The dynamic pattern of volatility spillovers between oil and agricultural markets

Alberto Saucedo¹, Bernhard Brümmer², Tinoush Jamali Jaghdani³

Department of Agricultural Economics and Rural Development
University of Göttingen

¹,²,³ Chair of Agricultural Market Analysis, Department of Agricultural Economics and Rural Development, Georg-August-Universität Göttingen, Germany
ULYSSES project assess the literature on prices volatility of food, feed and non-food commodities. It attempt to determine the causes of markets’ volatility, identifying the drivers and factors causing markets volatility. Projections for supply shocks, demand changes and climate change impacts on agricultural production are performed to assess the likelihood of more volatile markets. ULYSSES is concerned also about the impact of markets’ volatility in the food supply chain in the EU and in developing countries, analysing traditional and new instruments to manage price risks. It also evaluates impacts on households in the EU and developing countries. Results will help the consortium draw policy-relevant conclusions that help the EU define market management strategies within the CAP after 2013 and inform EU’s standing in the international context. The project is led by Universidad Politécnica de Madrid.

Internet: http://www.fp7-ulysses.eu/

Authors of this report and contact details

Name: Alberto Saucedo  
Partner: University of Göttingen. Acronym: UGOE  
Address: Platz der Göttinger Sieben 5, D-37073 Göttingen, Germany.  
E-mail: asauced@gwdg.de

Name: Bernhard Brümmer  
Partner: University of Göttingen. Acronym: UGOE  
Address: Platz der Göttinger Sieben 5, D-37073 Göttingen, Germany.  
E-mail: bbruemm@gwdg.de

Name: Tinoush Jamali Jaghdani  
Partner: University of Göttingen. Acronym: UGOE  
Address: Platz der Göttinger Sieben 5, D-37073 Göttingen, Germany.  
E-mail: tjamali@gwdg.de

When citing this ULYSSES report, please do so as:


Disclaimer:

“This publication has been funded under the ULYSSES project, EU 7th Framework Programme, Project 312182 KBBE.2012.1.4-05. Any information reflects only the author(s) view and not that from the European Union.”

“This information in this document is provided as is and no guarantee or warranty is given that the information is fit for any particular purpose. The user thereof uses the information at its sole risk and liability.”
# Table of contents

Figures .......................................................................................................................... 4

Tables ............................................................................................................................. 4

Executive summary......................................................................................................... 5

1 Introduction................................................................................................................ 6

2 Market development for biofuels ............................................................................. 8
   2.1 Price co-movements between oil and biofuels’ feedstocks ............................... 10

3 Literature review on volatility spillovers between food and energy markets .......... 12

4 Data and methodology .............................................................................................. 16
   4.1 Data ..................................................................................................................... 17
   4.2 Methodology ...................................................................................................... 17
      4.2.1 Realized Volatility ..................................................................................... 17
      4.2.2 Co-volatility ............................................................................................. 18
      4.2.3 Estimation of the volatility spillovers ...................................................... 18

5 Empirical findings ..................................................................................................... 19
   5.1 Co-Volatility ...................................................................................................... 19
   5.2 Volatility spillovers ......................................................................................... 22

6 Conclusions .............................................................................................................. 24

7 Policy recommendations ........................................................................................... 25

References .................................................................................................................... 27

Appendix ....................................................................................................................... 30
**Figures**

Figure 1: World’s leading biofuels producing countries, 2011 .......................................................... 9

Figure 2: World biofuel production and share of total oil consumption, 1991-2011 ......................... 9

Figure 3: Evolution of cereals and sugar prices, 1996 - 2014 .............................................................. 11

Figure 4: Evolution of vegetable oil prices, 1996 - 2014 .................................................................. 12

Figure 5: Co-volatilities between oil and the ethanol feedstocks ...................................................... 20

Figure 6: Co-volatilities between oil and the biodiesel feedstocks .................................................... 21

Figure 7: Volatility spillover index for the ethanol and biodiesel groups ............................................ 22

Figure 8: Volatility spillovers between oil and cereals & sugar ......................................................... 23

Figure 9: Volatility spillovers between oil and vegetable oils ............................................................. 24

**Tables**

Table 1: Volatility drivers ..................................................................................................................... 6

Table 2: Estimates of total support for the biofuel industry in developed countries ...................... 8

Table 3: Descriptive statistics of the data .......................................................................................... 17

Table 4: Summary of the literature review ......................................................................................... 30
Executive summary

1. After the food crisis of 2007-2008 much research concentrated on finding not only the determinants of high food prices, but also the drivers of food price volatility. From the group of potential volatility drivers, the most controversial for their political implications are the financialisation of agricultural markets and the promotion of biofuels. However, this study concentrates only on the latter, specifically, on the energy-food nexus induced by biofuel production and its political support.

2. Despite large amount of subsidies are assigned to the biofuel industry in developed countries, mainly in the US and the EU, the total share of ethanol and biodiesel on the global oil consumption represents only around 1% and 0.2%, respectively, raising the question on whether this is the most efficient way of reducing greenhouse gases, one of the main arguments for their promotion.

3. The productivity of ethanol on litres of fossil fuel equivalent per area basis is on average larger than the one of biodiesel. This implies that –“ceteris paribus” – the promotion of biodiesel will provoke higher competition for land with other crops than the ethanol would. This explains also why the ethanol production in 2011 is four times larger than the biodiesel and why the large difference of annual growth rates over the last 20 years between ethanol (9%) and biodiesel (67%).

4. The research on the volatility spillovers between energy and food markets applies predominantly Multivariate GARCH-type models to look for causality effects. Other studies look only for mere linear dependences between volatilities in these markets. Causality in variance tests are also applied to find causalities in the Granger sense.

5. For the volatility spillovers between oil, and sugar, corn and wheat, traditional ethanol feedstocks, there is a cyclical mean-reverting pattern with low and high volatility periods before, during and after the financial crisis. For the biodiesel group which comprises, besides the oil, the commonly used feedstocks (oil, soybean oil, rapeseed oil and palm oil), the spillover levels remain low for most of the pre-crisis period, but from December 2007, one year earlier than for the ethanol, it experiences a sustained increase that starts reverting only from the beginning of 2013.

6. The crop which is most affected by oil volatility spillovers is corn. Due to its high degree of substitution with wheat, shocks from oil markets may also be transmitted indirectly to wheat. In the case of biodiesel feedstocks, all three considered vegetable oils are affected by oil price volatility, especially at the beginning and at the end of the post-crisis period. Rapeseed remains relatively unaffected by spillovers in general, and in particular shows the lowest volatility spillovers from oil markets.
1 Introduction

The rise of food prices combined with high volatility periods leads to considerable economic private and social costs. It may impact countries differently depending on their productive structure (net food importing or exporting), degree of integration to the markets and domestic policies. Developing countries are particularly vulnerable since food expenditures represent a relative high share of the budget for the bulk of the population, especially for those living in urban areas, which are net food buyers. Price surges prevent them from acceding to food in appropriate quantity and quality. Additionally, price volatility hinders investments in agriculture putting further pressure in the mid term on food prices. This situation may lead to social unrest and political instability worldwide.

With tranquil agricultural markets following a historical downward trend in prices, only little research was devoted to understand the phenomenon of price volatility in food markets. However, after the 2007/08-crisis—which was coupled with high volatility periods– the issue of food price development was brought back to the top of the international political agenda. Since then, food price volatility is a major focus of research and policy advising of many international organisations (FAO, IMF, World Bank), research institutes (IFPRI, NBER), universities and researchers. Different working papers and peer-reviewed studies have been published, predominantly with the aim at understanding the roots of the problem and giving some prescriptions to deal with the high volatility episodes.

In the after crisis period many factors were identified as potential contributors to the steep upsurge in food prices and volatility. In Table 1 we present a synthesis of the most cited volatility drivers. We broadly group them as supply and demand driven, and with a short (shock) or long (structural) term impact.

Table 1: Volatility drivers

<table>
<thead>
<tr>
<th>Supply</th>
<th>Demand</th>
</tr>
</thead>
<tbody>
<tr>
<td>Underinvestment in agriculture</td>
<td>Income and population growth in developing countries</td>
</tr>
<tr>
<td>Declining yields in main cereals</td>
<td>Change in dietary preferences</td>
</tr>
<tr>
<td>Change from large scale to small size farming</td>
<td>Policies affecting land markets</td>
</tr>
<tr>
<td>Policies affecting land markets</td>
<td>Increasing frequency of extreme weather</td>
</tr>
<tr>
<td>Increasing frequency of extreme weather</td>
<td>Diminishing international grain stocks</td>
</tr>
<tr>
<td>Diminishing international grain stocks</td>
<td>Future development of biofuel policies</td>
</tr>
<tr>
<td></td>
<td>Outcome of the multilateral trade negotiations</td>
</tr>
<tr>
<td></td>
<td>Lack of reliable information on stock holdings</td>
</tr>
<tr>
<td></td>
<td>Development of macroeconomic policies</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Long term (Structural)</th>
<th>Short term (Shocks)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>News on expected harvests</td>
</tr>
<tr>
<td></td>
<td>News on stock holding levels</td>
</tr>
<tr>
<td></td>
<td>Speculative stock holdings</td>
</tr>
<tr>
<td></td>
<td>Weather shocks</td>
</tr>
<tr>
<td></td>
<td>Shocks from the oil market</td>
</tr>
<tr>
<td></td>
<td>Shocks from other non agricultural markets</td>
</tr>
<tr>
<td></td>
<td>Monetary policy shocks</td>
</tr>
<tr>
<td></td>
<td>Exchange rate volatility</td>
</tr>
<tr>
<td></td>
<td>Trade distorting policies</td>
</tr>
</tbody>
</table>

Source: Own elaboration.

