Long-run waves or short-run fluctuations – What establishes the correlation between oil and food prices?

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Abstract

The strong correlation between food prices and energy prices has gained much attention in the public debate, especially since the food price crisis in 2007/2008. The reason for this correlation however is a highly discussed issue in the empirical literature. In this paper we use the frequency domain Granger causality test of Breitung/Candelon (2006) to analyse short and long-run causality between energy prices and prices of food commodities. For the food index, barley and maize we find only week evidence for Granger causality. In the cases of EU sugar and palm oil our results indicate that the production of biofuel might be an explanation for the co-movement. Furthermore we get some indication that the oil price started to move together with the prices of palm oil, rice, EU sugar and soybean oil over shorter cycles during/after the food price crisis in 2007/2008. A possible explanation for this could be the financialization of commodity markets.

JEL classification: C32, Q02, Q43

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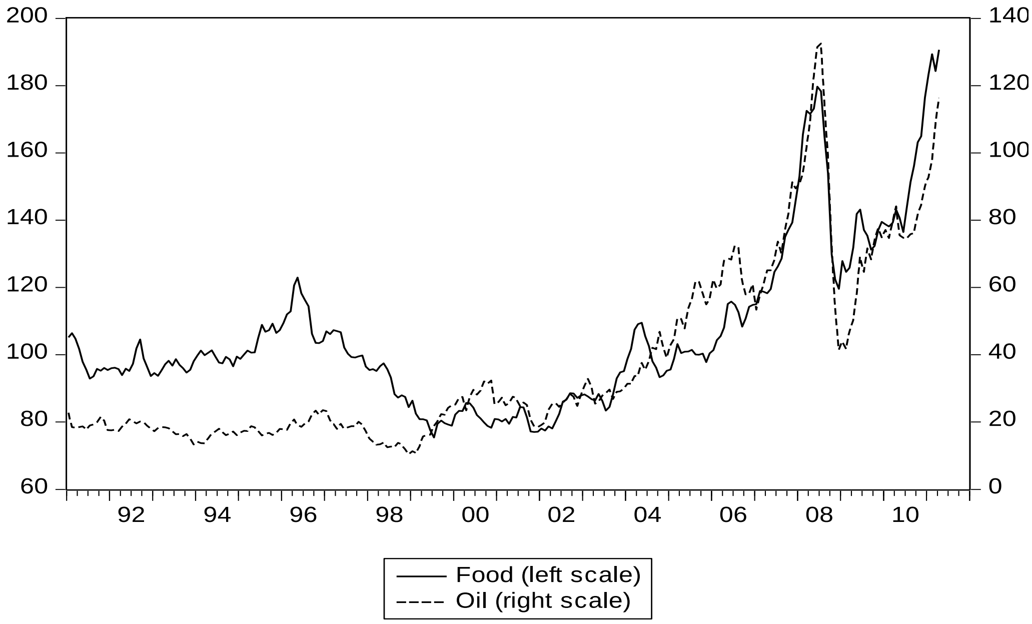
1. Introduction

Rising food prices and a possible entanglement of agricultural and energy markets have gained much attention in the public debate, especially since the food price crisis in 2007/2008. As it is well documented in the literature and shown in figure 1 a strong correlation between food prices and energy prices exists (e.g. United Nations Conference on Trade and Development 2009). The reason for this correlation however is a highly discussed issue in the empirical literature. Common macroeconomic developments, such as increasing demand for commodities from emerging markets and the importance of chemical and petroleum derived inputs in agricultural production are often seen as the main factors behind this co-movement (Headey/Fan 2008, Harri et al. 2009). However, if the correlation reflected one of these fundamental reasons, it should dissipate, when the development of global economic activity is taken into account. Another reason for this correlation might be the increasing importance of food commodities for the production of biofuels that could have led to the entanglement of agricultural and energy markets. Clearly, if biofuel became a noticeable substitute for petroleum both prices should move together over longer periods regardless of the current state of the economic cycle.

