estimators for all our risk measures.

This article is naturally connected to other work that analyzes volatility in agricultural commodity markets (Clapp (2009); Ghosh, Chakravarty, and Rajeshwor (2010); Roache (2010); Du, Yu, and Hayes (2011); Wright (2011); Babcock (2012); Nissanke (2012); Brümmer, Korn, Schlüßler, Jamali Jaghdani, and Saucedo (2013); Karali and Power (2013)). It adopts a different perspective than most papers, however, because it makes no attempt to identify or understand the economic drivers behind price volatility but exploits information from options markets for predictions. In this sense, it is closely related to work on early warning systems (Araujo, Araujo-Bonjean, and Brunelin (2012); Dawe and Doroudian (2012); Baquedano (2014); Martins-Filho, Yao, and Torero (2015)). In contrast to these papers, though, implied estimates are the central element of our approach and not models based on either historical time series or market fundamentals.

The remainder of the article is structured as follows. The next section introduces our risk measures and provides historical evidence on different aspects of risk for the wheat market. The following section derives model-free option-implied estimators of the risk measures. The empirical study on the properties of implied estimators and their information content for predicting future price moves is presented in the following section. The final section concludes the article.

[6]The literature on these concepts is voluminous. Useful sources are the books by Dowd (2007) and Hull (2012).

4.2 Risk measures for normal and large price moves

4.2.1 Definition of risk measures

This section introduces a set of risk measures that captures the detailed structure of unexpected price moves by decomposing an overall measure into different components. At the first level of decomposition, these components distinguish between normal price fluctuations and large price moves with severe economic consequences. At the second level, whether the price move is positive or negative is considered, because such information can be very important for the choice of appropriate policy measures.

Our approach is very general. Assume that we are currently at time t and want to measure the price risk for a horizon of length τ. Denote the total price move from t to $t+\tau$ by $S_{t+\tau} - S_t$, where S_t is the current commodity price and $S_{t+\tau}$ is the price at the end of the period, which is a random variable from the perspective of time t. The total price move can be decomposed into an expected part and an unexpected part.[7] The expected price move equals $E_t\ [S_{t+\tau}] - S_t$, where $E_t\ [S_{t+\tau}]$ denotes the expected end-of-period price, given all the information available at time t. Finally, the unexpected price move $\bar{S}$ is the difference between the total price move and the expected price move:

$$\bar{S} = (S_{t+\tau} - S_t) - (E\ [S_{t+\tau}] - S_t) = S_{t+\tau} - E\ [S_{t+\tau}]\,. \tag{4.1}$$

This unexpected price move is what constitutes risk and needs to be captured by risk measures. The first risk measure that we use is an overall one. It follows the intuitive notion of price risk as the expected absolute deviation between the end-of-period price and the expected price, that is, $E_t\left[\,|\,\bar{S}\,|\,\right]$. This expectation is our overall risk measure, called OM (overall move).[8]

[7] Note that in the context of grain markets, seasonality and trending behavior might constitute important components in the formation of expectations.

[8] An alternative would be to use the squared deviation or the root squared deviation instead of the absolute deviation, which leads to the variance or the standard deviation of a price move. However, as experimental evidence by Goldstein and Taleb (2007) shows, the mean absolute error is a more intuitive risk measure, even for investment professionals.

In a next step, we decompose the OM measure. Generally, price fluctuations per se do not cause problems, but a large price move exceeding a certain threshold will.[9] It is therefore important to know whether an overall increase in price movements is caused by generally more volatile prices or by a higher probability or magnitude of large price moves beyond the threshold. The relevant threshold itself may differ between markets (Assefa, Meuwissen, and Oude Lansink (2014)) and over time, depending on economic conditions. For this reason, the threshold is a free parameter in our approach, denoted A. The idea of distinguishing between normal (below the threshold) and large (above the threshold) price moves is captured by the following decomposition of OM:

$$E_t\left[\,|\,\bar{S}\,|\,\right] = p_l\; E_t\left[\,|\,\bar{S}\,|\;|\;|\,\bar{S}\,| > A\,\right] + (1-p_l)\; E_t\left[\,|\,\bar{S}\,|\;|\;|\,\bar{S}\,| \leq A\,\right]. \tag{4.2}$$

Equation (4.2) splits the overall risk into a weighted average of two conditional risks, one representing absolute price moves above the threshold A and the other one representing price moves below the threshold. The relative weight of these two conditional risks are determined by the probability p_l of a large move. The decomposition in equation (4.2) delivers three additional risk measures. First, $E_t\left[\,|\,\bar{S}\,|\;|\;|\,\bar{S}\,| > A\,\right]$ tells us what (on average) the magnitude of a large move will be. We call this risk measure LM_A (large move). Second, $E_t\left[\,|\,\bar{S}\,|\;|\;|\,\bar{S}\,| \leq A\,\right]$ provides the corresponding information on the magnitude of normal moves, that is, price moves that are smaller than A in absolute terms. We call this measure NM_A (normal move). Finally, the probability p_l tells us how likely it is that a large move will occur.

Large price moves are particularly relevant economically but, depending on whether it is a price increase or a price drop, the consequences can be very different. Price increases are often seen as critical for consumers, whereas price drops are critical for producers. For this reason, we suggest further decomposition at the second level and we decompose the risk measure LM_A in a way that provides information on the direction of a price move.[10]

[9] Assefa, Meuwissen, and Oude Lansink (2014) show that different actors in the agro-food chain indeed have specific price thresholds in mind when assessing risk.

[10] We could decompose NM_A in the same way, but we concentrate on large moves because of their greater relevance.

In particular, we express $E_t\left[\,|\,\bar{S}\,|\;|\;|\,\bar{S}\,| > A\,\right]$ as

$$E_t\left[\,|\,\bar{S}\,|\;|\;|\,\bar{S}\,| > A\,\right] = p_{+\,|\,l}\; E_t\left[\,\bar{S}\,|\,\bar{S} > A\,\right] + (1 - p_{+\,|\,l})\; E_t\left[\,-\bar{S}\,|\,\bar{S} < -A\,\right]. \tag{4.3}$$

Equation (4.3) again provides three additional risk measures. The first one is the expected magnitude of a large price move, provided that it is positive, that is, $E_t\left[\,\bar{S}\,|\,\bar{S} > A\,\right]$. We call this measure LM_{A+}. The corresponding measure for the expected magnitude of large negative price moves, that is, $E_t\left[\,-\bar{S}\,|\,\bar{S} < -A\,\right]$, is LM_{A-}. If these two measures are equal, the direction of the price move provides no information on its magnitude. Finally, we want to know how likely it is that a large price move is positive. This information is given by the probability $p_{+\,|\,l}$, which is the probability of a positive price move, provided that the price move is large. The conditional probability can be written as $p_{+\,|\,l} = p_{l,+}\,/\,p_l$, where $p_{l,+}$ is the (unconditional) probability that a price move is both large and positive. If $p_{+\,|\,l} = 0.5$, large positive price moves are equally likely as large negative price moves.

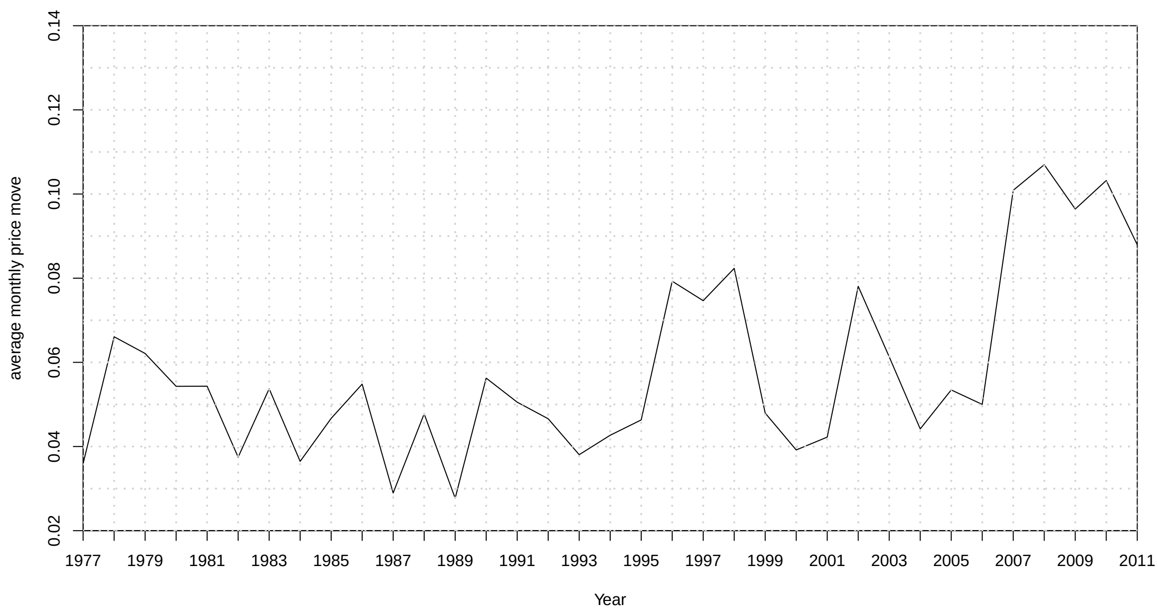
In summary, we introduce seven different risk measures that characterize the fine structure of unexpected price moves. They provide information on the overall price volatility (OM), the magnitudes of large price moves (LM_A) and normal price moves (NM_A), and the probability of a large price move p_l. With respect to the direction of a price move, they quantify the magnitudes of large positive (LM_{A+}) and negative (LM_{A-}) price moves and the probability of a large price move being positive ($p_{+\,|\,l}$).

4.2.2 Risk analysis for wheat

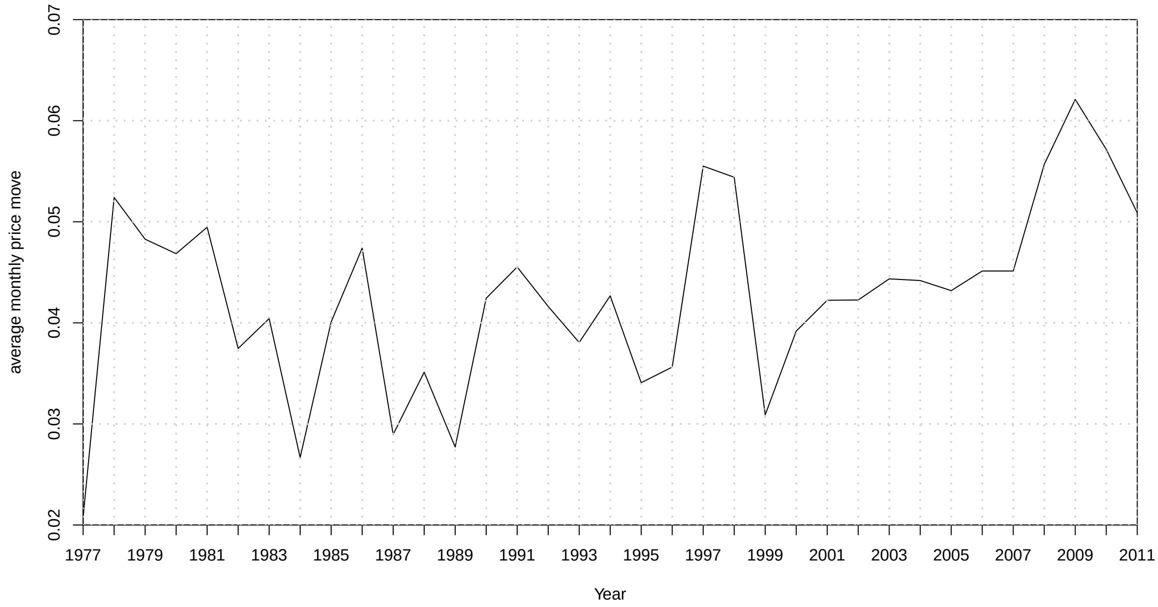
As an illustration of the usefulness of the presented risk measures, we provide an analysis of the wheat market from 1977 to 2011. This data period includes the time of the food price crisis of 2007–2008 and puts it in historical perspective by also covering the intermittent spikes from 1996 to 1998 and in 2002. The time horizon (τ) is one month and we use monthly price changes of wheat futures contracts with the shortest time to maturity traded at the Chicago Mercantile Exchange (CME). The expected wheat price change is obtained from the predictions of an autoregressive model of order one fitted to the time series of monthly relative price changes in a rolling window that contains the previous 60 months. The differences between total changes and expected changes, that is, the residuals of the AR(1) process, finally deliver a time series of monthly unexpected price changes. The threshold level A is generally set to 10% of the current futures price with the shortest maturity. Given these data and threshold specifications, we obtain historical risk measures for each year in the data period by calculating the appropriate sample averages of the 12 corresponding observations. Figure 4.1 shows the resulting values for the risk measures OM, NM_A, LM_A, and p_l. The values for OM, NM_A, and LM_A are given as a percentage of the current futures price (price at the beginning of the month) to make them comparable over time.

Figure 4.1: Historical risk measures for wheat

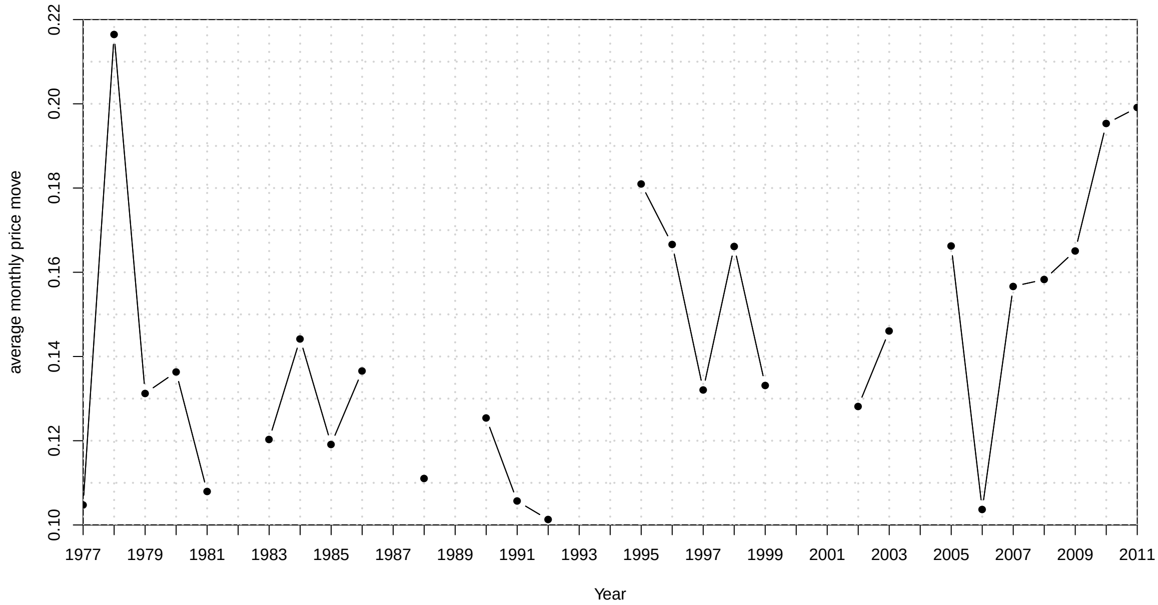
Panel A: Overall price moves (OM)