Gilbert & Morgan (2010) find that the decline of the supply and demand elasticities, the increased variability of demand and supply shocks, and the variability of the exchange rates are driving volatility. The structural factors cited in Table 1 make the already relative inelastic supply and demand for agricultural products less responsive to shocks, provoking unpredictable price fluctuations. During the adjustment process, higher volatility or longer periods of price variability are generated until supply and/or demand adjust to the new
market conditions. Besides the particular long and short term volatility drivers in the supply and the demand, there are other transversal drivers affecting simultaneously both sides of the market, namely the mid to long term biofuel mandates and support policies; the new rules governing international agricultural trade; the lack of accuracy and transparency of national stock holdings; and the discretionary development of macroeconomic policies in developed countries. In the short run one expects market disruptions and higher volatility episodes driven by monetary and exchange rate shocks, and by arbitrary trade distorting policies like the wheat export ban enforced by India and Ukraine in February 2007. From the above-presented drivers, the macroeconomic, trade and biofuel policies are the most overarching. These factors affect not only the supply and demand side simultaneously, but also shape the short and long term volatility dynamics of the market.

Although the existing literature attributes the increasing food price volatility to a multitude of different factors and their interactions, there is special interest in the scientific community in the following key drivers. These are the rapid financialisation of agricultural markets, the tightening relation between oil and agricultural markets, the declining and uncertainty on grain stocks levels, the exchange rate variability of US dollar-denominated agricultural international trade, and the biofuel promotion policies enforced by developed countries. Nevertheless, given the complexity of the economic system, no author has been able to clearly identify a causal order among these factors, nor quantify their impacts separately. From the set of drivers, however, the increasing participation of investment funds in agricultural markets and the biofuel boost are the most controversial. Will et al. (2012), in a literature review of 35 empirical studies, conclude that the alleged financial speculation in commodity futures markets does not have a significant impact on spot prices’ level or volatility, instead they find that fundamentals do have this impact. Mitchell (2008) estimates that the production of biofuels in the US and Europe explain between 70% and 75% the rise of food prices due to a reduction of the international grain stocks, changes in land use, increased speculative activity and export restrictions. Baffes & Haniotis (2010) on the other hand conclude that the impact of biofuels on rising food prices is not as high as previously thought, but that the use of commodities as a strategy of investment diversification by large institutional investors may be partly responsible for the rise. According to Nazlioglu et al. (2013) the relation between the energy markets and the food markets is driven by three factors: oil as an input for farming, transporting and processing crops; the “energy crops” used for producing biofuels (e.g. cereals, oil seeds and sugar crops), close substitutes and complements for diesel and gasoline; and the co-movements of both, energy commodities and agricultural commodities, due to investment funds’ activity. While evidence shows that the role of speculative positions on futures markets held by investment funds has no significant impact on grain price volatility, the input costs and the biofuels are the only plausible channels that may link energy markets and food markets.

Biofuels are widely debated as an important volatility driver of agricultural markets. The aim of this paper is to contribute to this discussion by shedding some light on the understanding of the energy-food nexus. We show the evolution of the volatility spillover dynamics between the oil and the commonly used energy crops for the production of biofuels, namely corn, wheat and sugar for ethanol, and soybean oil, rapeseed oil and palm oil for biodiesel. Many studies recognise a structural break around 2007-2008 and apply accordingly econometric techniques to account for the shift in the series. Others split the sample into two sub periods and apply separately their analysis. Our approach differs from the previous ones since we apply the spillover analysis over 158 subsamples by using a rolling window of 60 months,
which covers before, during and after crisis periods, providing more information on the volatility spillovers pattern.

The paper is organised as follows: in section 2 we present the development of the biofuel market; section 3 reviews the recent literature concerned with the volatility spillovers effects between energy and food markets; section 4 presents the data and the proposed methodology; section 5 shows our empirical findings; in section 6 we conclude and section 7 gives some policy recommendations.

2 Market development for biofuels

The biofuel market emerges as the result of technological progresses that make it possible to obtain ethanol and biodiesel, substitutes for gasoline and diesel, respectively, from starch, sugar and oil crops, as well as the development of flex-cars that are able to run with different biofuel blends. However, the rapid growth of the market is driven mainly by political decisions of developed countries, which start promoting biofuels as a means to reduce greenhouse gas emissions, to promote domestic energy diversification and to foster rural development.

With this purpose developed countries assign large budgets to the promotion of ethanol and biodiesel. In May 2003 the European Union (EU) past a first Directive 2003/30/EC to promote the use of renewable fuels, stipulating a 5.75% replacement of transport fuels with biofuels by the end of 2010. In April 2009 it releases a new Directive (2009/28/EC), which mandates a 20% of total energy consumption coming from renewable sources by 2020 and 10% of transport fuel from biofuels. The Global Subsidies Initiative (GSI) estimates that total support for ethanol in the EU was in 2011 between 1.3 and 1.8 Billion US$ and for biodiesel between 6.4 and 7.8 Billion US$. The United States (US) passes the US Energy Policy Act in 2005, which mandates the consumption of 28 Billion Lt. of biofuels (mainly ethanol) by 2012, but in December 2007 a new boost for biofuels is enforced through the Energy Independence and Security Act. It requires a consumption of 136 Billion Lt. by 2022 a more ambitious target. Different from the EU, the US promotes more the ethanol industry, with estimates of 7.7 Billion US$ in 2009, whereas the amount for biodiesel is only 0.4 Billion US$ for the same period.

By 2011 the largest ethanol producer is the US with 54 Billion Lt., a 63% share in world production, followed by Brazil with 21 Billion Lt. (24%), the EU with 2.7 Billion Lt. (3%) and China with 2 Billion Lt. (2%) (Figure 1). The US is also the largest net ethanol exporter with 2.5 Billion Lt. in 2011, followed by Brazil with 1 Billion Lt., while China’s exports are in comparison negligible (200 thousand Lt.) (FAPRI & ISU, 2012). From this group, Brazil is the most productive. It processes ethanol from sugar cane with an average yield of 5476 Lt./Ha while the US corn-based ethanol only attains 3751 Lt./Ha, a 30% less. The EU produces

Table 2: Estimates of total support for the biofuel industry in developed countries

<table>
<thead>
<tr>
<th>Ethanol (Million US$)</th>
<th>Biodiesel (Million US$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>United States</td>
<td>6940-8390</td>
</tr>
<tr>
<td>European Union</td>
<td>1096</td>
</tr>
<tr>
<td>Canada</td>
<td>224-251</td>
</tr>
<tr>
<td>Australia</td>
<td>46</td>
</tr>
<tr>
<td>Switzerland</td>
<td>3</td>
</tr>
</tbody>
</table>

Source: Own elaboration based on the Global Subsidies Initiative.
Note: Empty spaces mean no information is available.
ethanol mainly from wheat, but its yield is even lower than the corn (2760 Lt./Ha). Besides wheat and other minor cereals, the EU also produces ethanol from sugar beets, which performs much better in terms of yields, attaining 6380 Lt./Ha. When it comes to the biodiesel production, EU is the leading region, accounting for 30% of world production in 2011 (Figure 1). Within the EU, Germany has the highest production with 3 Billion Lt. followed by France (1.6 Billion Lt.), Spain (0.7 Billion Lt.), Italy (0.6 Billion Lt.) and the Netherlands (0.4 Billion Lt.). The next largest biodiesel producers are the US (3.2 Billion Lt.), Argentina (2.8 Billion Lt.) and Brazil (2.6 Billion Lt.). The EU is also the largest biodiesel importer with 2.5 Billion Lt. in 2011, close to 100% of net global imports. On the export side, Argentina is the largest net exporting country with 1.6 Billion Lt., followed by Indonesia (0.3 Billion Lt.) and the US (0.2 Billion Lt.) (FAPRI & ISU, 2012). Similar to the situation for ethanol, biodiesel yields are also very heterogeneous. The most efficient biodiesel producers are Malaysia and Indonesia with 4736 and 4092 Lt./Ha, respectively, derived from palm oil. The EU producers use mainly rapeseed oil as feedstock, but its yield of 1590 Lt./Ha is only about a third of palm oil-based biodiesel. Argentina, US and Brazil obtain their biodiesel from soybean oil, an even less productive feedstock with only 491 to 640 Lt./Ha.

**Figure 1: World’s leading biofuels producing countries, 2011**

![Biofuels Production Map](image)

Source: Own elaboration based on estimates of the Earth Policy Institute with data from F.O. Licht.

Over the last twenty years, the global production of ethanol and biodiesel grows at an average annual rate of 9% and 67%, respectively, reaching 86 Billion Lt. of ethanol and 21 Billion Lt. of biodiesel in 2011. One can observe a steeper increase in biofuels’ production since 2005-2007, time which coincides with the enforcement of US’ energy acts (Figure 2).

**Figure 2: World biofuel production and share of total oil consumption, 1991-2011**

![Biofuel Production Graph](image)

Source: Own elaboration based on Earth Policy Institute with data from F.O. Licht and the US International Energy Agency.

Note: (*) The production for 2012 has been estimated.
According to OECD & FAO (2010), in the period 2007-2009, on average 20% of sugar cane production, 9% of oilseeds and cereals, and 7% of sugar beet are used for biofuels. Nonetheless, the share of ethanol and biodiesel in terms of energy only attains around 1% and 0.2% of global oil consumption during 2011, respectively (Figure 2).

Several studies find that the demand for agricultural commodities as biofuel feedstocks increases the correlation between agricultural and energy markets. The imposition of permanent biofuel mandates by large agricultural producing and exporting countries diverts large amounts of grains from the food/feed markets to the biofuels’ industry. The mandates provoke an outwards shift of the overall consumption demand for grains and drive their prices up. While the stockholdings buffer to some extend the shift, due to the permanent character of the mandates and the low responsiveness of production (land constraints and stagnated productivity), the stock levels also decline (Wright, 2014). With low stocks there is no safeguard against market shocks resulting in periods of high price volatility (Bobenrieth et al., 2013). While at higher grain prices it makes more economic sense (ceteris paribus) to produce food/feed instead of biofuels, the subsidies paid by developed countries and the increasing oil prices have created the perfect incentives for expanding even further the biofuels’ production.

2.1 Price co-movements between oil and biofuels’ feedstocks

The ethanol group comprises, besides oil, the most used energy crops for ethanol i.e. sugar, corn and wheat. For the considered period, only around 12% of corn production and 19% of wheat is commercialized internationally. The international trade for these cereals is relative tight; most of their production is consumed domestically or exported as processed products like corn cakes and ethanol, or wheat flour. The international sugar market is, on the other hand, more loosely; sugar exports account for almost 30% of total production.

Corn is the main feedstock used for ethanol in terms of volume, but lies behind sugar cane when it comes to efficiency. The US is the largest user of corn for ethanol; nevertheless it is only price competitive with the Brazilian sugar cane-based ethanol through subsidies. The second feedstock in importance is sugar cane, widely used in Brazil, India and Thailand, but since it is a non-tradable commodity we use the international sugar price as a proxy. The last commodity of this group is wheat. It is used mainly in the EU and Canada; nevertheless, its global relevance as ethanol feedstock is negligible if compared to corn or sugar cane.
Figure 3: Evolution of cereals and sugar prices, 1996 - 2014

Figure 3 depicts the evolution of the international prices for these commodities. It also shows the successive policy interventions deployed by the US and the EU to support the biofuel production. Along the considered period corn and wheat series co-move while the sugar follows an own more cyclical pattern. While sugar tends to follow the development of oil prices more closely along the entire period, wheat and corn prices start following it later, around mid 2005, coinciding with the enacting of the US Energy Policy Act. From November 1996 the prices for wheat and corn start converging, attaining a minimal difference of 12 US$/Mt by April 2000. Since then, both prices moves apart again reaching a maximum gap price of 250 US$/Mt in February 2008. Nevertheless, over the end of 2006 and beginning of 2007, the growth rate of corn prices accelerates so that the price gap is substantially reduced (44 US$/Mt) by February 2007. In December 2007 the US increases the mandate levels even further, boosting cereal prices to new highs. After the crisis (bold line) however, both series get practically tied, commoving around very similar price levels and following a decreasing trend from the second half of 2012.

Vegetable oils are the main feedstocks for biodiesel. The biodiesel group is composed of the three most used vegetable oils for biodiesel, namely soybean oil, rapeseed oil and palm oil, and the crude oil. Rapeseed oil, similar to wheat, has a relative thin international market. Only 12% of this oil is commercialized internationally. The international trade for soybean oil is more important, attaining a 26% of its production. However, over the last years it has been increasingly exported as biodiesel, too. For instance, Argentina, the third largest soybean producer, over the last decade has developed a biodiesel cluster which exports reached a record of 1.9 Billion Lt. in 2011 (CARBIO, 2015). While the rapeseed and soybean oils are mainly domestically consumed or exported as biodiesel, the international market for palm oil accounts for roughly 70% of its global production, being the most widely traded vegetable oil of the group.

Soybean oil and rapeseed oil are used for biodiesel especially in temperate zones due to their lower viscosity if compared to palm oil. The US, Brazil and Argentina process mainly biodiesel form soybean oil, whereas the EU use rapeseed oil. Palm oil is the main feedstock in tropical countries like Indonesia, Malaysia and Thailand in Southeast Asia or Colombia and Ecuador in Latin America.
Comparatively, vegetable oils start following the oil price pattern much earlier than cereals. Figure 4 is indicative of a convergence of the price series from the beginning of 2000. By the end of 2000, the three vegetable oils start an upward trend that ends short before the financial crisis of September 2008 (bold line). Oil starts a similar trend around one year later, at the beginning of 2002. Nevertheless, it can be observed that from the beginning of 2007 vegetable oils and crude oil start also comoving tightly in addition to the similar trending behaviour. Rapeseed oil prices move very closely to soybean oil and palm oil till mid of 2000, but then it takes the lead. Between 2004 and 2007 the gap price between rapeseed oil and soybean oil reaches maximums in May 2006 (316 US$/Mt), November 2007 (387 US$/Mt) and December 2007 (416 US$/Mt). This behaviour shows the relative size of the rapeseed oil market if compared to soybean oil, as well as its high demand for biodiesel in Europe if compared to palm oil, constrained for this use in temperate zones due to technical issues. Soybean oil and palm oil maintain similar price levels along the considered period, except between 2003 and 2006, and 2012 and 2013 when soybean oil becomes more expensive. Rapeseed oil and crude oil reach a price peak in June 2008 with 1622 US$/Mt and 140 US$/Bb, respectively, while soybean oil (1448 US$/Mt) and palm oil (1340 US$/Mt) attain their highest prices just four months before in February 2008. Short before the crisis all prices start declining. In October 2008 palm oil price plummet to 485 US$/Mt, followed in January 2009 by oil (42 US$/Bb) and in February 2009 by soybean oil (611 US$/Mt) and rapeseed oil (737 US$/Mt). However, together with the recovery of the oil price during 2009, the EU enact a new biofuels directive in April requiring member States to replace 10% of transport fuels with biofuels by 2020.

In the next section we review the recent findings and the methods applied to uncover the food-energy linkages and the volatility spillovers thereof.

3 Literature review on volatility spillovers between food and energy markets

Some of the studies concerned with the relation between agricultural and energy markets identify structural breaks and divide their analysis accordingly in periods before and after
crisis. Others apply methodologies, which account for these breaks. Some of the research concentrates on finding only co-movements between markets, but most of them look also for directional causalities. Studies like Busse et al. (2011) and Liu (2014) analyse the cross correlation between energy and grain markets without showing any causal path, whereas Serra et al. (2011), Serra (2011) and Trujillo-Barrera et al. (2012) do. Du & McPhail (2012) and Nazlioglu et al. (2013) find regimes where the spillover level is significantly different before and after a critical time. Table 4 in the appendix shows a summary of the reviewed literature.

Liu (2014), using daily spot prices, tests the nonlinear cross correlations between crude oil (WTI) and agricultural commodities (corn, soybean, oat and wheat) in the US for the period starting in January 1994 to December 2012. The results show highly significant and persistent cross correlations between the volatility series of oil and each of the selected cereals, especially during the crisis period. He concludes that the high oil prices partly contribute to the food crisis. Busse et al. (2011) analyse the behaviour of price volatility of the EU biofuel markets during and after the 2006 – 2008 crisis episode and investigate the correlation in price volatility of different commodities and their evolution over time. They apply an Autoregressive Moving Average (ARMA) – Generalised Autoregressive Conditional Heteroscedasticity (GARCH) (1,1) and a Dynamic Conditional Correlation (DCC) models, using rapeseed futures (MATIF) and spot prices for soybean, rapeseed oil, soybean oil and Brent. They find highly persistent volatility series, too, and point that the model neither allows for conclusions about causal mechanisms of volatility spillovers nor is it able to capture the magnitude of the influence of one market on the others.

Du & McPhail (2012) identify a regime switch in March 2008 and split the series accordingly. They use a DCC-GARCH model to estimate the volatilities based on daily futures for corn, ethanol, gasoline and light crude oil in the US market for the 2005 – 2011 period. In the earlier period, the price change in one market does not have any statistically significant effect on the other market, but in the later period, corn, ethanol and gasoline prices are found to have significant and positive impact on each other. Additionally, the ethanol (corn) shocks have the largest impact on corn (ethanol) price. They conclude that higher ethanol-gasoline blends have significant volatility impacts not only on the pure gasoline but also in its blends.