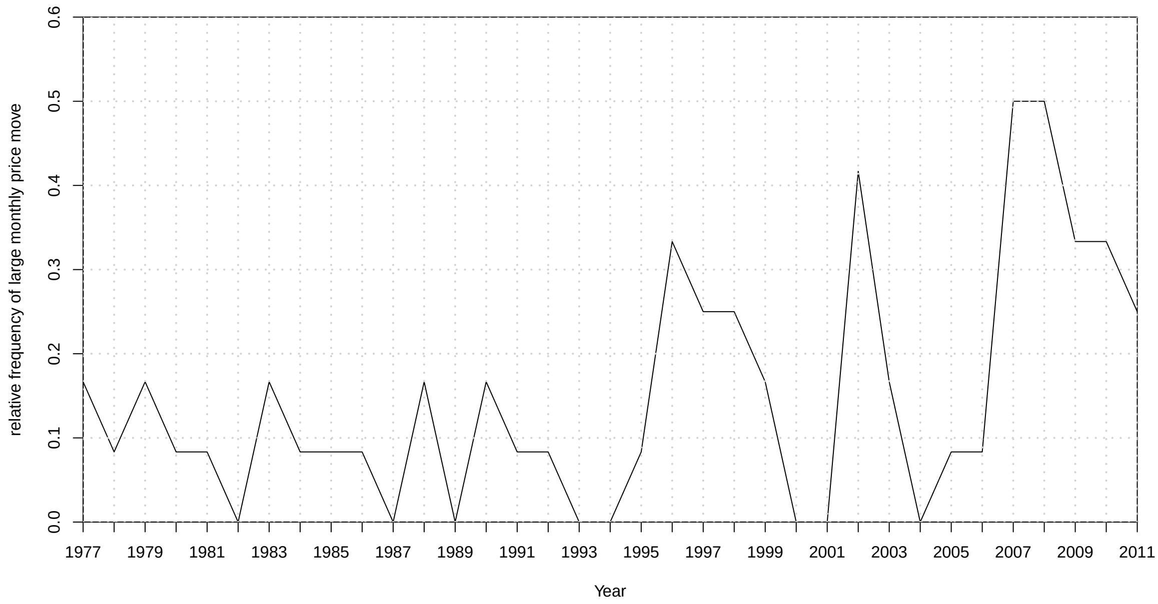
Panel B: Normal price moves ($NM_{10\%}$)



Panel C: Large price moves ($LM_{10\%}$)



Panel D: Relative frequency of large price moves (p_l)



This figure shows historical estimates of the risk measures OM, $NM_{10\%}$, $LM_{10\%}$, and p_l for wheat. The time horizon (τ) is one month and the values for OM, $NM_{10\%}$, and $LM_{10\%}$ are given as a percentage of the current futures price (price at the beginning of the month). The estimates for each year are obtained from the 12 monthly unexpected price changes within the year by taking the appropriate averages. Expected wheat price changes refer to the predictions of an autoregressive model of order one fitted to the time series of monthly relative price changes in a rolling window of the previous 60 months from 1977 to 2011. Prices are from wheat futures contracts with the shortest time to maturity traded at the CME. The threshold level A equals 10% of the current futures price.

Figure 4.1 provides evidence that different risk measures indeed capture different dimensions of risk. Panel A shows how the overall volatility measure evolves over time. Risk was very low at the beginning of the data period in 1977, with an average monthly price move of about 4%, and continued to be rather low until 2006, with somewhat higher values around 1996 and 2002. From 2007 onward, risk was much higher. One could conclude from panel A of figure 4.1 that the food price crisis indeed led to a huge increase in risk and the high risk level persisted until the end of the data period in 2011. Panels B to D of figure 4.1, however, give important additional information on the food price crisis. Panel B shows that the magnitude of normal price moves was not particularly high in 2007 and 2008, compared to the average value for the whole data period. The higher risk must therefore be due to large price moves. In this respect, the next question is whether a higher probability or a higher magnitude of such price moves was to blame. It could make an important difference if, for example, the probability were 0.5 and the expected magnitude

20% or the probability were 0.25 and the expected magnitude 40%. The latter situation could be particularly challenging because very high price increases (or price drops) could arise in a very short time, leaving little time for appropriate coping strategies. For the food price crisis of 2007 and 2008, the magnitudes of large price moves, as shown in panel C, were not exceptional. What really distinguishes the years 2007 and 2008 from the previous 30 years is the very high probability of a large price move. This probability reaches 50%, as panel D shows, a level that had not been previously observed. However, the years 2007 and 2008 also differ from the following years, 2009 to 2011, in important ways that cannot be seen from the overall risk measure in panel A. After 2008, the probability of large price moves decreases again, but the magnitudes of both normal and large price moves are very high, leading to almost no change in overall risk. By looking at the detailed structure of risk, we can therefore conclude that a characteristic of the food price crisis is the high number of large price moves while in the subsequent years the expected magnitude of a large price move is particularly high.

The historical risk estimates in figure 4.1 are useful for the analysis of the food price crisis in retrospect, but they have important limitations. Since large price moves are relatively rare, it is difficult to obtain information on their magnitude. With 12 monthly observations, we could end up with no large price move at all in a year, that is, there is no information on the magnitude of such price moves. As panel C of figure 4.1 shows, such a situation occurs in eight out of 35 years. However, even if one or two large price moves are observed, the resulting estimates are most likely very imprecise and the problem would even become worse if we tried to distinguish between positive and negative price moves. The problem could be mitigated by using longer time periods for the averaging. However, such averages over very long periods may be dominated by outdated information that is not useful under current economic conditions. For predictions and early warning systems, one would ideally rely on risk estimates that use current information only and are forward looking. Implied estimates based on option prices fulfill both requirements.

4.3 Forward-looking estimators of risk measures

A first idea to obtain forward-looking estimators of our risk measures is the use of option-implied moments. The most prominent example of such a moment is the Black–Scholes implied volatility, which goes back to Latané and Rendleman (1976). It is obtained by inverting the Black–Scholes option pricing formula to back out the volatility parameter using observed option prices. Implied volatility is forward looking because it captures the expectations of market participants about future volatility. Moreover, it uses only current price information. The major disadvantage, however, is its dependence on a specific pricing model, the Black–Scholes model, which might not be adequate for a specific market and a specific time. To overcome this problem, the concept of model-free implied volatility has been developed (Britten-Jones and Neuberger (2000); Jiang and Tian (2005)), following the idea that complete markets allow for the recovery of the whole (risk-neutral) price distribution from observed option prices. Based on the same idea, the concept of model-free implied volatility has been extended to higher-order moments of the price distribution, such as implied skewness and implied kurtosis (Bakshi, Kapadia, and Madan (2003); Neuberger (2012)).

If certain moments of the price distribution were unambiguously related to certain risk measures from the previous section, we could immediately apply model-free implied moment estimators. Intuitively, one could expect that higher variance has an increasing effect on the overall risk measure, greater (positive) skewness increases the probability and magnitude of a large positive price move, and higher kurtosis leads to a higher probability and magnitude of large price moves in general. However, as shown in the Appendix, these relations are not straightforward, because the resulting effects depend on the threshold level A. Therefore, we follow a different route and develop direct model-free option-implied estimators of our risk measures.

The derivation of implied estimators for our risk measures follows the same idea that underlies model-free implied moments. The starting point is the assumption of complete markets. If markets are complete, we can apply the principle of risk-neutral valuation, which states that the price of any derivative equals its discounted expected payoff, using risk-free interest rates and risk-neutral probabilities.[11] It is then our goal to express all risk measures in terms of the expected payoffs of portfolios of derivatives written on the commodity price. The (compounded) prices of these portfolios ultimately deliver the desired model-free implied estimates of the risk measures.

Consider the overall risk measure OM first. It can be written as the sum of two expectations:

$$OM \;=\; E_t\left[\,|\,\bar{S}\,|\,\right] \;=\; E_t\left[\,max\left[\,S_{t+\tau}-K,\,0\,\right]\,\right]+E_t\left[\,max\left[\,K-S_{t+\tau},\,0\,\right]\,\right], \tag{4.4}$$

where K equals $E_t\ [S_{t+\tau}]$, the expected price at $t+\tau$. Equation (4.4) shows that OM is just the sum of the expected payoffs of a call option and a put option with the same strike price K. It follows that

$$OM^{\,imp} \;=\; e^{r\tau}\left[\,C\,(\tau,\,K)+P\,(\tau,\,K)\,\right] \tag{4.5}$$

is the corresponding implied estimator, where r denotes the risk-free interest rate for the period from t to $t+\tau$, $C\,(\tau,\,K)$ is the price of a call option with time to maturity τ and strike price K at time t, and $P\,(\tau,\,K)$ denotes the corresponding price of a put option.

Next, we express the probability of a large price move in terms of expected payoffs:

$$p_l \;=\; E_t\left[1_{\{S_{t+\tau}\,>\,K+A\,\}}\right]+E_t\left[1_{\{S_{t+\tau}\,<\,K-A\,\}}\right], \tag{4.6}$$

where $1_{\{S_{t+\tau}\,>\,K+A\,\}}$ $(1_{\{S_{t+\tau}\,<\,K-A\,\}})$ is an indicator function that takes a value of one if $S_{t+\tau}>K+A$ $(S_{t+\tau}<K-A)$ and zero otherwise. The indicator function $1_{\{S_{t+\tau}\,>\,K+A\,\}}$ describes the payoff of a digital option that pays one currency unit if the price $S_{t+\tau}$ exceeds the value of $K+A$ and pays nothing otherwise. We use the expression "digital call" for such a digital option because a payment occurs if prices are above a specific level. Accordingly, we use the expression "digital put" for a digital option that makes a positive

[11] We return to the issue of potential risk adjustments that transform our risk measures into the corresponding real world risk measures in a later section.

payment if prices are below a certain level. The second term on the right-hand side of equation (4.6) is the expected payoff of such a digital put with strike price $K - A$.

Equation (4.6) therefore suggests the following implied estimator for the probability of a large price move:

$$p_l^{imp} \;=\; e^{r\tau} \left[\, D^C(\tau,\, K + A) + D^P\,(\tau,\, K - A)\,\right], \tag{4.7}$$

where $D^C(\tau,\, K + A)$ and $D^P\,(\tau,\, K - A)$ are the prices of the corresponding digital call and put options, respectively. Digital options on commodity prices are usually not traded in liquid markets, which means that market prices are not directly available. Such options can be well approximated, however, by long and short positions of plain vanilla calls and puts. Consider a portfolio that consists of $1/k$ plain vanilla call options with strike price $K + A$ and $-1/k$ call options with strike price $K + A + k$. If k goes to zero, the payoff function of this portfolio converges to the payoff function of a digital call with strike price $K + A$. A digital put can be similarly approximated by a portfolio of plain vanilla put options.[12]

In a next step, we derive an implied estimator of the magnitude of large price moves. The risk measure LM_A can be written as:

$$\begin{aligned} LM_A = E_t\left[\,|\,\bar{S}\,|\;|\;|\,\bar{S}\,| > A\right] \;=\; & \left(E_t\left[\,max\left[\,S_{t+\tau} - (K + A),\, 0\,\right]\,\right]\right. \\ & + E_t\left[A \cdot 1_{\{S_{t+\tau} > K+A\,\}}\right] \\ & + E_t\left[\,max\left[(K - A) - S_{t+\tau},\, 0\,\right]\,\right] \\ & \left. + E_t\left[A \cdot 1_{\{S_{t+\tau} < K-A\,\}}\right]\right)/p_l. \end{aligned} \tag{4.8}$$

Equation (4.9) shows that LM_A equals the expected payoff of an options portfolio with four components. The first one is an out-of-the money call with strike price $K + A$. The second one consists of a number of A digital call options with strike price $K + A$. These two components capture the magnitude of large positive price moves. The last two components refer to large negative price moves. They consist of a plain vanilla put option with strike

[12] We use such an approximation of digital options with $k = 0.001$ in the empirical part of this article.

price $K - A$ and a number of A digital put options with the same strike price. Finally, one has to divide by the probability of a large price move occurring because the measure is a conditional expectation. The resulting implied estimator reads

$$
\begin{aligned}
LM_A^{imp} \; = \; & e^{r\tau} \big(\, C\,(\tau,\, K + A) + A \cdot D^C(\tau,\, K + A) \\
& +P\,(\tau,\, K - A) + A \cdot D^P(\tau,\, K - A)\big) \,/ p_l^{imp}.
\end{aligned} \tag{4.9}
$$

An implied estimator of the magnitude of normal price moves (NM_A) is obtained from equation (4.2) by applying the three estimators $OM^{\,imp}$, p_l^{imp}, and LM_A^{imp}. The resulting estimator becomes

$$
NM_A^{imp} \; = \; \big(OM^{\,imp} - p_l^{imp}\, LM_A^{imp}\big) \,/\, (1 - p_l^{imp}). \tag{4.10}
$$

Finally, we provide estimators of the magnitudes of positive and negative large price moves, respectively, and the probability that a large price move is positive. We write the risk measure LM_{A+} as

$$
\begin{aligned}
LM_{A+} = E_t \left[\, \bar{S} \,|\, \bar{S} \, > A \, \right] \; = \; & (E_t \,[\, max \,[\, S_{t+\tau} - (K + A),\, 0 \,]\,] \\
& +E_t \left[A \cdot 1_{\{S_{t+\tau} > K + A\}} \right] \big) \,/ (p_{+|\,l} \cdot p_l)
\end{aligned} \tag{4.11}
$$

and the probability that a large price move is positive as

$$
p_{+|\,l} \; = \; \frac{E_t \left[1_{\{S_{t+\tau} > K + A\}} \right]}{E_t \left[1_{\{S_{t+\tau} > K + A\}} \right] + E_t \left[1_{\{S_{t+\tau} < K - A\}} \right]}. \tag{4.12}
$$

Then the corresponding estimators are

$$
LM_{A+}^{imp} \; = \; \frac{e^{r\tau} \big(\, C\,(\tau,\, K + A) + A \cdot D^C(\tau,\, K + A)\big)}{p_{+|\,l}^{imp} \cdot p_l^{imp}} \tag{4.13}
$$

and

$$p_{+|l}^{imp} = \frac{D^C(\tau,\, K+A)}{D^C(\tau,\, K+A) + D^P(\tau,\, K-A)}. \tag{4.14}$$

Using the relation in equation (4.3), we obtain an implied estimator of the magnitude of large negative price moves (LM_{A-}) from the previous estimators as

$$LM_{A-}^{imp} = \left(LM_A^{imp} - p_{+|l}^{imp}\, LM_{A+}^{imp}\right) / \, (1 - p_{+|l}^{imp}). \tag{4.15}$$

In summary, we have shown that all risk measures can be expressed as the expected payoffs of portfolios of plain vanilla and digital options. The corresponding compounded prices of these options portfolios therefore provide implied estimates of the risk measures. These estimates are model free, in the sense that they do not rely on the validity of a specific option pricing model.

4.4 Empirical study

4.4.1 Data and estimation approach

For the empirical analysis, we use price data for wheat, corn, and soybean futures and options traded at the CME. These three commodities are important as an agricultural output as well as an input factor for feedstock and biofuels. Therefore, the corresponding markets are of special interest for different groups of producers and consumers. Moreover, due to the importance of these markets, a relatively long history of option prices with different strike prices is available, which we require for the calculation of implied risk measures.

The beginning of our data period is determined by the availability of sufficient options data. It starts in March 1987 for wheat, in October 1987 for corn, and in May 1987 for soybeans. The end of the data period is June 2012. As for our previous historical estimates, we use a time horizon (τ) of one month, which means that options with times to maturity of one month are required to obtain implied estimates of the risk measures. Until May 1998, five expiration dates per year (March, May, July, September, and December) were available for options on wheat and corn futures and seven (January, March, May, July, August, September, and November) for options on soybean futures. Since June 1998, expiring options on all three commodities have been available each month. Thus we can estimate implied risk measures five (seven) times a year for the period until May 1998 and 12 times a year thereafter.