Nazlioglu et al. (2013) examine volatility transmission between oil and agricultural commodity prices (wheat, corn, soybeans, and sugar). They apply a newly developed Causality in Variance Lagrange Multiplier (CV-LM) test by Hafner & Herwartz (2006) and the impulse response functions. While the main body of literature find either unidirectional spillover effects from energy to agricultural markets or no spillover effects at all, their results indicate reverse volatility spillovers from wheat to oil in the pre-crisis period (1986 – 2005) and bidirectional causality for oil-soybean and oil-wheat in the post-crisis (2006 – 2011).

Harri & Hudson (2009), apply also causality in variance tests using daily futures for oil and corn in the US for the period 2003 – 2009. Their results confirm volatility spillovers from oil to corn after the food crisis.

Zhang et al. (2009) use US weekly spot prices for corn, soybean, ethanol, gasoline, and crude oil for the period 1989-2007. They assess in a first step the short and long run dynamics between fuel and agricultural prices by means of a Vector Error Correction Model (VECM) and then apply a Multivariate GARCH model to evaluate the volatility spillovers.
Their results confirm no long run relations among fuel (ethanol, oil and gasoline) and agricultural (corn and soybean) prices. They conclude that fuel prices may cause only transitory price inflation in the considered agricultural markets.

Alghalith (2010) examines the impact of oil price uncertainties on food prices in Trinidad and Tobago. He uses non-linear Ordinary Least Squares (OLS) with annual data. His findings show that an increase in oil price and its volatility yields higher food prices while an increase in oil supply reduces it. He concludes that there exists a risk transfer mechanism between the two markets.

Chang & Su (2010) use daily futures of crude oil, corn and soybean for the period 2000-2008. They apply a Bivariate Exponential GARCH model and find that volatility spillovers from oil to corn and soybean futures are insignificant while oil price remains at low levels, but get highly significant when oil price rises. This implies a substitution effect during high-oil price periods.

Alom et al. (2011) investigate volatility spillovers from international oil prices to food markets in selected Asia and Pacific countries. They use Vector Autoregressive (VAR) and GARCH models for the period 1995-2010. They find positive correlations between food and oil volatilities, however results vary across countries and periods. Volatility spillovers from oil to domestic markets are larger for recent periods.

Balcombe (2011) explores the determinants and the evolution of price volatility during the past decades. He analyses prices for 19 internationally traded agricultural commodities with different frequencies and for diverse periods. He estimates realised volatilities and uses them in a random parameter and a panel data models. Results confirm volatility transmissions across prices. Moreover, oil price volatility shows a positive impact on agricultural price volatilities.

Du et al. (2011b) investigate the role of speculation on crude oil volatility after controlling for other factors. They attempt to quantify the extent to which volatility in the crude oil market spills into agricultural commodity markets (corn and wheat) in the US. They estimate Stochastic Volatilities with Merton Jumps (SVMJ) for weekly crude oil, corn and wheat futures over the 1998-2009 period. They find volatility spillovers among crude oil, corn, and wheat markets after fall 2006, implying that investment funds may play a role.

Serra (2011) analyses the volatility spillovers between crude oil, ethanol and sugar weekly spot prices in Brazil for the 2000 – 2009 period. By means of a semi-parametric Multivariate GARCH model she finds that shocks in crude oil and sugar markets cause an increase in ethanol price volatility, but ethanol markets do not affect neither sugar nor oil volatilities. She further concludes that the parametric version of the Multivariate GARCH model can obtain misleading results.

Serra et al. (2011) combine a VECM with a Multivariate GARCH model to analyse the volatility spillovers among the Brazilian sugar and ethanol markets, and the international oil market. They use weekly spot prices for the period 2000-2009. Their findings show that an increase in the international oil price leads to higher ethanol prices. Moreover, the adjustment process is slow and ends up in higher ethanol volatility. Additionally, increments in sugar prices drive ethanol prices, both in terms of levels and volatilities.
Wu et al. (2011) use weekly futures and spot prices of crude oil and corn in the US market. To test for volatility spillover effects they apply a Multivariate GARCH and a Substitution Spillover Effect (SSE) model. They find that volatility spillovers from crude oil to corn spot and futures prices are significant and similar. Moreover, the volatility spillovers become larger after the introduction of the Energy Policy Act of 2005. They conclude that substantial volatility spillovers occur in periods of high ethanol–gasoline consumption rates.

Kristoufek et al. (2012) look for the existence of a biodiesel, ethanol, fuel and agricultural commodities relationship. The considered commodities are corn, wheat, sugar cane, soybean and sugar beet in the US and Germany. They use a Multivariate GARCH model with weekly and monthly futures and spot price observations for the period 2003-2011. They find weak correlations between fuels and biofuels with the considered agricultural commodities, but these correlations increase considerably in the post-crisis episode when food prices are higher. They conclude that even though biofuels are affected by food and fuel prices, the opposite does not hold.

Trujillo-Barrera et al. (2012) test the volatility spillovers among crude oil, corn and ethanol markets in the US with weekly futures for the period 2006-2011. The Multivariate GARCH model shows volatility transmission from crude oil to corn and ethanol markets and volatility spillovers from the corn to the ethanol market. They find no evidence of volatility spillovers from ethanol to corn.

Haixia & Shiping (2013) analyse the spillover effects among crude oil, corn and ethanol in China by using weekly spot prices for the period 2003-2012. By using a Multivariate GARCH model they find unidirectional spillovers from the crude oil to the corn and ethanol markets, but bidirectional spillovers between corn and ethanol markets. They find no significant reverse spillover effect from corn and ethanol to the crude oil market.

Gardebroek & Hernandez (2013) use a Threshold and a DCC Multivariate GARCH models with weekly spot prices to examine volatility transmissions among oil, ethanol and corn prices in the US (1997-2011). Results for the first model do not provide evidence of mean spillovers in price returns across energy and corn markets. However, with a segmentation of the time period, results support a higher correlation between the ethanol and corn markets, particularly after 2006, when ethanol became the sole alternative oxygenate for gasoline. They find significant volatility spillovers from the corn to ethanol prices, but no major cross-market volatility effects between oil and corn.

Serra (2013) summarises some recent empirical research on price volatility in biofuel markets. Her review shows that biofuel related price volatility studies focus mainly on the assessment of the volatility interactions between energy and food markets, and the main used methodologies are the GARCH type models. She concludes that biofuel markets do not drive long run feedstock price levels, but causality is significant in the other direction. Moreover, while energy markets do not determine corn and sugar long-run price levels, they are capable of inducing volatility in feedstock markets. Zilberman et al. (2012) argue that the main reason why some studies only find a weak energy-food relation is because the impact of biofuels on food prices is reflected only when the source of the change in food prices is taken into account.

This group of literature does not only aim at finding volatility spillovers between energy and food markets, but also extends the modelling framework by adding some variables, which
might affect price volatility. Serra & Gil (2013) study the monthly volatility spillovers between corn and biofuel spot prices during 1990-2010. They apply a parametric and semi-parametric Multivariate GARCH model, and additionally use the stock level and interest rate as exogenous drivers of food price volatility. Their findings show that the stock-to-disappearance forecasts lower corn price variability while interest rate unpredictability brings instability to food prices. Moreover, fluctuations in the ethanol market destabilises corn markets. They conclude that the impacts of stock-to-disappearance forecasts are higher in the short run compared to the effects of the energy price and the macroeconomic swings.

Algieri (2014) assess the impact of biofuels, the S&P 500 index and the US dollar-Euro exchange rate on the US daily futures of agricultural commodities. He considers the prices of ethanol, biodiesel, corn, rapeseed, soybean, soybean oil, sugar, wheat and crude oil for the period 2005-2013. He concludes that the stock market has a magnified effect on the commodity price returns, especially for sugar, wheat and soybean oil. He finds that the monetary liquidity does not impact commodity returns on a daily basis. The study shows that the good news generates less volatility than bad news for the corn market, while the opposite happens for wheat and sugar. Moreover, the lagged oil and the ethanol returns have a significant influence on corn, wheat, sugar and soybeans, implying that energy markets drive volatility in agricultural markets.

Mensi et al. (2014) analyse the volatility transmission between oil and cereal markets, and the effect of OPEC announcements on oil and cereal markets. They consider daily spot prices for oil, gasoline, heating oil, barley, corn, sorghum and wheat (mainly from the US market) for the period 2000-2013. They find widespread spillovers from oil to cereal markets but bidirectional effects only among barley, crude oil and gasoline. They mention that except for gasoline and sorghum, the rest of commodities are driven by a dynamic conditional correlation that shares an increasing tendency during the final crisis. They further conclude that the cut decisions by OPEC have a much larger effect on both, energy and agricultural markets.

A relatively smaller body of the literature applies general or partial equilibrium modelling frameworks to assess the impact of biofuel related policy measures. For instance, McPhail & Babcock (2012) use a partial equilibrium model to simulate the impact of the US Renewable Fuel Standard (RFS) and the blend wall on corn and gasoline price variability in the domestic market. They conclude that the current ethanol policies decrease the price elasticity of demand for corn and gasoline, and therefore increase the price variability.

4 Data and methodology

The focus of this study is to assess the evolution of the volatility spillovers between the oil market and the main agricultural commodities used for biofuels production. With this purpose we run a rolling window of 60 monthly volatility observations for the period between November 1996 and November 2014, which comprises 158 periods before, during and after crisis.
4.1 Data

We use international prices for cereals (wheat and corn), sugar, vegetable oils (soybean oil, rapeseed oil and palm oil) and oil (Brent). Table 3 provides a description of the series and presents its descriptive statistics.

Table 3: Descriptive statistics of the data

<table>
<thead>
<tr>
<th>Price levels</th>
<th>Max</th>
<th>Min</th>
<th>Mean</th>
<th>Std.Dev.</th>
<th>Skewness</th>
<th>Excess Kurtosis</th>
<th>JB p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wheat, No.2 Hard (Kansas) US$ Cts/BU</td>
<td>1407.00</td>
<td>238.75</td>
<td>504.86</td>
<td>191.08</td>
<td>1.00</td>
<td>0.67</td>
<td>0.00</td>
</tr>
<tr>
<td>Corn No.2 Yellow US$ Cts/BU</td>
<td>849.00</td>
<td>145.00</td>
<td>339.91</td>
<td>174.08</td>
<td>1.12</td>
<td>0.06</td>
<td>0.00</td>
</tr>
<tr>
<td>Raw Sugar (ISA) Daily Price US$ Cts/lb</td>
<td>32.57</td>
<td>4.70</td>
<td>12.95</td>
<td>6.14</td>
<td>0.86</td>
<td>-0.19</td>
<td>0.00</td>
</tr>
<tr>
<td>Soybean Oil, Crude Decatur US$ Cts/lb</td>
<td>67.69</td>
<td>11.84</td>
<td>30.87</td>
<td>12.94</td>
<td>0.63</td>
<td>-0.67</td>
<td>0.00</td>
</tr>
<tr>
<td>Palm Oil Crude MAL CIF Rdam US$/MT</td>
<td>1395.00</td>
<td>215.00</td>
<td>640.43</td>
<td>267.79</td>
<td>0.55</td>
<td>-0.68</td>
<td>0.00</td>
</tr>
<tr>
<td>Rapeseed Oil Dutch FOB NWE 1m fwd EUR/MT</td>
<td>1125.00</td>
<td>345.00</td>
<td>635.98</td>
<td>267.79</td>
<td>0.55</td>
<td>-0.68</td>
<td>0.00</td>
</tr>
<tr>
<td>Crude Oil WTI Cushing US$/BBL</td>
<td>145.31</td>
<td>10.82</td>
<td>56.64</td>
<td>31.93</td>
<td>0.30</td>
<td>-1.20</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Ln price returns

| Wheat, No.2 Hard (Kansas) US$ Cts/BU | 0.23    | -0.20   | 0.00    | 0.02     | 0.07     | 10.39          | 0.00       |
| Corn No.2 Yellow US$ Cts/BU | 0.11    | -0.12   | 0.00    | 0.02     | -0.13    | 3.18           | 0.00       |
| Raw Sugar (ISA) Daily Price US$ Cts/lb | 0.14    | -0.19   | 0.00    | 0.02     | -0.31    | 4.21           | 0.00       |
| Soybean Oil, Crude Decatur US$ Cts/lb | 0.08    | -0.08   | 0.00    | 0.02     | 0.11     | 2.20           | 0.00       |
| Palm Oil Crude MAL CIF Rdam US$/MT | 0.16    | -0.13   | 0.00    | 0.02     | 0.13     | 7.07           | 0.00       |
| Rapeseed Oil Dutch FOB NWE 1m fwd EUR/MT | 0.22    | -0.19   | 0.00    | 0.02     | 0.29     | 28.21          | 0.00       |
| Crude Oil WTI Cushing US$/BBL | 0.16    | -0.17   | 0.00    | 0.02     | -0.19    | 5.33           | 0.00       |

Source: Own elaboration.

Both, price levels and their logarithmic returns (ln-returns), fail the Jarque-Bera test for normality. While the price levels are closer to normality in terms of peakness, the log-returns show a relative high degree of kurtosis. The ln-returns for rapeseed oil show the highest kurtosis followed by wheat, palm oil and crude oil, meaning that price variations of these commodities present, with more frequency, extreme values. While sugar, corn and soybean oil also exhibit excess kurtosis, their values are closer to normality, being the soybean oil the lowest. Different to ln-returns, the kurtosis of the price levels are closer to normality and most of them are rather platykurtic, meaning a higher concentration of these series around their respective mean values. In terms of symmetry, both series are skewed. Price levels are predominantly positive skewed, while ln-returns show both positive and negative skewness. Nevertheless, the skewness of ln-returns is comparatively lower than price levels.

4.2 Methodology

4.2.1 Realized Volatility

To estimate the volatility we use the ex-post monthly-realized volatility (RV) estimator based on daily observations:

$$ RV = \sum_{j=1}^{m} r_{j\Delta \bar{A}}^2 $$

where $r_{j\Delta \bar{A}}$ is the squared of the daily logarithmic returns summed over the $m$ week-days observations in every month (between 20 and 23 days per month). The RV is further corrected for intra-month noise using a Moving Average process of order 1 (MA(1)) to account for the autocorrelation effect. The adjusted estimator is then:

$$ \hat{\sigma}^2 = m \varphi^2 (1 + \eta)^2 $$
where $\gamma^2$ and $\eta$ are the variance and the moving average coefficients, respectively, from the Maximum Likelihood (ML) estimate of the MA(1). We finally annualized its squared root by multiplying it by the square root of twelve. While most of the literature relies on the GARCH-type models to estimate the volatility, we chose the non-parametric RV estimator since this imposes less structure on the volatility process, an important advantage in highly volatile markets.

4.2.2 Co-volatility
The co-volatility (co-kurtosis) measures the strength of the linear relation between the second moments of two random variables. It is a positive value by construction ranging from 0 to 1. This value represents the probability that given a peak in one variable, a peak in the other variable also occur. Ang et al. (2006) define the co-volatility as follows:

$$Co-volatility = \frac{E(r_a - \mu_a)^2 E(r_b - \mu_b)^2}{\sqrt{E(r_a - \mu_a)^2} \sqrt{E(r_b - \mu_b)^2}}$$

, where $r_a$ and $r_b$ are the logarithmic returns of commodities $a$ and $b$, respectively, and $\mu_a$ and $\mu_b$ are their mean values.

4.2.3 Estimation of the volatility spillovers
There are different methods to estimate the volatility spillover effects, for instance the Multivariate GARCH (MGARCH) models with and without regime switches; the Stochastic Volatility (SV) models with Merton Jump; the Vector Auto Regressive (VAR) models; the Granger Causality in Variance approach; the Multiplicative Error Models (MEM); and the Copula approach. Each method has common and particular sets of features that make it suitable for specific data, theory and context.

Most of the reviewed literature on spillovers between energy and food markets relies on the BEKK specification of Multivariate GARCH models, however, for systems with more than three variables these models suffer from over-parameterization. Another issue to apply this modeling framework to our dynamic multi-period assessments is the lag order selection for each of the 158 different Multivariate GARCH systems. Instead, we use a VAR model, which captures the linear interdependencies among the variables and does not require a deep prior knowledge about their drivers. They need instead a hypothetical relation among them. In this sense, we assume a predominantly unidirectional volatility price transmission from oil to the considered agricultural markets, as the oil market is comparatively much deeper. We separate the commodities in two systems, one for oil and ethanol feedstocks, and one for oil and biodiesel feedstocks. Moreover, in order to identify each of the systems we further assume an ordering of the agricultural commodities according to their relevance as biofuel feedstocks and size of their markets. For the ethanol group we adopt the following structure: oil, sugar, corn, and wheat, whereas for the biodiesel group we assume the next ordering: oil, soybean oil, rapeseed oil and palm oil.