For our risk measures, we need options with strike prices K, $K + A$, and $K - A$. Since such options are not always traded, we use an interpolation method based on all available strikes. We follow the standard approach in the literature and do not interpolate between prices directly but between the corresponding implied volatilities (Chang, Christoffersen, Jacobs, and Vainberg (2012)). The procedure has several steps. First, we select all call options with a moneyness[13] of at least 0.97 and all put options with a moneyness of not more than 1.03, excluding in-the-money options, which are usually less liquid. Second, we record the corresponding settlement prices[14] from the electronic market, if available, because electronic trading has currently a much higher trading volume than floor trading does. For the early years of our data period, when no electronic trading was available, we use prices from the floor market. Third, we apply data filters[15] and exclude all prices below or equal to $ 3/8 as well as prices that violate the model-free no-arbitrage bounds or the monotonicity condition with respect to the strike price.[16] Fourth, we translate prices into implied volatilities via a discrete version of the Black model for options on futures (Black (1976)) that accounts for their potential early exercise.[17] It is important to note that we do not assume the Black model holds. The formula is just used as a data transformation that makes interpolation numerically more stable. Fifth, we fit a cubic spline to the implied volatilities in the moneyness dimension with a smoothing parameter of 0.3. This procedure delivers an implied volatility curve as a continuous function of

[13]Moneyness is defined as the ratio of the strike price and the price of the underlying.

[14]In some cases, the settlement price is not available and the closing price is used instead.

[15]These filters are standard in the literature, see Jiang and Tian (2005).

[16]The next steps are conducted only if at least two call and two put options remain after the data filtering.

[17]Since options traded at the CME are American-style options and our risk measures refer to the expected payoffs of European options, we have to make such an adjustment.

moneyness. Finally, the volatility curve is translated back into the price dimension via the Black formula and provides (interpolated) prices for a continuum of strike prices. To obtain option prices with exactly 30 days to maturity on the last trading day of each month, we estimate two volatility curves, one for the shortest time to maturity ($\tau < 30$) and one for the second shortest time to maturity ($\tau > 30$). The required volatilities for a maturity of 30 days are obtained as a weighted average of the corresponding values from the two volatility curves, with weights being inversely proportional to the distance of the actual maturity from the desired 30-day maturity.

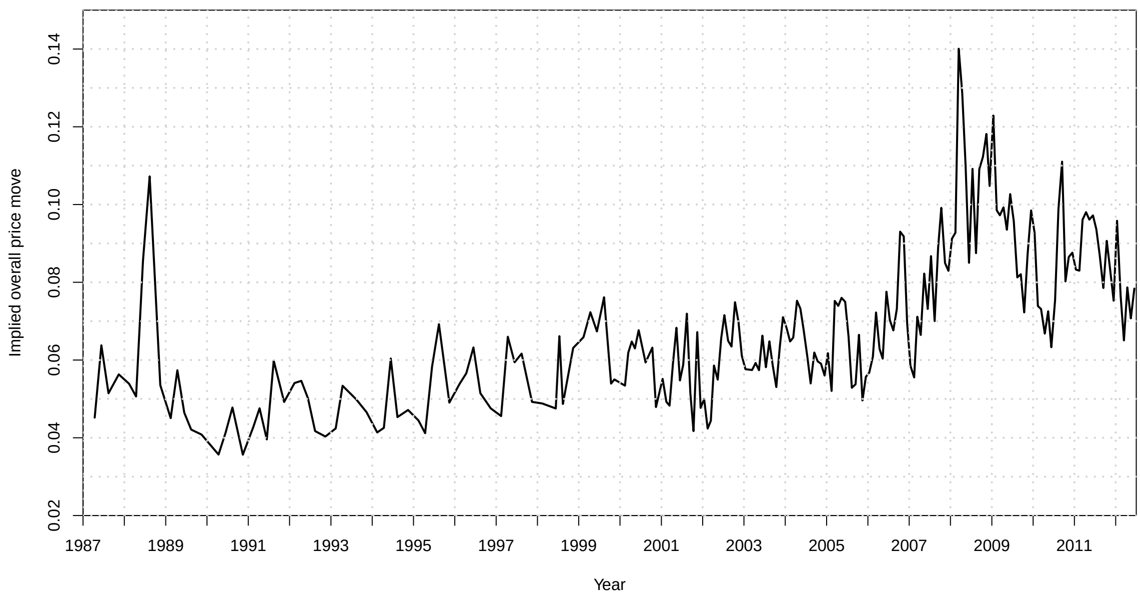
Finally, we have to specify the expected commodity price $E_t\ [S_{t+\tau}] = K$ and the threshold level A. In this respect, we follow the same procedure as previously for the analysis of the wheat market. The expected commodity price for a horizon of 30 days is obtained from the predictions of an autoregressive model of order one fitted to the time series of the monthly relative price changes of futures contracts with the shortest available time to maturity in a 60-month rolling window. In several robustness checks, we use alternative ways to estimate the expected commodity price. Instead of using a rolling window, we fit an autoregressive model of order one to the monthly relative price changes in the whole data period. We also include dummy variables for each calendar month to account for potential seasonality in futures returns. Finally, we analyze total price changes instead of unexpected price changes. Our base case results are qualitatively unchanged in all robustness checks. The threshold level A is set equal to 10% of the current commodity futures price for the analysis in the next two sections.

4.4.2 Properties of forward-looking estimates

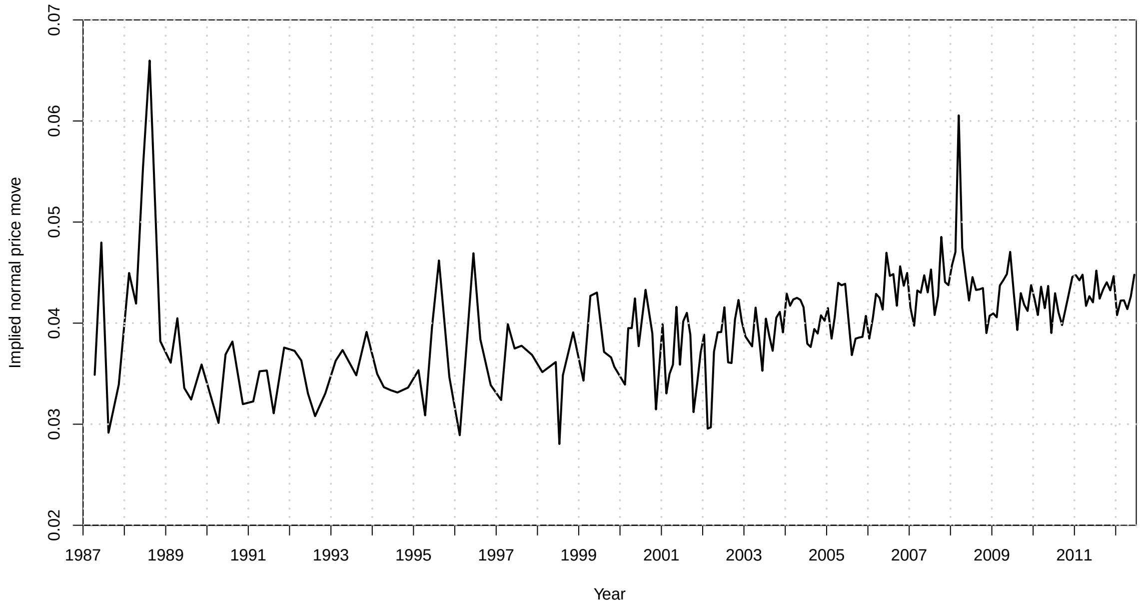
A first important aspect of the implied risk estimates is how they evolve over time. In contrast to our earlier analysis for the wheat market, which is based on realized prices and allows us an assessment of risks in retrospect, implied estimates incorporate the market's ex ante view. Severe changes in the market's risk assessment over short periods are especially interesting, indicating a critical situation that might call for adequate preparation or action. Figure 4.2 depicts the forward-looking risk estimates for the wheat market. The figure has seven panels (panels A to G), one for each of the risk measures. The numbers for OM, NM_A, LM_A, LM_{A+}, and LM_{A-} are given as a percentage of the price at the beginning of the month.

Figure 4.2: Forward-looking risk measures for wheat

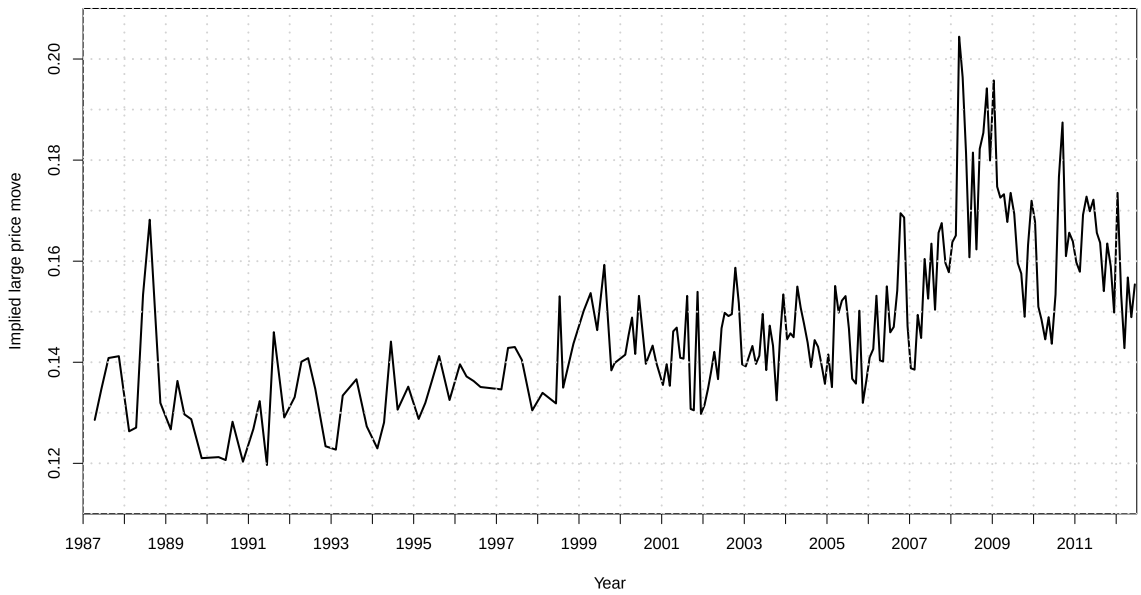
Panel A: Overall price moves (OM^{imp})



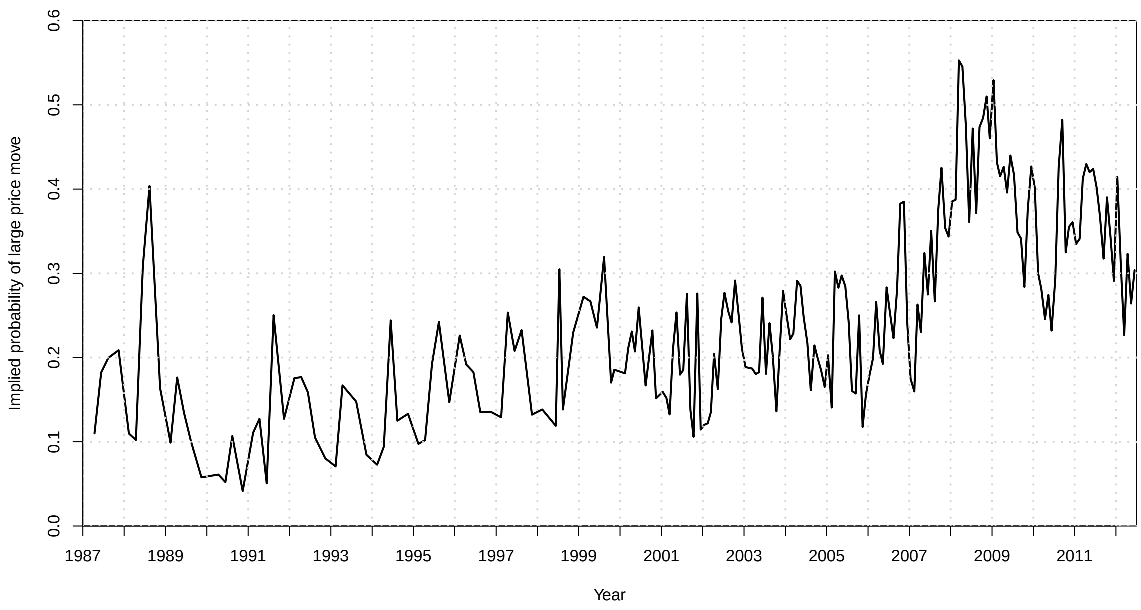
Panel B: Normal price moves ($NM^{imp}_{10\%}$)



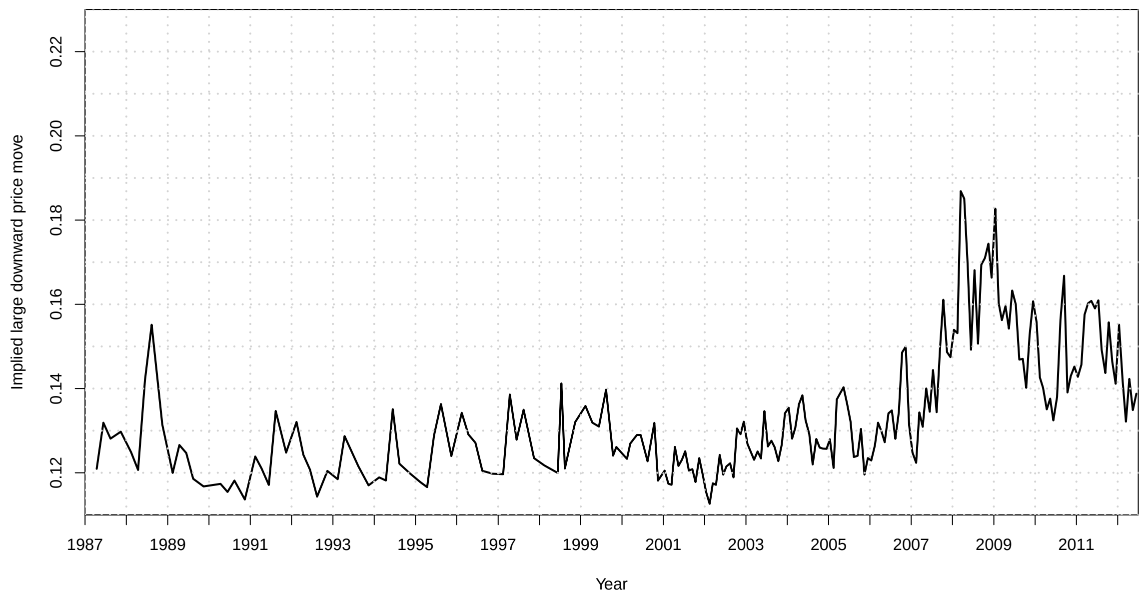
Panel C: Large price moves ($LM_{10\%}^{imp}$)



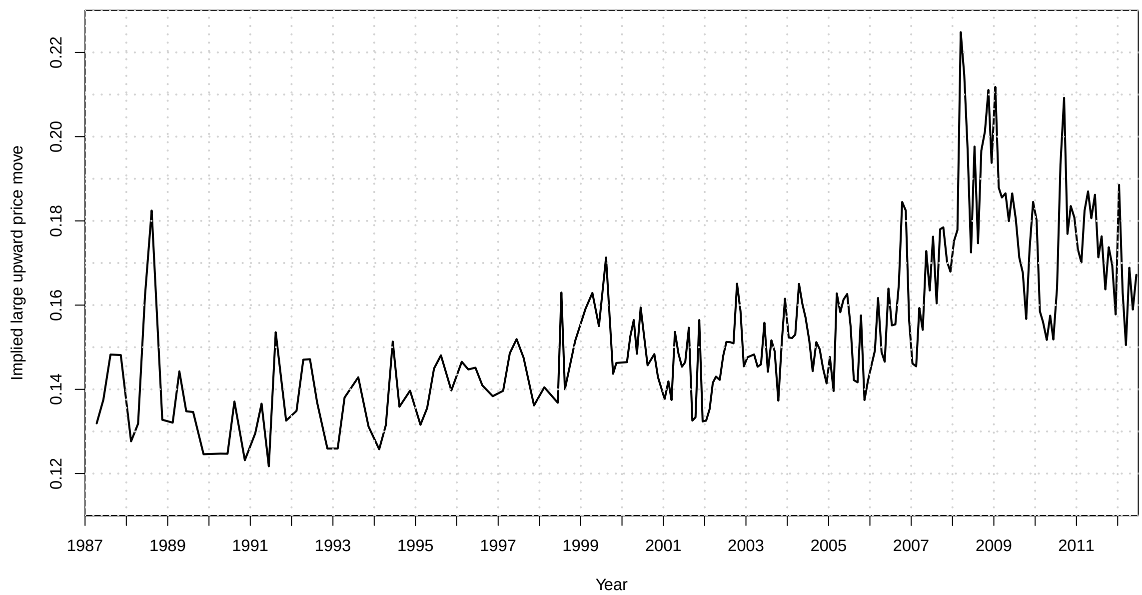
Panel D: Implied probability of large price moves (p_l^{imp})