Based on the forecast error variance decompositions (FEVD) of the two VAR systems, we estimate the ‘Spillover Index’ proposed by Diebold & Yilmaz (2009). The error variance of the H step forecast of a VAR model is decomposed into own (the portion of the error variance due to shocks in the same commodity) and cross (the portion of the error variance due to shocks in the other commodities) variance shares or spillovers. Considering that the one-step ahead forecast of a bivariate VAR system given by
\[ e_{t+1,t} = x_{t+1} - x_{t+1,t} = A_0u_{t+1} = \begin{bmatrix} a_{0,11} & a_{0,12} \\ a_{0,21} & a_{0,22} \end{bmatrix} \begin{bmatrix} u_{1,t+1} \\ u_{2,t+1} \end{bmatrix} \]

, has a covariance matrix
\[ E(e_{t+1}e'_{t+1,t}) = A_0A'_0 \]

, the 1 step-ahead error in forecasting \( x_{t+1} \) is \( a_{0,11}^2 + a_{0,12}^2 \) and in forecasting \( x_{2,t} \) is \( a_{0,21}^2 + a_{0,22}^2 \). So the own variance shares are given by \( a_{0,11}^2 + a_{0,22}^2 \) and the cross variance shares or spillovers are then \( a_{0,12}^2 + a_{0,21}^2 \). The spillover index can be defined as the total spillovers relative to the total forecast error variation:

\[ S = \frac{a_{0,12}^2 + a_{0,21}^2}{\text{trace}(A_0A'_0)} \times 100 \]

The spillover index is then run over a rolling window of 60 months beginning in November 1996 and ending in November 2014. Each new window drops out the first month and includes a new one at the end of the series. In our case we run the VAR model over 158 windows comprising periods before, during and after the 2007-2008 food and financial crisis, with the aim at uncovering the dynamic pattern of the volatility spillovers between the considered markets.

5 Empirical findings

5.1 Co-Volatility

This section presents the evolution of the co-movements between the volatilities of oil and each of the six considered biofuel feedstocks, namely wheat, corn and sugar, and soybean oil, palm oil and rapeseed oil.

Figure 5 depicts the average volatility levels of oil and every ethanol feedstock separately, for each of the 158 monthly-rolling periods (left hand side). Every figure also includes the co-volatility coefficient (right hand side) between oil and the respective feedstock, and the bold vertical line indicates the outbreak of the crisis in September 2008. Figure 5 (a) shows the evolution of the volatilities for oil and sugar markets. The volatility level for oil is consistently higher than sugar for the entire period, except during 2014 when oil prices start decreasing. In the pre-crisis episode both series converge to a level around 0.26 between June and September 2008, but from October 2008 they start diverging again with oil volatility taking the lead. From the plummeting of the oil price in December 2008, its volatility remains at high levels between 0.30 and 0.35 until October 2013. From this point it starts shrinking and reaches its lowest value in August 2014 (0.21). However, from March 2014 onwards, the volatility of sugar surpasses the volatility of oil. During 2004 the co-volatility of the series reaches a maximum of 0.51. Before 2005 not only the volatility levels of the series are high, but also their co-volatility, pointing to some degree of co-movement between oil and sugar. However, that is not the case for the post-crisis episode, since the co-volatility coefficient decreases steadily and reaches a minimum of 0.14 in 2010 to rebound to 0.23 by the end of 2014. This behaviour suggests that other factors, different from effects spilling over from the oil markets, drive sugar price volatility after the crisis.
Figure 5: Co-volatilities between oil and the ethanol feedstocks

Figure 5 (b) presents the average volatility levels for oil and corn markets. The volatility gap between oil and corn is considerably higher than for sugar. Nevertheless, the overall pattern is similar to the oil – sugar returns discussed above. Both series start converging and reach a similar level around 0.26 short before the crisis. They fully converge later in May 2011 to 0.34. Between March 2012 and May 2013, oil and corn volatilities practically remain both at the same level (0.33), but from December 2013 onwards the corn series take the lead exhibiting higher volatility. While sugar and oil co-volatility starts at high levels before the crisis and then decreases over the entire period, the corn co-volatility declines only until February 2004 (0.24) and then begins an upward trend that attains a peak of 0.65 in September 2008 (bold line). Short after the crisis the co-volatility coefficient weakens and moves close to 0.48 between October 2008 and August 2013. By September 2013 it drops back to 0.28 for a few months, but then stabilizes around 0.37 over the last semester of 2014. Between September 2004 and September 2013 the co-volatility between corn and oil remains in average close to 0.50 pointing at potential spillover effects from the oil market, especially during and after the crisis.

Finally, Figure 5 (c) depicts the behaviour of the wheat and oil volatilities. Similar to the previous feedstocks, there is a convergence of the volatilities in December 2008, close to the crisis outbreak, and again in January 2014. Different from the previous series, wheat price volatility is higher than oil price volatility at two occasions, between March and November 2008, and during 2014. However, it shows a relative low and stable degree of co-volatility with the oil along the considered period. The periods of higher co-volatility are between June 2002 and May 2003 (0.35), in September 2008 (0.36) and an overall maximum of 0.37 in May 2009. Despite oil and wheat volatilities seem not to be co-moving directly, one has to
consider also indirect channels like the corn, which shows higher co-movements with the oil and is a substitute for wheat.

**Figure 6: Co-volatilities between oil and the biodiesel feedstocks**

![Image of co-volatilities between oil and the biodiesel feedstocks](image)

Source: Own elaboration.

Figure 6 presents the average volatility levels of oil and each of the considered biodiesel feedstocks (left hand side). Right hand side values correspond to the co-volatility coefficients with oil. Different from the cereals and sugar, the vegetable oils show relative lower volatilities and, despite converging to some degree with oil, they do not fully attain or surpass oil price volatility levels along the analysed period. From the group, soybean oil price volatility is the highest, with levels close or above 0.2, followed by palm oil and rapeseed oil which presents the lowest volatility values, well below 0.2 for the pre-crisis period, but approaching to this level in the after crisis episode. All three series present an increasing trend of their co-volatility levels until October 2008. However, after the crisis only the rapeseed oil plummets from 0.56 in September to 0.28 in October 2008 and stabilizes around 0.33 for the remaining time, except for a breve period between December 2013 and March 2014 when the co-volatility drops to 0.16 (Figure 6 (b)). Soybean oil co-volatility only falls slightly from 0.61 in October to 0.60 in November 2008 and keep on decreasing gradually to stabilize around 0.57. However, between March and September 2013 it reaches new peaks around 0.80, but then falls back to an average level of 0.50 for the remaining time (Figure 6 (a)). Palm oil shows the highest co-volatility coefficients. It attains an overall peak of 0.83 in October 2008, which then soothes around 0.71 until September 2013, when, similar to soybean oil (and three months before rapeseed oil), drops to pre-crisis levels (0.31) (Figure 6 (c)).
5.2 Volatility spillovers

To measure the volatility spillovers among the commodities in each group, we present in Figure 7 the spillover index proposed by Diebold & Yilmaz (2009), rolled over 158 consecutive sub-periods of 60 months, to reveal the spillover dynamics among oil, and ethanol and biodiesel feedstocks, respectively.

Figure 7: Volatility spillover index for the ethanol and biodiesel groups

Source: Own elaboration.
Note: The black Xs indicate the first observation at a higher or lower spillover level, where the levels increase in 5% steps.

Results show that the volatility spillover index for the ethanol group comprising oil, sugar, corn and wheat remains at a moderate average level of 6% up to November 2008, when it almost doubles (11%). By the end of 2012 the index moves down to 9%, but starting 2013 it commences a new period of higher volatility reaching an average level of 13%. With the sharp decline in the oil price, the index moves back to 9% during the last quarter of 2014.

The spillover index for the biodiesel group (i.e. oil, soybean oil, rapeseed oil and palm oil) confirms more instability in vegetable oils compared to the cereals and sugar markets. During the first semester of 2003 there is only one relative high but short volatility episode (12%), which coincides with the enforcement of the EU directive 2003/30/EC. However, after the peak of May 2003 (13%), it follows a relative calm period from mid 2003 to the end of 2007, with an average spillover level of 7%. Different from the ethanol, the calm period for this group ends one year earlier. From December 2007, – corresponding with a second and more ambitious biofuel mandate introduced by the US (Energy Independence and Security Act) – the biodiesel group experiments successive periods of higher volatility spillovers.

Different from the US Energy Policy Act of 2005, the new bill requires not only a sixth fold increase of biofuels by 2022, but also obliges to attain 60% of the target by using non-cornstarch feedstocks, namely sugar crops, oilseeds and cellulose. Between 2009 and mid 2012 the spillover index increases to 23%, a more than three times higher level. In April 2009 the EU introduces a new directive (2009/28/EC) requiring a substitution of 10% of transport fuels by biofuels in 2020. From April 2009 to September 2010 both spillover indexes show an upward trend, with a more marked development for biodiesel. In the second half of 2012 it attains an overall maximum of 31%, but in 2013 the tendency is reverted and the biodiesel index moves back to 26% and keeps on descending during 2014 to stabilize at a new mean level of 14% by the last quarter of this year. Despite the successive introduction of biofuel
support policies may not be the only factor driving prices and volatility spillovers, they play definitely an important role.

In order to assess the volatility spillover patterns between oil and the major biofuel feedstocks, Figure 8 presents the share of the variance in volatility of each ethanol feedstock (left panel) explained by price volatility in oil, and the feedback effects, i.e., the corresponding share in oil volatility explained by the respective feedstocks (right panel).

**Figure 8: Volatility spillovers between oil and cereals & sugar**

![](image)

Source: Own elaboration.