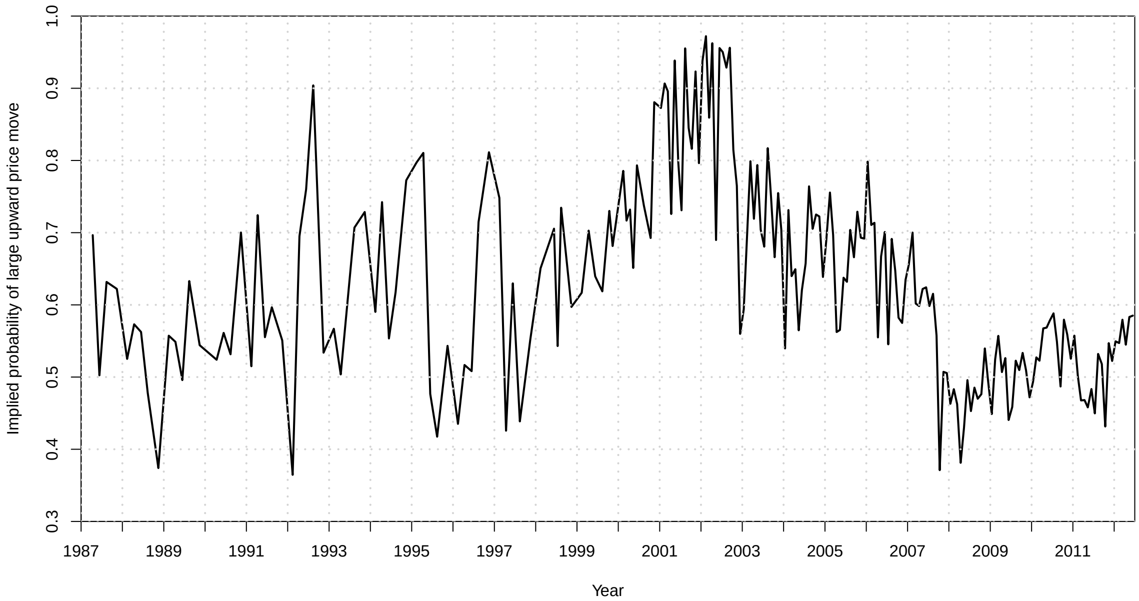
Panel E: Large negative price moves ($LM^{imp}_{10\%-}$)



Panel F: Large positive price moves ($LM^{imp}_{10\%+}$)



Panel G: Implied probability of a large positive price move being positive ($p_{+|l}$)



This figure shows implied estimates of the risk measures OM^{imp}, $NM_{10\%}^{imp}$, $LM_{10\%}^{imp}$, p_{l}^{imp}, $LM_{10\%-}^{imp}$, $LM_{10\%+}^{imp}$, and $p_{+|l}^{imp}$ for wheat. The estimates are obtained from prices of options on wheat futures traded at the CME. The time horizon (τ) is one month and the values for OM^{imp}, $NM_{10\%}^{imp}$, $LM_{10\%}^{imp}$, $LM_{10\%-}^{imp}$, and $LM_{10\%+}^{imp}$ are given as a percentage of the current futures price (price at the beginning of the month). Expected wheat price changes refer to the predictions of an autoregressive model of order one fitted to the time series of the monthly relative price changes of the wheat futures contract with the shortest time to maturity in a 60-month rolling window from March 1987 to June 2012. The threshold level A equals 10% of the current futures price.

All risk measures are clearly time varying and we can identify periods of relatively high and relatively low risk. A particularly interesting issue is the food price crisis in 2007 and 2008. The overall risk measure OM (panel A) shows that the information in option prices indicates a massive increase in risk from about 6% per month at the beginning of 2007 to about 12% at the end of 2008. This increase is not caused by a higher magnitude of normal price moves, as shown in panel B. It is both the magnitude of large price moves and its probability (see panels C and D) that leads to the increase. In particular, the probability of a large price move makes a massive jump from about 15% to over 50%. Changes in the magnitude of large price moves are difficult to assess from historical estimates, since such price moves might not occur at all for long time periods (compare panel C of figure 4.1). Forward-looking implied estimates are especially valuable in such a situation, because a market assessment of the expected magnitude of large price moves does always exist, irrespective of the actual occurrence of such events. As the results of panel C show, an increase in the expected magnitude of large price moves clearly plays a role for the general risk perception during the food price crisis. Information on the direction of large price moves is even more difficult to obtain from historical data. Panels E to G of figure 4.2 show that option-implied information can deal with this issue. Large positive price moves are usually seen to be more severe than negative ones and the magnitudes of both positive and negative price moves increase during the food price crisis. Interestingly, the food price crisis also has an effect on the probability that a large price move is positive. This probability is generally above 50%, but drops over the course of the crisis until both directions are equally likely.

Table 4.1 presents descriptive statistics of the risk measures for all three grain markets. A first observation is that the means and standard deviations of all risk measures are very similar for wheat and corn, whereas they are lower for soybeans. A second finding concerns the comparison between large positive and large negative price moves. For all three markets, option-implied information shows that the magnitude of large price increases is expected to be larger than the magnitude of large price decreases. Moreover, the average probability of a large price move being positive is well above 0.5 for all three markets. Finally, all risk measures show a strong positive autocorrelation. This persistence reflects the fact that there are long periods of relatively high risk and relatively low risk for all three markets.

An interesting question is how far the different risk measures move together over time or react differently to new information. Table 4.2 reports evidence on this issue by showing the correlations between the relative changes of different measures. The results are given separately for each of the three markets in panels A to C.

Table 4.1: Descriptive statistics of forward-looking risk measures

Panel A: Wheat

	Mean	**Std. Dev.**	**Autocor.**
OM^{imp}	0.068	0.019	0.804
$NM^{imp}_{10\%}$	0.040	0.005	0.543
$LM^{imp}_{10\%}$	0.148	0.016	0.775
p^{imp}_{l}	0.246	0.112	0.790
$LM^{imp}_{10\%+}$	0.156	0.020	0.784
$LM^{imp}_{10\%-}$	0.134	0.015	0.826
$p^{imp}_{+\|l}$	0.630	0.136	0.695

Panel B: Corn

	Mean	**Std. Dev.**	**Autocor.**
OM^{imp}	0.066	0.020	0.628
$NM^{imp}_{10\%}$	0.039	0.006	0.322
$LM^{imp}_{10\%}$	0.147	0.016	0.586
p^{imp}_{l}	0.238	0.113	0.692
$LM^{imp}_{10\%+}$	0.154	0.021	0.525
$LM^{imp}_{10\%-}$	0.133	0.015	0.692
$p^{imp}_{+\|l}$	0.636	0.170	0.524

Panel C: Soybeans

	Mean	**Std. Dev.**	**Autocor.**
OM^{imp}	0.059	0.019	0.713
$NM^{imp}_{10\%}$	0.037	0.005	0.644
$LM^{imp}_{10\%}$	0.141	0.016	0.632
p^{imp}_{l}	0.197	0.111	0.717
$LM^{imp}_{10\%+}$	0.148	0.019	0.630
$LM^{imp}_{10\%-}$	0.129	0.014	0.764
$p^{imp}_{+\|l}$	0.594	0.172	0.725

Note: This table reports descriptive statistics of the implied estimates of the risk measures OM^{imp}, $NM^{imp}_{10\%}$, $LM^{imp}_{10\%}$, p^{imp}_{l}, $LM^{imp}_{10\%-}$, $LM^{imp}_{10\%+}$, and $p^{imp}_{+|l}$ for wheat (panel A), corn (panel B), and soybeans (panel C). Estimates of the risk measures are obtained for every month with maturing options contracts and available prices in the periods March 1987 to June 2012 (wheat), October 1987 to June 2012 (corn), and May 1987 to June 2012 (soybeans), leading to 209, 201, and 232 observations, respectively. The variable OM^{imp}, $NM^{imp}_{10\%}$, $LM^{imp}_{10\%}$, $LM^{imp}_{10\%-}$, and $LM^{imp}_{10\%+}$ are given as a percentage of the current futures price (price at the beginning of the month).

Table 4.2: Correlations between different forward-looking risk measures

Panel A: Wheat

	OM^{imp}	$NM_{10\%}^{imp}$	$LM_{10\%}^{imp}$	p_l^{imp}	$LM_{10\%+}^{imp}$	$LM_{10\%-}^{imp}$	$p_{+\mid l}^{imp}$
OM^{imp}	1.000	0.462	0.886	0.819	0.871	0.852	-0.256
$NM_{10\%}^{imp}$	–	1.000	0.109	0.125	0.106	0.244	-0.211
$LM_{10\%}^{imp}$	–	–	1.000	0.776	0.986	0.805	-0.033
p_l^{imp}	–	–	–	1.000	0.768	0.705	-0.195
$LM_{10\%+}^{imp}$	–	–	–	–	1.000	0.810	-0.056
$LM_{10\%-}^{imp}$	–	–	–	–	–	1.000	-0.548
$p_{+\mid l}^{imp}$	–	–	–	–	–	–	1.000

Panel B: Corn

	OM^{imp}	$NM_{10\%}^{imp}$	$LM_{10\%}^{imp}$	p_l^{imp}	$LM_{10\%+}^{imp}$	$LM_{10\%-}^{imp}$	$p_{+\mid l}^{imp}$
OM^{imp}	1.000	0.593	0.864	0.843	0.810	0.816	-0.226
$NM_{10\%}^{imp}$	–	1.000	0.278	0.267	0.204	0.337	-0.214
$LM_{10\%}^{imp}$	–	–	1.000	0.773	0.935	0.717	0.017
p_l^{imp}	–	–	–	1.000	0.735	0.735	-0.209
$LM_{10\%+}^{imp}$	–	–	–	–	1.000	0.588	0.092
$LM_{10\%-}^{imp}$	–	–	–	–	–	1.000	-0.503
$p_{+\mid l}^{imp}$	–	–	–	–	–	–	1.000

Panel C: Soybeans

	OM^{imp}	$NM_{10\%}^{imp}$	$LM_{10\%}^{imp}$	p_l^{imp}	$LM_{10\%+}^{imp}$	$LM_{10\%-}^{imp}$	$p_{+\mid l}^{imp}$
OM^{imp}	1.000	0.690	0.908	0.873	0.923	0.840	-0.206
$NM_{10\%}^{imp}$	–	1.000	0.425	0.463	0.476	0.463	-0.286
$LM_{10\%}^{imp}$	–	–	1.000	0.796	0.987	0.782	0.036
p_l^{imp}	–	–	–	1.000	0.802	0.716	-0.174
$LM_{10\%+}^{imp}$	–	–	–	–	1.000	0.779	0.009
$LM_{10\%-}^{imp}$	–	–	–	–	–	1.000	-0.428
$p_{+\mid l}^{imp}$	–	–	–	–	–	–	1.000

Note: This table reports correlations between the relative changes of implied estimates of the risk measures OM, $NM_{10\%}^{imp}$, $LM_{10\%}^{imp}$, p_l^{imp}, $LM_{10\%-}^{imp}$, $LM_{10\%+}^{imp}$, and $p_{+\mid l}^{imp}$ for wheat (panel A), corn (panel B), and soybeans (panel C). Estimates of the risk measures are obtained for every month with maturing options contracts and available prices in the periods March 1987 to June 2012 (wheat), October 1987 to June 2012 (corn), and May 1987 to June 2012 (soybeans), leading to 208, 200, and 231 observations, respectively.

A comparison of the three panels of table 4.2 shows that all markets provide more or less the same picture. Some risk measures show a very high correlation, as expected, such as the magnitude of a large price move (LM_A) and the magnitude of a large positive price move (LM_{A+}). The correlation coefficient is well above 0.9 for all three markets; which is consistent with market participants expecting large prices moves typically to be positive. This possibly reflects the typical price pattern for storable commodities, with steep price spikes in situations with low stocks (Williams and Wright (1991)). However, there is a lower correlation between other measures. In particular, the magnitude of normal price moves (NM_A) and large price moves (LM_A) always has a correlation below 0.5. This result shows that the two risk components can be quite different, which is further motivation to distinguish between them. Another striking result is the negative correlation of the probability of a large price move being positive with most other risk measures. If risk is generally high, the probability of a large price move being positive is relatively low. We have seen this phenomenon already in figure 4.2 for the wheat market. One interpretation is that a market situation that market participants perceive as very risky must have a high chance for both large positive and large negative price moves, because prices would otherwise explode. In contrast, in a market situation that market participants perceive as calm or normal, large price moves, if they occur at all, can be predominantly positive.

Another interesting issue is how the risk measures for different commodities move together, reflecting market linkages. Table 4.3 shows the correlations between the relative changes of risk measures for all three possible combinations of markets.

Table 4.3: Correlations between forward-looking risk measures of different commodities

	Cor(W, C)	Cor(W, S)	Cor(C, S)
OM^{imp}	0.510	0.482	0.713
$NM^{imp}_{10\%}$	0.098	0.122	0.177
$LM^{imp}_{10\%}$	0.495	0.431	0.758
p^{imp}_{l}	0.504	0.432	0.593
$LM^{imp}_{10\%+}$	0.503	0.434	0.745
$LM^{imp}_{10\%-}$	0.510	0.359	0.558
$p^{imp}_{+\mid l}$	0.086	-0.030	0.310

Note: This table reports correlations between the relative changes of implied estimates of the risk measures (OM^{imp}, $NM^{imp}_{10\%}$, $LM^{imp}_{10\%}$, p^{imp}_{l}, $LM^{imp}_{10\%-}$, $LM^{imp}_{10\%+}$, and $p^{imp}_{+\mid l}$) of different commodities. Here Cor(W,C) denotes the correlation between wheat and corn, Cor(W,S) the correlation between wheat and soybeans, and Cor(C,S) the correlation between corn and soybeans. Estimates of the risk measures are obtained for every month with maturing options contracts and available prices in the periods March 1987 to June 2012 (wheat), October 1987 to June 2012 (corn), and May 1987 to June 2012 (soybeans). The correlations are based on 181 observations.

As expected, all but one correlation are positive, reflecting a similar evolution of risk over time for all markets. However, the correlations are always far below one. This finding indicates important market-specific risk components in addition to common factors. Another result is that the wheat and soybean markets show the lowest correlation of all combinations, which could be explained by their lower substitutability in use. In terms of their risk dynamics over time, corn and soybeans show the greatest similarities, reflecting the direct competition between these crops for planting area.

4.4.3 Forward-looking estimates and future price moves

An important application of our risk measures is to provide evidence on upcoming adverse price moves. Now we test the extent to which the implied estimates of these measures are useful in this respect. For each commodity and each month of the data period, we calculate the realized absolute unexpected price move and classify it as normal or large, depending on its magnitude. In addition, we construct two time series of indicator variables. The first one takes a value of one if the realized price move is large and zero if it is normal. The second one takes a value of one if a large price move is positive and zero if it is negative.

These indicator variables serve as "observations" for the probability of a large price move and the conditional probability of a large positive price move. Then we use predictive regressions to test whether next month's realized absolute price moves (OM), normal price moves ($NM_{10\%}$), large price moves ($LM_{10\%}$), and probabilities (p_l and $p_{+|l}$) can be forecast by the corresponding implied risk measure.[18] For the probabilities, we apply logit regressions. All standard errors for the regression coefficients are based on the Newey and West (1987) covariance matrix estimator with automated lag selection. Table 4.4 presents the regression results.

[18]We do not test the predictive performance for $LM_{10\%+}$ and $LM_{10\%-}$ because of the low number of realized values for these events.

Table 4.4: Regression results: Explaining realized price moves with forward-looking risk measures

Panel A: Wheat

	OM	$NM_{10\%}$	$LM_{10\%}$	p_l	$p_{+\mid l}$
Constant	0.002	0.013	0.053	-3.061***	-7.501***
	(0.886)	(0.338)	(0.368)	(0.000)	(0.003)
Imp	0.940***	0.772**	0.660*	6.164***	13.949***
	(0.000)	(0.028)	(0.077)	(0.000)	(0.005)
R^2	0.102	0.017	0.036	0.076	0.235
N	209	168	41	209	41

Panel B: Corn

	OM	$NM_{10\%}$	$LM_{10\%}$	p_l	$p_{+\mid l}$
Constant	0.020*	0.043***	-0.036	-2.801***	-2.143*
	(0.061)	(0.002)	(0.575)	(0.000)	(0.054)
Imp	0.700***	0.021	1.284***	5.221***	3.765*
	(0.000)	(0.951)	(0.005)	(0.000)	(0.066)
R^2	0.058	0.000	0.070	0.054	0.048
N	201	163	38	201	38

Panel C: Soybeans

	OM	$NM_{10\%}$	$LM_{10\%}$	p_l	$p_{+\mid l}$
Constant	-0.008	0.020	-0.037	-3.216***	-1.935
	(0.498)	(0.202)	(0.384)	(0.000)	(0.180)
Imp	1.145***	0.583	1.248***	7.058***	3.891
	(0.000)	(0.165)	(0.000)	(0.000)	(0.150)
R^2	0.183	0.011	0.301	0.105	0.045
N	232	194	38	232	38

Note: This table reports the results of regressions that explain realized monthly unexpected price moves by the corresponding estimates of the implied risk measures at the beginning of the month. P-values are given in brackets, with *,**,*** denoting significance at the 10%, 5%, 1% levels, respectively. Panel A shows the results for wheat, panel B for corn, and panel C for soybeans. Estimates of the risk measures are obtained for every month with maturing options contracts and available prices in the periods March 1987 to June 2012 (wheat), October 1987 to June 2012 (corn), and May 1987 to June 2012 (soybeans). Realized price moves are calculated for the same periods from commodity futures contracts with the shortest available time to maturity. Both futures and option prices refer to contracts traded at the CME. The threshold level A equals 10% of the current commodity futures price.

The regressions clearly show that implied risk measures have predictive power for future price moves. For the 15 regressions, we find 12 significant coefficients, nine at the 1% significance level and all with the expected positive sign. The results for the overall risk measure (OM), the magnitude of large price moves ($LM_{10\%}$), and the probability of a large price move (p_l) are significant for all three markets and the implied estimates for the conditional probability of large price moves being positive ($p_{+|l}$) has significant predictive power for wheat and corn. The prediction of the magnitude of normal price moves ($NM_{10\%}$) seems to be more difficult, since for the former there is a significant coefficient (at the 5% level) only for wheat. The reason could be that normal price moves have by far the lowest variation over time of all risk measures and there is just not much time variation to explain or predict.

In a next step, we investigate whether historical estimates provide any additional information about future price moves that is not contained in implied estimates. As a test, we consider both implied and historical estimates as predictors in the regression models. Historical estimates of the risk measures use rolling estimation windows of 60 months. The results of table 4.5 provide very clear evidence. Out of 12 significant coefficients for the implied estimates from table 4.4, 11 remain significant, but only two of the coefficients for the historical estimates become significant. These two significant coefficients ($LM_{10\%}$ for corn and $p_{+|l}$ for soybeans) even have negative signs. Accordingly, we can conclude that implied estimates already capture all the information about future price moves that is contained in historical estimates.

Table 4.5: Regression results: Explaining realized price moves with forward-looking and historical risk measures

Panel A: Wheat

	OM	$NM_{10\%}$	$LM_{10\%}$	p_l	$p_{+\|l}$
Constant	0.003	0.014	0.073	-2.908***	-9.261***
	(0.851)	(0.521)	(0.436)	(0.000)	(0.001)
Imp	0.962***	0.799**	0.745*	7.346***	14.294***
	(0.000)	(0.016)	(0.068)	(0.000)	(0.0.006)
Hist	-0.047	-0.058	-0.221	-2.582	2.644
	(0.894)	(0.911)	(0.733)	(0.307)	(0.221)
R^2	0.102	0.017	0.039	0.081	0.2589
N	209	168	41	209	41

Panel B: Corn

	OM	$NM_{10\%}$	$LM_{10\%}$	p_l	$p_{+\|l}$
Constant	0.012	0.046**	0.195**	-2.952***	0.133
	(0.564)	(0.045)	(0.018)	(0.000)	(0.925)
Imp	0.632***	0.031	2.229***	3.627**	3.535
	(0.001)	(0.928)	(0.000)	(0.031)	(0.192)
Hist	0.214	-0.066	-2.529***	3.334	-4.200
	(0.623)	(0.882)	(0.000)	(0.155)	(0.135)
R^2	0.060	0.000	0.357	0.064	0.0916
N	201	163	38	201	41

Panel C: Soybeans

	OM	$NM_{10\%}$	$LM_{10\%}$	p_l	$p_{+\|l}$
Constant	-0.008	0.017	-0.019	-3.251***	1.274
	(0.556)	(0.297)	(0.720)	(0.000)	(0.514)
Imp	1.145***	0.510	1.318***	6.905***	3.193
	(0.000)	(0.281)	(0.000)	(0.000)	(0.330)
Hist	0.002	0.141	-0.193	0.469	-4.853***
	(0.994)	(0.695)	(0.566)	(0.843)	(0.005)
R^2	0.183	0.011	0.308	0.105	0.110
N	232	194	38	232	38

Note: This table reports the results of regressions that explain realized monthly unexpected price moves by the corresponding implied and historical risk estimates at the beginning of the month. P-values are given in brackets, with *,**,*** denoting significance at the 10%, 5%, 1% levels, respectively. Panel A shows the results for wheat, panel B for corn, and panel C for soybeans. Implied and historical estimates for the risk measures are obtained for every month with maturing options contracts and available prices in the periods March 1987 to June 2012 (wheat), October 1987 to June 2012 (corn), and May 1987 to June 2012 (soybeans). Historical estimates use a rolling estimation window of 60 months. Realized price moves are calculated for the same periods from commodity futures contracts with the shortest available time to maturity. Both futures and option prices refer to contracts traded at the CME. The threshold level A equals 10% of the current commodity futures price.

Since implied estimators exploit the expectations of market participants via observed option prices, they could contain all relevant information on future price moves, including all information about market fundamentals. However, market participants may not fully incorporate such fundamental information or misinterpret it. In this case, fundamental drivers of volatility would be useful supplements to the forward-looking risk measures. For this reason, we add potential volatility drivers to the predictive regressions. In particular, we use the stocks to use ratio (*Stocks*), the Southern Oscillation Index (*SOI*), the volatility of relative oil price changes (*Oil Vol.*), and the volatility of relative changes of the dollar against a trade-weighted portfolio of seven major currencies (*Dollar Vol.*), which have been used in previous studies as potential determinants of commodity price volatility (Roache (2010); Brümmer, Korn, Schlüßler, and Jamali Jaghdani (2014)). The Southern Oscillation Index is split into its positive part, (*SOI+*), which is an indication of the La Niña phenomenon, and its negative part, (*SOI-*), indicating the strength of the El Niño effect. Oil volatility is an implied value estimated from options traded on the New York Mercantile Exchange. A detailed description of the data sources and the calculation of the variables is given by Brümmer, Korn, Schlüßler, and Jamali Jaghdani (2014). It is important to note that we do not hypothesize a particular sign for the coefficients of the fundamental explanatory variables. The reason is that we measure their effects in addition to what is already captured by the implied risk measures, reflecting the expectations of market participants, and we do not know if market participants underestimate or overestimate the impact of the further explanatory variables on volatility.

Table 4.6: Regression results: Explaining realized price moves with forward-looking risk measures, historical risk measures, and different drivers of supply and demand

Panel A: Wheat

	OM	$NM_{10\%}$	$LM_{10\%}$	p_l	$p_{+\|l}$
Constant	0.012	0.004	0.059	-1.304*	-9.949**
	(0.515)	(0.880)	(0.613)	(0.094)	(0.024)
Imp	1.017***	0.834**	0.713	8.350***	16.428***
	(0.000)	(0.016)	(0.220)	(0.000)	(0.001)
Hist	0.186	-0.089	-0.348	0.648	3.366
	(0.642)	(0.889)	(0.552)	(0.781)	(0.302)
Stocks	-0.018	0.000	0.056	-1.906*	1.356
	(0.118)	(0.990)	(0.480)	(0.087)	(0.590)
SOI+	-0.015*	-0.001	-0.013	-0.626*	-0.135
	(0.067)	(0.886)	(0.443)	(0.062)	(0.815)
SOI–	0.008	-0.003	0.040**	0.397	1.012
	(0.264)	(0.605)	(0.034)	(0.380)	(0.393)
Oil Vol.	-0.019	0.023	0.022	-2.222	-6.224*
	(0.528)	(0.189)	(0.805)	(0.185)	(0.078)
Dollar Vol.	-0.008	0.012	0.270	-3.366	17.381
	(0.967)	(0.884)	(0.415)	(0.713)	(0.118)
R^2	0.130	0.030	0.131	0.129	0.302
N	209	168	41	209	41

Panel B: Corn

	OM	$NM_{10\%}$	$LM_{10\%}$	p_{l}	$p_{+\|l}$
Constant	0.016	0.044*	-0.045	-1.289	-0.131
	(0.539)	(0.068)	(0.628)	(0.160)	(0.964)
Imp	0.687***	-0.040	2.880***	3.698*	7.356
	(0.008)	(0.902)	(0.000)	(0.066)	(0.202)
Hist	0.177	-0.253	-1.606	1.300	-5.621*
	(0.701)	(0.591)	(0.004)	(0.673)	(0.059)
Stocks	-0.013	-0.023	0.218***	-4.811	-6.377*
	(0.862)	(0.249)	(0.002)	(0.198)	(0.055)
SOI+	0.001	0.007**	-0.011	-0.257	1.384*
	(0.912)	(0.031)	(0.375)	(0.497)	(0.067)
SOI–	-0.001	-0.009**	-0.013	0.764	-0.082
	(0.850)	(0.035)	(0.444)	(0.246)	(0.947)
Oil Vol.	0.013	0.014	0.068	-0.614	1.709
	(0.643)	(0.583)	(0.183)	(0.694)	(0.742)
Dollar Vol.	-0.146	0.072	-0.736***	-0.171	-27.297
	(0.507)	(0.472)	(0.002)	(0.985)	(0.208)
R^2	0.063	0.060	0.525	0.088	0.201
N	201	163	38	201	38

Panel C: Soybeans

	OM	$NM_{10\%}$	$LM_{10\%}$	p_l	$p_{+\|l}$
Constant	0.027	0.031*	-0.004	-1.066	3.551
	(0.141)	(0.081)	(0.894)	(0.301)	(0.203)
Imp	1.051***	0.416	1.355***	5.438***	2.899
	(0.000)	(0.332)	(0.000)	(0.002)	(0.429)
Hist	-0.025	-0.236	0.021	1.003	-5.700***
	(0.922)	(0.565)	(0.870)	(0.704)	(0.005)
Stocks	-0.111***	-0.023	-0.122	-7.882**	-1.098
	(0.004)	(0.364)	(0.204)	(0.016)	(0.875)
SOI+	-0.005	-0.001	0.001	-0.375	-0.558
	(0.503)	(0.709)	(0.958)	(0.317)	(0.398)
SOI–	0.005	0.004	-0.003	0.160	1.044
	(0.507)	(0.188)	(0.861)	(0.712)	(0.255)
Oil Vol.	-0.006	0.038**	-0.043	-3.005*	-3.111
	(0.814)	(0.030)	(0.116)	(0.092)	(0.518)
Dollar Vol.	-0.046	-0.059	-0.278*	10.074	3.511
	(0.694)	(0.489)	(0.057)	(0.238)	(0.862)
R^2	0.209	0.045	0.389	0.146	0.145
N	232	194	38	232	38

Note: This table reports the results of regressions that explain realized monthly unexpected price moves by the corresponding implied and historical risk estimates at the beginning of the month and additional drivers of supply and demand. P-values are given in brackets, with *,**,*** denoting significance at the 10%, 5%, 1% levels, respectively. Panel A shows the results for wheat, panel B for corn, and panel C for soybeans. Implied and historical estimates of the risk measures are obtained for every month with maturing options contracts and available prices in the periods March 1987 to June 2012 (wheat), October 1987 to June 2012 (corn), and May 1987 to June 2012 (soybeans). Historical estimates use a rolling estimation window of 60 months. Realized price moves are calculated for the same periods from commodity futures contracts with the shortest available time to maturity. Both futures and option prices refer to contracts traded at the CME. The threshold level A equals 10% of the current commodity futures price. The additional drivers of supply and demand are the stocks-to-use ratio (*Stocks*), the Southern Oscillation Index (*SOI*) split into its positive (*SOI+*) and negative (*SOI-*) parts, the volatility of relative oil price changes (*Oil Vol.*), and the volatility of relative changes of the dollar against a trade-weighted portfolio of seven major currencies (*Dollar Vol.*).

The results of the predictive regressions for the extended set of explanatory variables are given in table 4.6. The most important finding is that the effects of the implied risk measures are almost unchanged. They are significant in 10 out of 15 regressions and are by far the most important explanatory variable. Of the additional explanatory variables, the stocks-to-use ratio is the most important. The corresponding coefficient has a negative sign in the logit regressions explaining p_l for all three markets, with two significant coefficients.

This result suggests that the impact of low stocks on the probability of large price moves is underestimated by the implied probability and low stocks are an additional useful indicator. Overall, there are five significant coefficients for the stocks-to-use ratio. The other explanatory variables seem to be less important, with four (*SOI+*), three (*Oil Vol.*), or two (*SOI-*, *Dollar Vol.*, *Hist*) significant coefficients and no systematic pattern across markets.

A conceptual issue concerning implied risk measures is their calculation from risk-neutral probabilities. If option prices contain significant risk premiums, the resulting values could be biased estimates of the corresponding real-world risk measures. As a robustness check, we investigate to what extent certain risk adjustments affect our regression results. In the framework of a representative investor model, Brinkmann and Korn (2014) show how expected payoffs of put and call options under real-world probabilities can be obtained from observed option prices and the preferences of the representative investor (Brinkmann and Korn 2014, equations (4) and (5)). We implement this approach for an investor with constant relative risk aversion utility and a relative risk aversion parameter equal to two.[19] The results of the predictive regressions with implied estimates replaced by risk-adjusted implied estimates (*Adj. Imp*) are reported in table 4.7.

[19] Relative risk aversion between one and four is standard in the literature. Our results are qualitatively unchanged if we vary the risk aversion within this range.