From the ethanol feedstocks, only the sugar shows low volatility spillovers from oil, both before and after the crisis (bold line). It is in average 2% with a peak of 6% in June 2008, short before the crisis outbreak. Between June 2003 and May 2004 oil spillovers on wheat attain an average level of 11%, registering a peak of 15% in September 2003. For the remaining time it stays below 5%, with a jump to 7% in December 2008. Corn on the other hand remains at low levels until November 2008, but abruptly rises to 21% in December 2008, coinciding with the oil price collapse. However, it declines slowly, showing persistent volatility spillovers from oil for most of the after-crisis episode.

As expected, the spillovers from the wheat and sugar to the oil market are negligible, especially before the crisis (right graph). The only exception is corn, which exhibits an average level of 4%, with values close to 0% at the beginning and at the end of the pre-crisis timeframe. Between October 2006 and June 2008 the corn spillovers present an atypical high average level of 7% and a maximum of 10% in July 2007. However, applying impulse-response analysis to the consecutive peaks in October 2006 (7%), February 2007 (9%) and July 2007 (10%) we find that this levels are statistically not significant (triangles). After the crisis, while sugar and wheat remain at relative low levels (well below 5% for most of the period), corn shows again counterintuitive spillover values (squares). The impulse-response analysis, while indicating this time statistically significant spillover effects, their values however are not significant in an economic sense. Some authors like Nazlioglu et al. (2013), with similar feedback effects, argue that the financialisation of agricultural markets may play a role in this behaviour; others point out at nonlinearities in the data. Some global and common factors, like macroeconomic policies or exchange rate oscillations may contribute to the apparent incidence of corn on oil by simultaneously shocking these markets.

Figure 9 depicts the spillovers between oil and vegetable oils, as well as their respective feedback effects. Different from cereals and sugar, oil volatility spillovers on vegetable oils...
are much larger. While the spillovers remain below the 5% level in the former case, they can reach up to 10% for the latter.

**Figure 9: Volatility spillovers between oil and vegetable oils**

Source: Own elaboration.

Oil spillovers on soybean oil show a cyclical pattern before the crisis, fluctuating from highs of 11% in July 2002, to lows of 1% in July 2004 and again from 9% in September 2006 to 2% in August 2008. After the crisis this series moves around an average of 6%, but during 2013 it rises to 15% and between September and October it peaks to 22%. Rapeseed oil presents an average spillover of 2% for most of the pre-crisis period, but between February and August 2008 the level rises temporarily to 6%, to drop back to 1% in September 2008. Similar to the soybean oil series, rapeseed oil attain its highest values during 2013, with a peak of 26% in May. While during the months following the crisis soybean oil and rapeseed oil remain around 10% and 5%, respectively, palm oil reaches its largest value of 22% in January 2009 to stabilize around the 6% level for the remaining time.

Regarding the feedback effects of the vegetable oils on oil (right graph), soybean oil and rapeseed oil show effects around or below 5% along the entire period. Nevertheless, the after crisis period presents relative higher volatility spillovers than the previous period. As for the corn series, palm oil exhibits unexpected spillover effects on the oil market. Applying the impulse-response analysis we arrive at similar conclusions, some high values around the crisis and at the end of the series (triangles) are not statistically significant, while some higher values are observed in the after-crisis episode (squares).

### 6 Conclusions

Biofuel production is mainly driven by political decisions in developed (and to an increasing extent, in developing) countries, which assign large budgets to promote the ethanol and biodiesel industries as a way to reduce greenhouse gases and manage their grain surpluses.

While ethanol production is concentrated in two countries, the US (63%) and Brazil (24%), and around two major feedstocks, corn and sugar cane, where sugar cane is more productive than corn, biodiesel is more evenly distributed among different countries (Germany, France, US, Argentina and Brazil) and despite the feedstocks are more diverse,
they have similar (low) productivities (oil seeds), except for palm oil, which has the highest potential.

Comparatively, the ethanol feedstocks are far more productive – on a liter per land-used basis – than the biodiesel. This fact reflects in the production levels for both biofuels. While the world production of ethanol is 86 Billion Lt. in 2011, it only attains 21 Billion Lt. for biodiesel (25%). Nevertheless, in 2011 ethanol and biodiesel represent only 1% and 0.2% of the global oil consumption, respectively.

Only corn, soybean oil and rapeseed oil present high linear dependence with oil price volatility in the after-crisis period. However during the pre-crisis episode all three variables show already increasing levels of co-volatility.

While many studies consider only periods of low volatility spillovers before the 2007-2008 crisis and periods of high volatility after it, we show that for the ethanol group there is a cyclical mean-reverting pattern with low and high volatility periods before, during and after the financial crisis. For biodiesel, similar to ethanol, the volatility level remains low for most of the pre-crisis period, but from December 2007, one year earlier than in the case of ethanol, it experiments a sustained increase that starts reverting only from the beginning of 2013.

If considered in isolation, the oil volatility spillovers are higher especially in the after-crisis episode and affect mainly the corn market for the ethanol group and all the vegetable oils for the biodiesel group. However, the shocks occur in distinct periods, with singular intensities and with different durations.

In the ethanol group, corn is most strongly affected by oil price volatility spillovers. Due to its high degree of acreage competition with wheat in production and the (limited) substitutability in consumption between corn and wheat, shocks from the oil market may also be transmitted indirectly to wheat. Corn is therefore responsible to a large degree for the ethanol spillover index fluctuations. In the case of the biodiesel feedstocks, oil price volatility is found to affect all three vegetable oils, especially at the beginning and at the end of the post-crisis period. However, only the co-volatility level with rapeseed oil remains at low levels after the crisis.

This situation suggests that the high values of the spillover index for the biodiesel group come mainly from the shocks to soybean oil and palm oil, and the interaction between them. Rapeseed prices are much more stable in the observed period. Rapeseed oil presents the main raw material for the EU biodiesel production, and the EU is the major production area for rapeseed. Thus, rapeseed is traded only to a lesser extent than the other vegetable oils, which might partially explain the low influence of the other prices in this group. In addition, the technical and sustainability requirements introduced by the EU for the biodiesel production, limit the use of substitutes like palm oil.

7 Policy recommendations

The analysis of volatility spillovers in the two groups has clearly indicated that these spillovers between the products rarely follow a simple pattern. We find episodes when the notoriously high oil price fluctuations induce additional volatility in key agricultural markets. These episodes are generally characterized by some common characteristics. First, the spillovers seem to be particularly strong when the prices of the agricultural products are comparatively high. This suggests that volatility spillovers are more likely to occur in periods when stocks are low. Second, the magnitude of spillovers in these episodes has increased
over time. Finally, the prevalence of spillover periods is product specific, and seems to be driven by substitutability of the products in food, feed, or biofuel use.

These three characteristics suggest that the biofuel policies do indeed contribute to higher volatility spillovers from the oil market to key agricultural products. Hence, the biofuel policies should be carefully re-considered, taking this finding into account. The fact that spillovers are relatively small for most of the pre-crisis period cannot be used as argument that price volatility spillovers would not matter. The key episodes, even if they are limited in number, are the ones that are politically important. At those times, the impact of oil price volatility on agricultural markets, which are already suffering from higher price levels and inflated uncertainty, exacerbates the situation, harming poor and vulnerable consumers, and reducing the incentives to agriculture at a time when the price level would particularly favors an expansion of production.

However, biofuel policies are unlikely to be radically reformed, at least in the short run. Our analysis of volatility spillovers suggests that mitigating measures, which have the potential to limit the transmission of price volatility from oil to agriculture, might constitute a politically feasible yet helpful approach. These measures could include a more flexible handling of blending requirements for biodiesel and bioethanol, an approach, which is already partially in use in Brazil and the US. Developing countries contemplating about a stronger support to biofuels should keep this in mind when designing their policies. Publicly managed buffer stocks hold by a single country, on the other hand, seems to be considered as an alternative tool by policy makers, too. However, their potential for curbing price volatility seems rather limited, especially in those periods when oil markets drive agricultural price volatilities, given the drastic difference in the relative size of the markets.
References