Table 4.7: Regression results: Explaining realized price moves with forward-looking risk measures under the physical probability measure, historical risk measures, and different drivers of supply and demand

Panel A: Wheat

	OM	$NM_{10\%}$	$LM_{10\%}$	p_l	$p_{+\|l}$
Constant	0.018	0.008	0.091	-1.558*	-13.540***
	(0.369)	(0.765)	(0.392)	(0.071)	(0.002)
Adj. Imp	0.855***	0.850**	0.440	9.332***	19.790***
	(0.000)	(0.014)	(0.318)	(0.000)	(0.000)
Hist	0.227	-0.185	-0.319	0.646	3.251**
	(0.560)	(0.779)	(0.599)	(0.800)	(0.010)
Stocks	-0.019	0.000	0.052	-2.003*	1.098
	(0.134)	(0.952)	(0.506)	(0.091)	(0.522)
SOI+	-0.014*	-0.001	-0.012	-0.589*	-0.241
	(0.067)	(0.889)	(0.473)	(0.078)	(0.384)
SOI–	0.008	-0.003	0.040**	0.384	1.111***
	(0.260)	(0.616)	(0.031)	(0.406)	(0.004)
Oil Vol.	-0.021	0.021	0.027	-2.259	-7.149***
	(0.484)	(0.218)	(0.765)	(0.189)	(0.000)
Dollar Vol.	0.001	0.003	0.278	-2.956	17.004***
	(0.994)	(0.973)	(0.408)	(0.747)	(0.000)
R^2	0.123	0.033	0.125	0.130	0.304
N	209	168	41	209	41

Panel B: Corn

	OM	$NM_{10\%}$	$LM_{10\%}$	p_l	$p_{+\|l}$
Constant	0.021	0.041*	0.096	-1.432	-2.053
	(0.433)	(0.087)	(0.271)	(0.132)	(0.611)
Adj. Imp	0.499***	0.044	1.520***	4.220*	9.100
	(0.009)	(0.891)	(0.001)	(0.055)	(0.177)
Hist	0.292	-0.269	-1.314**	1.354	-5.590*
	(0.524)	(0.567)	(0.018)	(0.657)	(0.054)
Stocks	-0.020	-0.021	0.215***	-4.870	-6.313*
	(0.794)	(0.296)	(0.008)	(0.198)	(0.058)
SOI+	0.001	0.007**	-0.013	-0.242	1.376*
	(0.886)	(0.031)	(0.366)	(0.523)	(0.067)
SOI–	-0.001	-0.010**	-0.007	0.763	-0.059
	(0.906)	(0.033)	(0.733)	(0.252)	(0.962)
Oil Vol.	0.011	0.014	0.091	-0.526	1.534
	(0.681)	(0.568)	(0.173)	(0.735)	(0.773)
Dollar Vol.	-0.133	0.067	-0.773***	-0.728	-28.411
	(0.531)	(0.498)	(0.004)	(0.936)	(0.195)
R^2	0.054	0.061	0.428	0.090	0.257
N	201	163	38	201	38

Panel C: Soybeans

	OM	$NM_{10\%}$	$LM_{10\%}$	p_l	$p_{+\|l}$
Constant	0.029	0.031*	0.083***	-1.185	3.206
	(0.123)	(0.076)	(0.009)	(0.259)	(0.308)
Adj. Imp	0.799***	0.417	0.741***	5.611***	2.864
	(0.001)	(0.309)	(0.000)	(0.002)	(0.477)
Hist	0.146	-0.229	-0.023	1.464	-5.717***
	(0.552)	(0.568)	(0.859)	(0.575)	(0.004)
Stocks	-0.122***	-0.023	-0.184*	-8.176**	-0.798
	(0.002)	(0.353)	(0.080)	(0.013)	(0.908)
SOI+	-0.004	-0.001	0.001	-0.368	-0.549
	(0.559)	(0.726)	(0.909)	(0.325)	(0.404)
SOI–	0.004	0.004	-0.001	0.155	1.028
	(0.530)	(0.183)	(0.957)	(0.723)	(0.264)
Oil Vol.	-0.004	0.037**	-0.022	-2.900	-3.132
	(0.896)	(0.040)	(0.465)	(0.100)	(0.515)
Dollar Vol.	-0.027	-0.062	-0.244*	10.240	3.265
	(0.812)	(0.467)	(0.052)	(0.226)	(0.872)
R^2	0.190	0.045	0.291	0.145	0.197
N	232	194	38	232	38

Note: This table reports the results of regressions that explain realized monthly unexpected price moves by the corresponding implied and historical risk estimates at the beginning of the month and additional drivers of supply and demand. P-values are given in brackets, with *,**,*** denoting significance at the 10%, 5%, 1% levels, respectively. Panel A shows the results for wheat, panel B for corn, and panel C for soybeans. Implied and historical estimates of the risk measures are obtained for every month with maturing options contracts and available prices in the periods March 1987 to June 2012 (wheat), October 1987 to June 2012 (corn), and May 1987 to June 2012 (soybeans). Implied estimates are computed under the physical probability measure using a representative investor with constant relative risk aversion utility and a relative risk aversion of 2. Historical estimates use a rolling estimation window of 60 months. Realized price moves are calculated for the same periods from commodity futures contracts with the shortest available time to maturity. Both futures and option prices refer to contracts traded at the CME. The threshold level A equals 10% of the current commodity futures price. The additional drivers of supply and demand are the stocks-to-use ratio (*Stocks*), the Southern Oscillation Index (*SOI*) split into its positive (*SOI+*) and negative (*SOI-*) parts, the volatility of relative oil price changes (*Oil Vol.*), and the volatility of relative changes of the dollar against a trade-weighted portfolio of seven major currencies (*Dollar Vol.*).

The results are basically unchanged compared to those in table 4.6. Implied estimates remain to be significant in 10 out of 15 cases and the stocks-to-use ratio remains the second most important variable. Since the risk adjustment does not lead to a systematic improvement of the regressions' R^2 values either, we can conclude that the risk-adjusted implied risk measures have no advantage over the simple ones.

4.4.4 Implied thresholds

The distinction between large and normal price moves rests on the choice of a specific threshold that defines a critical price level.[20] An alternative way of defining large price moves is to fix the probability of their occurrence, which leads to a time-varying threshold level for distinguishing between large and normal moves. Such a threshold could be interpreted as a protection level for price increases (decreases) for which one should be prepared.[21] Our methodology allows for the option-implied estimation of such a time-varying threshold. Equation (4.7) shows that an estimate of the probability of a large price move can be obtained from the prices of digital options with strike prices $K + A$ and $K - A$. An implied estimate of A arises from the inversion of this relation:

$$p_l \; = \; e^{r\tau} \left[\, D^C(\tau,\, K + A^{imp}) + D^P\,(\tau,\, K - A^{imp}) \, \right], \tag{4.16}$$

where p_l is the chosen probability and $K + A^{imp}$ and $K - A^{imp}$ are the strike prices of digital call and put options, respectively, ensuring that equation (4.16) holds. We have seen, however, that the probabilities for large positive and large negative price moves can be quite different. Accordingly, it is useful to distinguish between positive and negative price moves with respect to the threshold as well. If we fix the probabilities for large positive price moves ($p_{l,+}$) and large negative price moves ($p_{l,-}$), the corresponding implied thresholds A_+^{imp} and A_-^{imp} are obtained from the conditions

$$p_{l,+} \; = \; e^{r\tau} \left[\, D^C(\tau,\, K + A_+^{imp}) \, \right], \tag{4.17}$$

$$p_{l,-} \; = \; e^{r\tau} \left[\, D^P(\tau,\, K - A_-^{imp}) \, \right]. \tag{4.18}$$

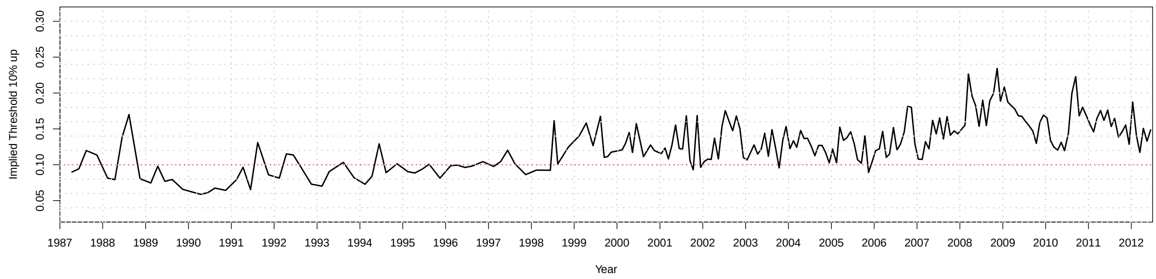
Estimates of A_+^{imp} and A_-^{imp} for wheat, corn, and soybeans for probabilities $p_{l,+} = p_{l,-} = 0.1$ are depicted in figure 4.3. For each commodity, the upper graph shows the results for A_+^{imp} and the lower graph the results for A_-^{imp}.

[20] In our previous analysis, this critical price level was set at 10% above (below) the expected price. The results for other fixed threshold levels support the main findings of our study and are available upon request.

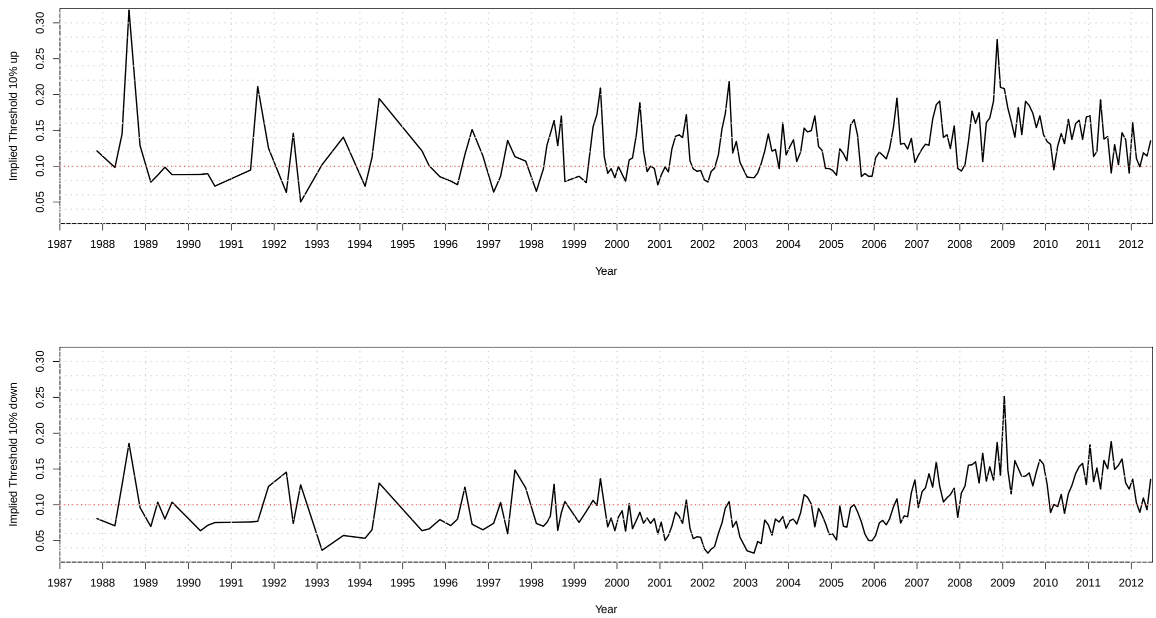
[21] This is basically the idea of the value-at-risk concept, which has been extensively used as a risk measure by financial institutions.

Figure 4.3: Implied thresholds for positive and negative price moves.

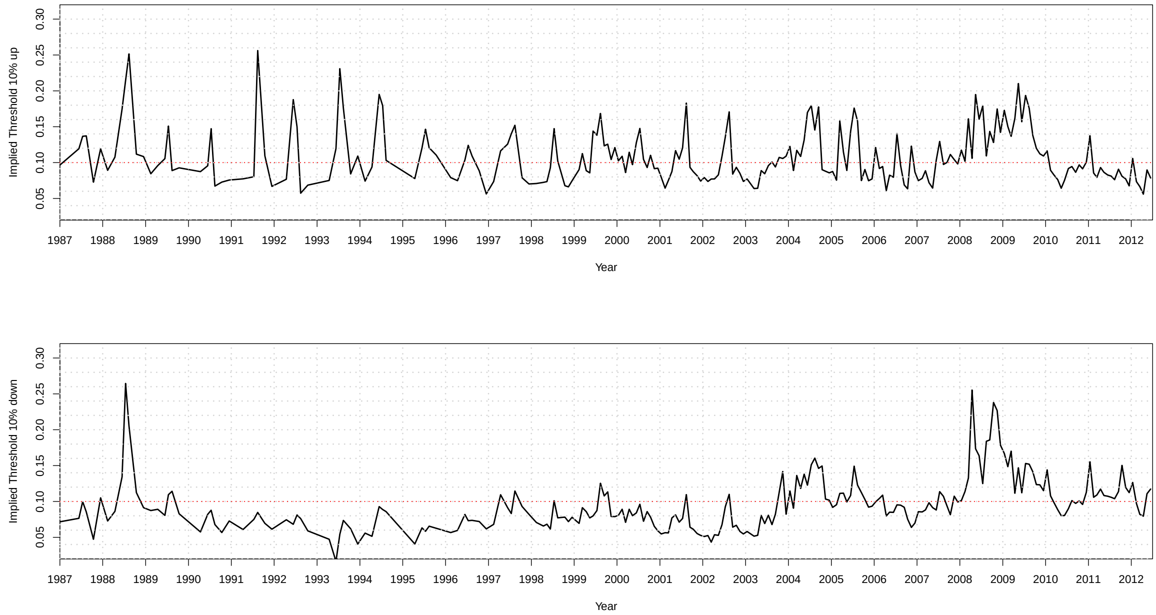
Panel A: Implied thresholds for wheat



Panel B: Implied thresholds for corn



Panel C: Implied thresholds for soybeans



This figure shows implied estimates of the threshold levels A_+^{imp} and A_-^{imp} for wheat (panel A), corn (panel B), and soybeans (panel C). The upper graph for each panel shows the results for A_+^{imp} and the lower graph the results for A_-^{imp}. The estimates are obtained from prices of options on futures traded at the CME. The time horizon (τ) is one month and the values for A_+^{imp} and A_-^{imp} are given as a percentage of the current futures price (price at the beginning of the month). Expected price changes refer to the predictions of an autoregressive model of order one fitted to the time series of the monthly relative price changes of the futures contract with the shortest time to maturity in a 60-month rolling window for the periods March 1987 to June 2012 (wheat), October 1987 to June 2012 (corn), and May 1987 to June 2012 (soybeans). The probabilities $p_{l,+}$ and $p_{l,-}$ are fixed at 0.1.

The implied thresholds are quite volatile over time and there is no clear evidence for thresholds being generally higher or lower for one of the three commodities. A general pattern, however, for all three commodities, is an asymmetry between positive and negative price moves. The thresholds for positive price moves are higher, on average, meaning that the protection level for the event of a large price increase needs to be higher (for a given probability) than the protection level for a large price drop. All three commodities have another feature in common: their behavior in the food price crisis. Threshold levels were not particularly high at the beginning of 2007, compared to historical averages. By the end of 2008 they had more than doubled for all commodities and for both positive and negative price moves.

4.5 Conclusions

A better understanding of price volatility in agricultural commodity markets is crucial for consumers, producers, traders, and policy makers alike. This article contributes in different ways to such an understanding. On the methodological side, it introduces a set of related risk measures that characterize the detailed structure of unexpected price moves. These measures decompose overall price moves into large and normal ones, considering both their expected magnitudes and probabilities of occurrence. Large moves are further decomposed into positive and negative ones, because the direction of a price move is crucial in determining its economic consequences. A second methodological contribution of this article is the derivation of implied estimators of the risk measures. These estimators are forward looking because they extract market expectations about future commodity price moves contained in current option prices. On the empirical side, the article provides an extensive volatility analysis for three major markets (wheat, corn, and soybeans) based on the implied risk measures and their historical counterparts.

Our empirical results show that different measures indeed capture different aspects of price volatility. For example, we see that, for wheat, the distinguishing feature of the food price crisis of 2007–2008 is the higher probability of large price changes but not the magnitude of either normal or large price moves. This finding may explain why farmers and traders felt that volatility was much higher during the food price crisis than suggested by standard volatility measures. Our results also indicate that the magnitude of large positive price moves is generally expected to be greater than the magnitude of negative ones and that the conditional probability of large price jumps being positive decreases in periods of market turmoil. Another key finding of our study is that the implied estimators of our risk measures have very plausible properties and show a much higher information content for future price moves than historical estimators do.