## Appendix

### Table 4: Summary of the literature review

<table>
<thead>
<tr>
<th>Paper</th>
<th>Products</th>
<th>Region</th>
<th>Model</th>
<th>Timeframe</th>
<th>Frequency</th>
<th>Findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Algeri (2014)</td>
<td>Endogenous: ethanol, corn, rapeseed, soybeans, soybean oil, sugar, wheat, crude oil, biodiesel, Exogenous: S&amp;P 500 index, the dollar/euro exchange rate</td>
<td>US</td>
<td>different univariate GARCH models, BEKK-MGARCH</td>
<td>2005 - 2013</td>
<td>daily</td>
<td>1-Magnified effect of stock market on commodity price returns. 2-Monetary liquidity does not influence commodity returns on a daily basis. 3-good news generates less volatility than bad news for corn market, while the contrary happens for wheat and sugar. 4-Both lagged oil and ethanol returns have a significant influence on corn, wheat, sugar and soybeans.</td>
</tr>
<tr>
<td>Liu (2014)</td>
<td>Crude oil, Corn, Soybean, Oat, Wheat</td>
<td>US</td>
<td></td>
<td>1994 - 2012</td>
<td>daily</td>
<td>1-Highly significant cross correlation between oil and agricultural commodity volatility series. 2-During the period of crisis, cross correlation coefficient between crude oil and agricultural commodity markets are stronger than those during common period.</td>
</tr>
<tr>
<td>Mensi et al. (2014)</td>
<td>Oil, gasoline, heating oil, barley, corn, sorghum, wheat</td>
<td>US, EU</td>
<td>VAR(1), BEKK-GARCH, DCC-GARCH</td>
<td>3.1.2000-29.1.2013</td>
<td>daily</td>
<td>1-Presence of spillovers of shocks and volatility between oil and cereal markets. 2-Bidirectional effects across barley and each of the crude oil and gasoline market. 3-The cut decisions by OPEC have a much larger effect on both type of commodity markets.</td>
</tr>
<tr>
<td>Gardebroek and Hernandez (2013)</td>
<td>Crude oil, ethanol and corn</td>
<td>US</td>
<td>T-BEKK-MGARCH and BEKK-MGARCH</td>
<td>9.1997-10.2011</td>
<td>weekly</td>
<td>1-There are no volatility spillovers from oil or ethanol to corn. 2-Shock in corn price volatility leads to a short-run shock in ethanol price volatility. 3-Segmentation of sample to 2 periods shows the ethanol market has become more directly exposed to past spillovers. 4-The impulse-response analysis confirm the presence of volatility spillovers from corn to ethanol both prior to 2006 and after 2008.</td>
</tr>
<tr>
<td>Nazlioglu et al. (2013)</td>
<td>Oil, wheat, corn, soybean, sugar</td>
<td>International</td>
<td>GARCH (1,1), causality in variance test</td>
<td>1986-2011</td>
<td>daily</td>
<td>preciotics: only causation from wheat to oil; postcriticism: bidirectional causation oil-soybean and oil-wheat and unidirectional causation from oil to corn.</td>
</tr>
<tr>
<td>Serra and Gil (2013)</td>
<td>Endogenous: corn, ethanol. Exogenous: stock level, interest rate</td>
<td>US</td>
<td>BEKK-MGARCH, parametric and semiparametric</td>
<td>1.1990-12.2010</td>
<td>monthly</td>
<td>1-Stock-to-disappearance forecasts are found to turn down corn price instability. 2-Interest rate variability bring more volatile food prices. 3-Instability in ethanol markets destabilises corn markets.</td>
</tr>
<tr>
<td>Serra (2013)</td>
<td></td>
<td></td>
<td>Literature review</td>
<td></td>
<td></td>
<td>1- GARCH type of models are mainly used. 2- While biofuel markets do not drive long-run feedstock price levels, causality is significant in the other direction. 3-Energy markets are capable of inducing volatility in feedstock markets.</td>
</tr>
<tr>
<td>Du and McPhail (2012)</td>
<td>Corn, ethanol, gasoline, light crude oil</td>
<td>US</td>
<td>DCC-MGARCH, IDH-SVAR, Variance decomposition analysis</td>
<td>25.3.2005-25.3.2011</td>
<td>daily</td>
<td>1-Structural break in March 2008. 2-In the earlier period, no spillover effect. 3-In the later period, corn, ethanol and gasoline prices are found to have significant and positive impact on each other. 4-The ethanol (corn) shocks have the largest impact on corn (ethanol) price.</td>
</tr>
<tr>
<td>Kristoufek et al. (2012)</td>
<td>Crude oil, ethanol, corn, wheat, sugar cane, soybeans, sugar beets, biodiesel</td>
<td>International, USA, Germany</td>
<td>Minimal spanning and hierarchical trees</td>
<td>2003-2011</td>
<td>weekly, monthly</td>
<td>*Before the crisis: food prices are low, fuels and biofuels are mildly connected. *Post crisis, 1) ethanol is well connected to corn, wheat and soybeans, 2) biodiesel in short term is very lowly correlated with the rest of the system but in medium term strongly connected to other fuels commodities, 3) corn, wheat and soybeans are well connected with the whole network, 4) sugars are less correlated.</td>
</tr>
<tr>
<td>McPhail and Babcock (2012)</td>
<td>Gasoline, ethanol, corn</td>
<td>US</td>
<td>partial equilibrium model</td>
<td></td>
<td></td>
<td>Current ethanol policies decrease the price elasticity of demand for both commodities, and therefore increase price variability.</td>
</tr>
<tr>
<td>Trujillo-Barrera et al. (2012)</td>
<td>Crud oil, corn, ethanol</td>
<td>US</td>
<td>Threshold GARCH, Vector error correction-Multivariate (BEKK) GARCH</td>
<td>2006-2011</td>
<td>weekly</td>
<td>*Spillover effect: 1) crude oil to the corn and ethanol, 2) corn to ethanol, 3) not from ethanol to corn. *Interconnection between ethanol and corn market</td>
</tr>
<tr>
<td>Paper</td>
<td>Products</td>
<td>Region</td>
<td>Model</td>
<td>Timeframe</td>
<td>Frequency</td>
<td>Findings</td>
</tr>
<tr>
<td>---------------</td>
<td>---------------------------------------</td>
<td>-------------------------------------------</td>
<td>--------------------------------------</td>
<td>-----------------</td>
<td>-----------</td>
<td>---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Alom et al. (2011)</td>
<td>Oil, food price index</td>
<td>Australia, New Zealand, South Korea, Singapore, Hong Kong, Taiwan, India and Thailand</td>
<td>Vector Autoregressive (VAR)-GARCH</td>
<td>1995-2010</td>
<td>daily</td>
<td>World oil prices positively influence food prices of the selected countries both in mean and in volatility and not vice versa,</td>
</tr>
<tr>
<td>Busse et al (2011)</td>
<td>Oil, rapeseed, rapeseed oil, soybean, soybean oil</td>
<td>EU (France, Netherlands)</td>
<td>Dynamic conditional correlation-Multivariate GARCH</td>
<td>1999-2009</td>
<td>daily</td>
<td>1) a non-stable and increasing correlation between the returns of rapeseed in MATIF and crude oil prices found, 2) the correlations of rapeseed price returns with vegetable oil and soybean price returns on the spot market are much lower than that with crude oil</td>
</tr>
<tr>
<td>Balcombe (2011)</td>
<td>Different commodities</td>
<td>FAO</td>
<td>Random parameter model, realised volatility-panel</td>
<td>different periods</td>
<td>different frequencies</td>
<td>Oil price volatility had a positive impact on commodity price volatility.</td>
</tr>
<tr>
<td>Du et al. (2011)</td>
<td>Crude oil, corn, wheat</td>
<td>US</td>
<td>Stochastic volatility with Merton jumps</td>
<td>1998-2009</td>
<td>weekly</td>
<td>Oil price shocks triggered sharp price changes in the corn and wheat</td>
</tr>
<tr>
<td>Serra (2011)</td>
<td>Oil, ethanol, sugar</td>
<td>Brazil</td>
<td>Semi parametric GARCH, BEKK-MGARCH</td>
<td>2000-2009</td>
<td>Weekly</td>
<td>1) shocks in crude oil a sugar market increases ethanol price volatility, 2) volatility spillover from sugar on the ethanol, 3) instability in sugar and crude oil are not hardly affected by ethanol, 4) parametric MGARCH model can lead to misleading results.</td>
</tr>
<tr>
<td>Serra et al. (2011 b)</td>
<td>Crude oil, ethanol, sugar</td>
<td>International, Brazil</td>
<td>Error correction model (ECM)-Multivariate (BEKK) GARCH</td>
<td>2000-2009</td>
<td>weekly</td>
<td>1) Increase in crude oil prices leads to higher ethanol prices, 2) low adjustment process ends up in higher volatility in ethanol, 3) Increase in sugar prices level cause ethanol price levels and volatility to increase</td>
</tr>
<tr>
<td>Alghalith (2010)</td>
<td>Oil, food basket price index</td>
<td>Trinidad and Tobago</td>
<td>Non-linear OLS</td>
<td>1974-2007</td>
<td>annual</td>
<td>Small oil-producing country (a price taker in both oil and food markets) can reduce food prices (or prevent the prices from rising) by increasing oil production and/or reducing oil price uncertainty by hedging the oil quantity in futures contracts.</td>
</tr>
<tr>
<td>Chang &amp; Su (2010)</td>
<td>Oil, corn, soybean</td>
<td>US</td>
<td>Bivariate exponential GARCH</td>
<td>2000-2008</td>
<td>daily</td>
<td>Spillover effect from crude oil futures to corn and soybean futures 1) insignificant during the lower crude oil price, 2) positively significant during the higher crude oil price</td>
</tr>
<tr>
<td>Zhang et al. (2009)</td>
<td>Ethanol, corn, soybean, gasoline, and oil</td>
<td>US</td>
<td>Vector error correction-Multivariate (BEKK) GARCH</td>
<td>1989-2007</td>
<td>weekly</td>
<td>1) In recent years there are no long-run relations among fuel (ethanol, oil and gasoline) prices and agricultural commodity (corn and soybean) prices, 2) fuel prices may cause transitory short-run agricultural commodity price inflation.</td>
</tr>
</tbody>
</table>