The application of our implied risk measures still faces different challenges. A first issue is the choice of an appropriate threshold level that defines large price moves. Such a choice should be made in light of the potential consequences of a price change and may be a complex market-specific issue. Our approach offers the flexibility, however, of treating the threshold as a free parameter that can also change over time and to obtain implied estimates of the threshold. A clear limitation of our approach is the requirement of reliable option prices, which limits the number of commodity markets that qualify for an application of implied risk measures. For large threshold levels, we face the additional problem that options with strike prices far out of the money have to be available. In terms of application, another challenging problem is the integration of implied risk measures into sophisticated early warning systems. We have provided evidence that implied estimators contain useful information about future price changes, but the best way to combine (implied) expectations of option market participants with more traditional market indicators and fundamental volatility drivers is still an open issue for further research.

Appendix

This appendix illustrates the relation between the second to fourth moments of unexpected price moves and our risk measures via the Gram–Charlier distribution (Jondeau and Rockinger (2001)). The Gram–Charlier distribution is an extension of the normal distribution that allows for non-zero skewness and excess kurtosis. It has four parameters, each of which corresponds to a specific moment. The first one determines the mean, the second one the standard deviation, the third one skewness, and the fourth one excess kurtosis. Therefore, the Gram–Charlier distribution is ideally suited for disentangling the effects of different moments.

Table 4.8 shows the values of all seven risk measures under the assumption that an unexpected price change follows a Gram–Charlier distribution. We consider four different parameter combinations. The starting point is $GC(0, 1, 0, 0)$, which refers to a Gram–Charlier distribution with mean zero, unit standard deviation, zero skewness, and zero excess kurtosis, that is, a standard normal distribution. The second distribution ($GC(0, 1.1, 0, 0)$) has an increased standard deviation of 1.1, but still zero skewness and excess kurtosis. The third distribution ($GC(0, 1, 1, 0)$) introduces a positive skewness of one without excess kurtosis and the fourth distribution ($GC(0, 1, 0, 2.5)$) has an excess kurtosis of 2.5 but no skewness. In addition, table 4.8 considers three different threshold levels A (1,2, and 3).

Table 4.8: Risk measures for different distributions and thresholds

	$GC\,(0,\,1,\,0,\,0)$	$GC\,(0,\,1.1,\,0,\,0)$	$GC\,(0,\,1,\,1,\,0)$	$GC\,(0,\,1,\,0,\,2.5)$
OM	0.798	0.878	0.827	0.715
NM_1	0.460	0.467	0.467	0.424
LM_1	1.526	1.599	1.571	1.770
p_l	0.317	0.363	0.327	0.216
LM_{1+}	1.526	1.599	1.779	1.770
LM_{1-}	1.526	1.599	1.375	1.770
$p_{+\mid l}$	0.500	0.500	0.485	0.500
NM_2	0.723	0.762	0.730	0.506
LM_2	2.376	2.436	2.492	2.746
p_l	0.045	0.069	0.055	0.068
LM_{2+}	2.376	2.436	2.532	2.746
LM_{2-}	2.376	2.436	2.122	2.746
$p_{+\mid l}$	0.500	0.500	0.902	0.500
NM_3	0.791	0.862	0.809	0.661
LM_3	3.288	3.336	3.356	3.422
p_l	0.003	0.006	0.007	0.019
LM_{3+}	3.288	3.336	3.356	3.422
LM_{3-}	3.288	3.336	–	3.422
$p_{+\mid l}$	0.500	0.500	1.000	0.500

Note: This table reports the risk measures OM, NM, LM, p_l, LM_-, LM_+, and $p_{+\mid l}$ for different distributions of unexpected price changes and different threshold levels A. We consider four different distributions that belong to the class of Gram–Charlier (GC) distributions. These distributions have four parameters. The first one specifies the expected value, the second one the standard deviation, the third one skewness, and the fourth one excess kurtosis. The threshold level is chosen to be either 1, 2, or 3.

Starting from the reference point of a standard normal distribution, we see that an increase in the standard deviation leads to higher values for all risk measures, irrespective of the threshold level. The only exception is the (conditional) probability of a large price move being positive, which is 0.5 for all symmetric distributions. If the standard deviation were the only parameter that changed over time, all risk measures would always move in the same direction. This is not what we observe for the wheat market, however. Our earlier analysis has shown that the probability of a large price move decreases substantially from 2008 to 2009 while at the same time the magnitude of both normal and large price moves increases. These findings suggest that knowledge of the standard deviation alone, be it historical or implied, is not sufficient to understand the fine structure of risk.

For skewness and kurtosis, we see from table 4.8 that their effects can depend on the threshold level A. A skewness of one leads to a lower (conditional) probability of a large positive price move than in the analogous symmetric distribution (0.485 versus 0.5) for $A = 1$. If $A = 2$, this relation is reversed (0.902 versus 0.5). A similar effect can be seen for kurtosis. Excess kurtosis of 2.5 leads to a decrease of the probability of a large price move (from 0.317 to 0.216) for $A = 1$. If $A = 2$, the probability increases from 0.045 to 0.055.

In summary, our illustrations show that a single volatility measure, be it implied or historical, is not sufficient to characterize the detailed structure of risk. Moreover, to supplement this measure by information on implied skewness and kurtosis might not be sufficient either, because the effect of greater skewness and kurtosis depends on the relevant threshold level that defines large price moves.

5

Conclusions

This thesis gives insights into the genesis and development of volatility on agricultural markets by focussing on three research questions. First, in Chapter 2, I conduct a comprehensive analysis of volatility on three agricultural commodity markets that allows to answer the question how volatility has developed since the food price crisis. Second, Chapter 3 provides findings on the determinants of volatility by analyzing a broad set of commodity markets and (potential) volatility drivers. Finally, Chapter 4 takes a closer look at how volatility and specific price risks can be forecast. The main results are briefly summarized in the following.

The analysis of different volatility measures in three agricultural commodity markets and the analysis' implications have shown that the choice of the precise application of a volatility measurement method influences the properties of a volatility estimate and the description of volatility development can—at least in some cases—depend on the estimation method. The investigation further points out that the three commodities analyzed all exhibit high volatility between 2007-2011, but that the amount of volatility increase and the uniqueness of this high volatility level strongly depend on the specific market. Instead of defining criteria for finding the best method for estimating volatility, the analysis encourages thinking about the different issues that are necessary for the application of a measurement method and for drawing conclusions carefully or looking at alternative methods for a robustness analysis. The recognition of different characteristics of the volatility estimates is not only important when making statements with regards to the volatility development, but also for further analyses based on volatility estimates.

The analysis of volatility drivers stresses that general conclusions for agricultural markets cannot be drawn because, just as the volatility itself, also the drivers of volatility vary among markets. Besides identifying certain drivers external to the markets, the investigation points out that part of the volatility can be explained by commodity markets' internal factors, namely spillovers between markets that are supposed to be substitutes for specific purposes. Moreover, it seems that some markets behave as volatility "leaders", while other markets follow in their behavior. These insights can be helpful for policy makers since they show which markets they should focus on first and which impacts can be expected for other markets from actions on one market. Additionally, the results of the chapter indicate that it is more promising to focus on the measures that can help affected market participants to cope with higher volatility than to try to reduce price volatility on specific markets.

Finally, the disaggregation of a general risk measure and the development of option-implied estimators provides a helpful tool for detecting specific price risks in advance. First, the ex post investigation shows that the disaggregation leads to new insights with respect to the causes of a high overall volatility measure. Since different market participants are affected differently by unexpected price moves and unexpected large price moves within a short time interval are especially worrying, risk measures that are more specific than the usually applied standard deviation of returns are valuable, as they allow for measures that are better connected to the consequences of a volatility increase. Second, forward-looking estimators for those risk measures have been developed. The empirical analysis indicates that on the one hand implied estimates exhibit more predictive power than simple historical estimates, but on the other hand do not contain all relevant information for future price movements because additional explanatory variables are a valuable supplement. Since my analysis uses a relatively simple system of explanatory variables, it is worthwhile to have a closer look on the variables that should be included and to consider potential lagged effects in order to improve the prediction quality and therewith ameliorate this kind of early warning system.

Overall, this thesis demonstrates that the G20 agricultural ministers' call to manage the risk and mitigate the impacts of excessive price volatility can only be satisfied if one is aware of which commodity markets are affected, which specific kind of price risk one faces, and consequently which group of market participants needs protection, and if this risk is recognized early enough to undertake helpful measures.

Bibliography

Algieri, Bernardina, 2012, Price volatility, speculation and excessive speculation in commodity markets: sheep or shepherd behaviour ?, ZEF-Discussion Papers on Development Policy No. 166, Zentrum für Entwicklungsforschung, Bonn.

——— , 2014, A roller coaster ride: an empirical investigation of the main drivers of the international wheat price, *Agricultural Economics* 45, 459–475.

Andersen, Torben G., and Tim Bollerslev, 1998, Answering the skeptics: Yes, standard volatility models do provide accurate forecasts, *International Economic Review* 39, 885–905.

——— , and Francis X. Diebold, 2009, Parametric and nonparametric volatility measurement, in Yacine Ait-Sahalia, and Lars Peter Hansen (eds.), *Handbook of Financial Econometrics,* 67–138 (Elsevier, Amsterdam).

Andrews, Donald W. K., and Hong-Yuan Chen, 1994, Approximately median-unbiased estimation of autoregressive models, *Journal of Business & Economic Statistics* 12, 187–204.

Araujo, Claudio, Catherine Araujo-Bonjean, and Stéphanie Brunelin, 2012, Alert at maradi: Preventing food crises by using price signals, *World Development* 40, 1882–1894.

Assefa, Tsion T., Miranda Meuwissen, and Alfons Oude Lansink, 2014, Price volatility perceptions and management strategies in European food supply chains, Scientific Paper No. 6, ULYSSES project, EU 7th Framework Programme, Project 312182 KBBE.2012.1.4-05, Wageningen.

Babcock, Bruce A., 2012, The impact of US biofuel policies on agricultural price levels and volatility, *China Agricultural Economic Review* 4, 407–426.

Baker, Malcolm, and Jeffrey Wurgler, 2007, Investor sentiment in the stock market, *Journal of Economic Perspectives* 21, 129–151.

Bakshi, Gurdip, Nikunj Kapadia, and Dilip Madan, 2003, Stock return characteristics, skew laws, and the differential pricing of individual equity options, *Review of Financial Studies* 16, 101–143.

Balcombe, Kevin, 2011, The nature and determinants of volatility in agricultural prices: an empirical study, in Adam Prakash (ed.), *Safeguarding Food Security In Volatile Global Markets,* 89–110 (FAO, Rome).

Baquedano, Felix G., 2014, *Developing an indicator of price anomalies as an early warning tool: A technical compendium* (FAO, Rome).

Barone-Adesi, Giovanni, and Robert E. Whaley, 1987, Efficient analytic approximation of american option values, *Journal of Finance* 42, 301–320.

Barrett, Christopher B., and Marc F. Bellemare, 2011, Why food price volatility doesn't matter, Foreign affairs, accessed: 2015-04-30, https://www.foreignaffairs.com/articles/2011-07-12/why-food-price-volatility-doesnt-matter.

Bellemare, Marc F., 2015, Rising food prices, food price volatility, and social unrest, *American Journal of Agricultural Economics* 97, 1–21.

——— , Christopher B. Barrett, and David R. Just, 2013, The welfare impacts of commodity price volatility: evidence from rural Ethiopia, *American Journal of Agricultural Economics* 95, 877–899.

Benavides, Guillermo, 2009, Price volatility forecasts for agricultural commodities: an application of historical volatility models, option implieds and composite approaches for futures prices of corn and wheat, *Revista de Administracion, Finanzas y Economia (Journal of Management, Finance and Economics)* 3, 40–59.

Black, Fischer, 1976, The pricing of commodity contracts, *Journal of Financial Economics* 3, 167–179.

——— , and Myron Scholes, 1973, The pricing of options and corporate liabilities, *Journal of Political Economy* 81, 637–654.

Blair, Bevan J., Ser-Huang Poon, and Stephen J. Taylor, 2001, Forecasting S&P 100 volatility: the incremental information content of implied volatilities and high-frequency index returns, *Journal of Econometrics* 105, 5–26.

Bobenrieth, Eugenio, Brian Wright, and Di Zeng, 2013, Stocks-to-use ratios and prices as indicators of vulnerability to spikes in global cereal markets, *Agricultural Economics* 44, 43–52.

Bollerslev, Tim, 1986, Generalized autoregressive conditional heteroskedasticity, *Journal of Econometrics* 31, 307–327.

——— , 1987, A conditionally heteroskedastic time series model for speculative prices and rates of return, *Review of Economics and Statistics* 69, 542–547.

Borin, A., and V. Di Nino, 2012, The role of financial investments in agricultural commodity derivatives markets, Temi di discussione No. 849, Bank of Italy, Rome.

Botman, Dennis, 2011, Food price volatility, IMF Resident Representative Office in the Philippines, accessed: 2015-05-04, http://www.imf.org/external/country/PHL/RR/2011/021510.pdf.

Brenner, Robin J., Richard H. Harjes, and Kenneth F. Kroner, 1996, Another look at models of the short-term interest rate, *Journal of Financial and Quantitative Analysis* 31, 85–107.

Brinkmann, Felix, and Olaf Korn, 2014, Risk-adjusted option-implied moments, Working Paper, Georg-August-Universität Göttingen, Göttingen.

Britten-Jones, Mark, and Anthony Neuberger, 2000, Option prices, implied price processes, and stochastic volatility, *Journal of Finance* 55, 839–866.

Brümmer, Bernhard, Olaf Korn, Tinoush Jamali Jaghdani, Alberto Saucedo, and Kristina Schlüßler, 2013, Food price volatiltiy drivers in retrospect, Policy Briefing No. 1, ULYSSES project, EU 7th Framework Programme, Project 312182 KBBE.2012.1.4-05, Göttingen.

Brümmer, Bernhard, Olaf Korn, Kristina Schlüßler, and Tinoush Jamali Jaghdani, 2014, Volatility analysis: Causation impacts in retrospect (2007-2011) and preparing for the future, Scientific Paper No. 1, ULYSSES project, EU 7th Framework Programme, Project 312182 KBBE.2012.1.4-05, Göttingen.

——— , and Alberto Saucedo, 2013, Volatility in the after crisis period – A literature review of recent empirical research, Working Paper No. 1, ULYSSES project, EU 7th Framework Programme, Project 312182 KBBE.2012.1.4-05, Göttingen.

Carr, Peter, and Liuren Wu, 2009, Variance risk premiums, *Review of Financial Studies* 22, 1311–1341.

Cashin, Paul, Hong Liang, and C. John McDermott, 2000, How persistent are shocks to world commodity prices?, IMF Staff Papers, Vol. 47, No. 2, International Monetary Fund, Washington, D.C.

Chang, Bo-Young, Peter Christoffersen, Kris Jacobs, and Gregory Vainberg, 2012, Option-implied measures of equity risk, *Review of Finance* 16, 385–428.

Chen, Zhiyao, Robert T. Daigler, and Ali M. Parhizgari, 2006, Persistence of volatility in futures markets, *Journal of Futures Markets* 26, 571–594.

Christoffersen, Peter, Kris Jacobs, and Bo-Young Chang, 2012, Forecasting with option implied information, in Graham Elliott, and Allan Timmermann (eds.), *Handbook of Economic Forecasting, Volume 2a,* 581–656, North-Holland, Amsterdam.

Clapp, Jennifer, 2009, Food price volatility and vulnerability in the global south: considering the global economic context, *Third World Quarterly* 30, 1183–1196.

CNCD 11.11.11, SOS Faim, Oxfam-Solidarité, Réseau Financement Alternatif, FAIRFIN, 2013, Financial speculation intensifies agricultural price volatility, momagri: Focus on issues, accessed: 2015-11-05, http://www.momagri.org/UK/focus-on-issues/Financial-speculation-intensifies-agricultural-price-volatility_1296.html.

Cox, John C., and Stephen A. Ross, 1976, The valuation of options for alternative stochastic processes, *Journal of Financial Economics* 3, 145–166.

Dawe, David, and Ali Doroudian, 2012, *A simple price monitoring tool to assess monthly changes in food prices* (FAO, Rome).

Diaz-Bonilla, Eugenio, and Juan Francisco Ron, 2010, Food security, price volatility and trade: Some reflections for developing countries, Issue Paper No. 28, International Centre for Trade and Sustainable Development (ICTSD), Geneva.

Diebold, Francis X., Andrew Hickman, Atsushi Inoue, and Til Schuermann, 1997, Converting 1-day volatility to h-day volatility: scaling by h is worse than you think, Working Paper No. 97/34, Wharton Financial Institutions Center, University of Pennsylvania.

Doornik, Jurgen A., 2009, Autometrics, in Jennifer L. Castle, and Neil Shephard (eds.), *The Methodology and Practice of Econometrics: A Festschrift in Honour of David F. Hendry,* 88–121 (Oxford University Press, Oxford).

Dowd, Kevin, 2007, *Measuring Market Risk* (Wiley, Chichester et al.) 2. edn.

Du, Xiaodong, Cindy L. Yu, and Dermot J. Hayes, 2011, Speculation and volatility spillover in the crude oil and agricultural commodity markets: A bayesian analysis, *Energy Economics* 33, 497–503.

ECLAC, FAO, and IICA, 2011, Price volatility in agricultural markets (2000-2010): implications for Latin America and policy options, Newsletter No. 1/2011, Economic Commission for Latin America and the Caribbean and United Nations Food and Agriculture Organization and Inter-American Institute for Cooperation on Agriculture, Santiago.

Ederington, Louis H., and Wei Guan, 2006, Measuring historical volatility, *Journal of Applied Finance* 16, 5–14.

FAO, 2008, Volatility in agricultural commodities – an update, *Food Outlook – Global Market Analysis* June 2008, 55–57.

——— , 2011, Food price volatility and the right to food, Right To Food Issues Brief No. 1, FAO, Rome.

——— , IFAD, IMF, OECD, UNCTAD, WFP, the World Bank, the WTO, IFPRI, and the UN HLTF, 2011, Price volatility in food and agricultural markets: Policy responses, Policy Report for the G20 leaders coordinated by FAO and OECD, Rome and Paris.

Fleming, Jeff, 1998, The quality of market volatility forecasts implied by S&P 100 index option prices, *Journal of Empirical Finance* 5, 317–345.

——— , 1999, The economic significance of the forecast bias of S&P 100 index option implied volatility, *Advances in futures and options research* 10, 219–252.

G20 Agricultural Ministers, 2011, Action plan on food price volatility and agriculture, Ministerial Declaration of the Meeting of the G20 Agriculture Ministers in Paris, 22 and 23 June 2011.

Galtier, Frank, and Bruno Vindel, 2013, Managing food price instability in developing countries, *À Savoir* 17.

Garcia, Philip, and Raymond M. Leuthold, 2004, A selected review of agricultural commodity futures and options markets, *European Review of Agricultural Economics* 31, 235–272.

Garman, Mark B., and Michael J. Klass, 1980, On the estimation of security price volatilities from historical data, *Journal of Business* 53, 67–78.

Ghosh, Nilabja, Sangeeta Chakravarty, and M. Rajeshwor, 2010, Effect of trade liberalisation on volatility: the experience of indian agriculture, *International Journal of Economic Policy in Emerging Economies* 3, 253–271.

Giamouridis, Daniel, and George Skiadopoulos, 2012, The informational content of financial options for quantitative asset management, in Bernd Scherer, and Kenneth Winston (eds.), *Handbock of Quantitative Asset Management,* 243–265, (Oxford University Press, Oxford).

Gilbert, Christopher L., and C. Wyn Morgan, 2010, Food price volatility, *Philosophical Transactions of the Royal Society B: Biological Sciences* 365, 3023–3034.

Gilbert, Christopher L., and Simone Pfuderer, 2014, The role of index trading in price formation in the grains and oilseeds markets, *Journal of Agricultural Economics* 65, 303–322.

Glosten, Lawrence R., Ravi Jagannathan, and David E. Runkle, 1993, On the relation between the expected value and the volatility of the nominal excess return on stocks, *Journal of Finance* 48, 1779–1801.

Goldstein, Daniel G., and Nassim N. Taleb, 2007, We don't quite know what we are talking about when we talk about volatility, *Journal of Portfolio Management* 33, 84–86.

Gordon, J. Douglas, 1985, The distribution of daily changes in commodity futures prices, Technical Bulletin No. 1702, United States Department of Agriculture, Washington D.C.

Gorton, Gary, and K. Geert Rouwenhorst, 2006, Facts and fantasies about commodity futures, *Financial Analysts Journal* 62, 47–68.

Greenfield, Jim, and Abdolreza Abbassian, 2011, Strengthening global food market monitoring, in Adam Prakash (ed.), *Safeguarding food security in volatile global markets,* 459–478 (FAO, Rome).

Grosche, Stephanie-Carolin, 2014, What does granger causality prove? a critical examination of the interpretation of granger causality results on price effects of index trading in agricultural commodity markets, *Journal of Agricultural Economics* 65, 279–302.

Hamilton, James D., and Jing Cynthia Wu, 2014, Risk premia in crude oil futures prices, *Journal of International Money and Finance* 42, 9–37.

Headey, Derek, and Shenggen Fan, 2008, Anatomy of a crisis: the causes and consequences of surging food prices, *Agricultural Economics* 39, 375–391.

Hendry, David F., and Hans-Martin Krolzig, 1999, Improving on 'Data mining reconsidered' by K.D. Hoover and S.J. Perez, *Econometrics Journal* 2, 202–219.

——— , 2005, The properties of automatic GETS modelling, *Economic Journal* 115, C 32–C 61.

Hicks, John, 1946, *Value and Capital: an inquiry into some fundamental principles of economic theory* (Clarendon Press, Oxford) 2. edn.

Hilliard, Jimmy E., and Jorge A. Reis, 1999, Jumps processes in commodity futures prices and option prices, *American Journal of Agricultural Economics* 81, 273–286.

HLPE, 2011, Price volatility and food security, HLPE Report No. 1, Committee on World Food Security, High Level Panel of Experts on Food Security and Nutrition (HLPE), Rome.

Hoover, Kevin D., and Stephen J. Perez, 1999, Data mining reconsidered: encompassing and the general-to-specific approach to specification search, *Econometrics Journal* 2, 167–191.

Huchet-Bourdon, Marilyn, 2011, Agricultural commodity price volatility: an overview, OECD Food, Agriculture and Fisheries Papers No. 52, AgroCampus-Ouest, Rennes.

Hull, John C., 2009, *Options, futures, and other derivatives* (Pearson Prentice Hall, Upper Saddle River, NJ) 7. edn.

——— , 2012, *Risk Management and Financial Institutions* (Wiley, Chichester et al.) 3. edn.

Irwin, Scott H., and Dwight R. Sanders, 2012, Testing the masters hypothesis in commodity futures markets, *Energy Economics* 34, 256–269.

Jiang, George J., and Yisong S. Tian, 2005, The model-free implied volatility and its information content, *Review of Financial Studies* 18, 1305–1342.

Jondeau, Eric, and Michael Rockinger, 2001, Gram-Charlier densities, *Journal of Economic Dynamics and Control* 25, 1457–1483.

Kaplanski, Guy, and Haim Levy, 2010, Sentiment and stock prices: the case of aviation disasters, *Journal of Financial Economics* 95, 174–201.

Karali, Berna, and Gabriel J. Power, 2013, Short- and long-run determinants of commodity price volatility, *American Journal of Agricultural Economics* 95, 724–738.

Keynes, John Maynard, 1930, *A Treatise on Money: in 2 Volumes* (Macmillan & Company, London).

Knetter, Michael M., 1993, International comparisons of pricing-to-market behavior, *American Economic Review* 83, 473–486.

Koekebakker, Steen, and Gudbrand Lien, 2004, Volatility and price jumps in agricultural futures prices – evidence from wheat options, *American Journal of Agricultural Economics* 86, 1018–1031.

Kristoufek, Ladislav, Karel Janda, and David Zilberman, 2012, Correlations between biofuels and related commodities before and during the food crisis: A taxonomy perspective, *Energy Economics* 34, 1380–1391.

Krugman, Paul, 1986, Pricing to market when the exchange rate changes, NBER Working Paper No. 1926, National Bureau of Economic Research, Cambridge, MA.

Latané, Henry A., and Richard J. Rendleman, 1976, Standard deviations of stock price ratios implied in option prices, *Journal of Finance* 31, 369–381.

Liao, Shu-Yi, Sheng-Tung Chen, and Chi-Chung Chen, 2010, Modelling the ENSO forecast on soybean spot and future prices, *Journal of Agriculture and Forestry* 59, 91–103.

Lo, Andrew W., and Archie Craig MacKinlay, 1988, Stock market prices do not follow random walks: evidence from a simple specification test, *Review of Financial Studies* 1, 41–66.

Loretan, Mico, 2005, Indexes of the foreign exchange value of the dollar, *Federal Reserve Bulletin* 91, 1–8.

Manfredo, Mark R., Raymond M. Leuthold, and Scott H. Irwin, 2001, Forecasting fed cattle, feeder cattle, and corn cash price volatility: the accuracy of time series, implied volatility, and composite approaches, *Journal of Agricultural and Applied Economics* 33, 523–538.

Marquering, Wessel, and Marno Verbeek, 2004, The economic value of predicting stock index returns and volatility, *Journal of Financial and Quantitative Analysis* 39, 407–429.

Martins-Filho, Carlos, Feng Yao, and Maximo Torero, 2015, High-order conditional quantile estimation based on nonparametric models of regression, *Econometric Reviews* 34, 906–957.

McPhail, Lihong Lu, Xiaodong Du, and Andrew Muhammad, 2012, Disentangling corn price volatility: The role of global demand, speculation, and energy, *Journal of Agricultural and Applied Economics* 44, 401–410.

Mitchell, Donald, 2008, A note on rising food prices, Policy Research Working Paper No. 4682, The World Bank, Washington D.C.

Naylor, Rosamond L., and Walter P. Falcon, 2010, Food security in an era of economic volatility, *Population and Development Review* 36, 693–723.

Neuberger, Anthony, 2012, Realized skewness, *Review of Financial Studies* 25, 3423–3455.

Newey, Whitney K., and Kenneth D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–708.

Nissanke, Machiko, 2012, Commodity market linkages in the global financial crisis: Excess volatility and development impacts, *Journal of Development Studies* 48, 732–750.

Onour, Ibrahim Ahmed, and Bruno S. Sergi, 2011, Modeling and forecasting volatility in the global food commodity prices, *Agricultural Economics-Czech* 57, 132–139.

Parkinson, Michael, 1980, The extreme value method for estimating the variance of the rate of return, *Journal of Business* 53, 61–65.

Poon, Ser-Huang, and Clive Granger, 2003, Forecasting volatility in financial markets: a review, *Journal of Economic Literature* 41, 478–539.

——— , 2005, Practical issues in forecasting volatility, *Financial Analysts Journal* 61, 45–56.

Poon, Ser-Huang, and Stephen J. Taylor, 1992, Stock returns and volatility: an empirical study of the UK stock market, *Journal of Banking & Finance* 16, 37–59.

Prakash, Adam, 2011, Why volatility matters, in Adam Prakash (ed.), *Safeguarding Food Security In Volatile Global Markets,* 1–24, FAO, Rome.

Prokopczuk, Marcel, and Chardin Wese Simen, 2014, The importance of the volatility risk premium for volatility forecasting, *Journal of Banking & Finance* 40, 303–320.

Rathke, G.-W., Brian Wienhold, Wallace Wilhelm, and W. Diepenbrock, 2007, Tillage and rotation effect on corn–soybean energy balances in eastern Nebraska, *Soil and Tillage Research* 97, 60–70.

Roache, Shaun K., 2010, What explains the rise in food price volatility?, Working Paper No. 10/129, International Monetary Fund, Washington D.C.

Rogers, L. C. G., and S. E. Satchell, 1991, Estimating variance from high, low and closing prices, *The Annals of Applied Probability* 1, 504–512.

Sanders, Dwight R., and Scott H. Irwin, 2013, Measuring index investment in commodity futures markets, *Energy Journal* 34, 105–127.

Sarris, Alexander, 2014, Options for developing countries to deal with global food commodity market volatility, Working Paper No. P98, FERDI, University of Athens, Athens.

Schwert, G. William, 1990, Stock volatility and the crash of '87, *Review of Financial Studies* 3, 77–102.

Serra, Teresa, David Zilberman, and Jose Gil, 2011, Price volatility in ethanol markets, *European Review of Agricultural Economics* 38, 259–280.

Sims, Christopher, 1980, Macroeconomics and reality, *Econometrica* 48, 1–48.

Tomek, William G, and Hikaru Hanawa Peterson, 2001, Risk management in agricultural markets: a review, *Journal of Futures Markets* 21, 953–985.

Tothova, Monika, 2011, Main challenges of price volatility in agricultural commodity markets, in Isabelle Piot-Lepetit, and Robert M'Barek (eds.), *Methods to Analyse Agricultural Commodity Price Volatility,* 13–29 (Springer, New York).

Triantafyllou, Athanasios, George Dotsis, and Alexandros H. Sarris, 2015, Volatility forecasting and time-varying variance risk premiums in grains commodity markets, *Journal of Agricultural Economics* 66, 329–357.

Trostle, Ronald, 2008, Global agricultural supply and demand: factors contributing to the recent increase in food commodity prices, A Report from the Economic Research Service WRS-0801, United States Department of Agriculture, Washington D.C.

——— , 2011, Why another food commodity price spike?, United States Department of Agriculture, accessed: 2015-10-12, http://www.ers.usda.gov/amber-waves/2011-september/commodity-price-spike.aspx#.VhtypJek2ac.

Ubilava, David, and Matt Holt, 2013, El Niño southern oscillation and its effects on world vegetable oil prices: assessing asymmetries using smooth transition models, *Australian Journal of Agricultural & Resource Economics* 57, 273 – 297.

Von Braun, Joachim, and Getaw Tadesse, 2012, Global food price volatility and spikes: an overview of costs, causes, and solutions, ZEF Discussion Papers on Development Policy No. 161, Zentrum für Entwicklungsforschung, Bonn.

Will, Matthias Georg, Sören Prehn, Ingo Pies, and Thomas Glauben, 2013, Is financial speculation with agricultural commodities harmful or helpful? – A literature review of current empirical research, Working Paper, University of Wittenberg et al., Wittenberg et al.

Williams, Jeffrey C., and Brian D. Wright, 1991, *Storage and Commodity Markets* (Cambridge University Press: Cambridge).

Working, H., 1960, Speculation on hedging markets, *Stanford University: Food Research Institute Studies* 1, 185–220.

Wright, Brian D., 2011, The economics of grain price volatility, *Applied Economic Perspectives and Policy* 33, 32–58.

Yang, Dennis, and Qiang Zhang, 2000, Drift-independent volatility estimation based on high, low, open, and close prices, *Journal of Business* 73, 477–492.

Yang, Jun, Huanguang Qiu, Jikun Huang, and Scott Rozelle, 2008, Fighting global food price rises in the developing world: the response of China and its effect on domestic and world markets, *Agricultural Economics* 39, 453–464.

Zheng, Yuqing, Henry W. Kinnucan, and Henry Thompson, 2008, News and volatility of food prices, *Applied Economics* 40, 1629–1635.

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Ort, Datum

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