In the short run herd behaviour and speculation could drive the co-movement between food and energy prices. Pindyck/Rotemberg (1990) e.g. find that the link holds even after controlling for changes in economic activity. They argue that this co-movement exceeds the degree that can be explained by common macroeconomic factors. Although they did not distinguish between short- and long-term causality in their analytical approach, they concluded that this excess co-movement was driven by herd behaviour. This view was challenged by recent empirical studies (Lescaroux 2009, Vansteenkiste 2009), though, that do not find strong evidence for the excess co-movement hypothesis stated by Pindyck and Rotemberg.

Figure 1: Oil and food prices from 1991 to 2011



Source: IMF primary commodity prices database.

Another strand of the literature tries to distinguish short- and long-run effects by applying cointegration tests and vector error correction models[1]. However, in these studies it is not quite clear what short and long run exactly mean. In this paper we therefore analyze the link between crude oil and food commodity prices more closely by using the frequency domain Granger causality approach (Breitung/Candelon 2006; Lemmens et al. 2008). This testing procedure allows new insights because tests are performed for particular frequencies. Hence, as it is possible to transform each frequency to a corresponding cycle length, we can directly see whether the link results from long-run waves, business cycles or short-run dynamics.[2] To provide our conclusions with a solid empirical basis, we use a wide range of food commodities and their prices as our data series. In addition to bivariate VAR models we perform the Granger causality tests also for trivariate VAR models that include industrial production, besides crude oil and the studied food commodity, to control for global economic activity. We furthermore test for Granger causality only in the 1980 – 2006 pre-crisis period, to gain some information about what could have change during the crisis.

[1] See e.g. Arshad/Hameed 2009, Saghaian 2010, Zhang et al. 2010.

[2] A growing number of studies (e.g. Assenmacher-Wesche/Gerlach 2008; Gronwald 2009; Croux/Reusens 2011) show the usefulness of these tests.

Abstracting from the issue of frequency we find some evidence that the oil price Granger causes the prices of the studied food commodities. However, in the cases of the overall food index, barley and maize we find, if at all, only weak evidence for Granger Causality. Furthermore our results reveal some important differences with respect to the frequencies involved, the type of model used and the period covered in the tests.

The paper is organized as follows. Section two gives an overview on the relevant literature. Section three sets out the testing procedure. Section four presents the empirical results and section five concludes.

2. Literature Review

The empirical literature pays much attention to the link between energy prices and the prices of other, especially food commodities. Generally one can distinguish diverse reasons for the co-movement of commodities that correspond to different time periods. In the short run, herd behaviour and short-term speculation can explain why the prices of commodities oscillate together. Herd behaviour refers to the phenomenon when investors are either optimistic or pessimistic on all commodities (Pindyck/Rotemberg 1990). Thus, an increase in e.g. the price of crude oil would lead to an increase in the prices of other commodities just because traders would expect them to rise as well and therefore would have a higher demand for these commodities. Short-term speculation may lead to an excess co-movement between energy and food commodities because investors allocate funds to commodity indexes rather than to specific commodities. Thus, an (expected) increase in the oil price could lead to higher investments in commodity indexes and therefore result in an increase in the prices of other commodities, too, although their fundamentals may have stayed the same. In particular, for the recent economic crisis there is some evidence that the co-movement between oil and food commodity prices increased due to financial investments (UN 2009; Silvennoinen/Thorp 2010). Furthermore Gilbert (2008) shows that index trading had a significant positive effect on soybeans prices, but not on the prices for corn, soybean oil and wheat.

In the medium run common macroeconomic shocks can explain why different commodity prices tend to move together. Increasing demand for commodities from emerging markets and higher oil and fertilizer prices are often seen as main factors driving this co-movement (Vansteenkiste 2009, Harri et al. 2009). Long-run factors like economic development may also intensify the co-movement of oil and food commodity prices. In what follows we do not distinguish medium- and long-run co-movement because in both cases it is driven by macroeconomic fundamentals.

Many empirical studies refer to the excess co-movement hypothesis stated by Pindyck and Rotemberg (1990) and analyse whether the co-movement arises from common macroeconomic shocks attributing or is due to herd behaviour or speculation. On a database that includes various non-energy commodities, Baffes (2007, 2010) shows that especially food commodities tend to move together with the oil price even after controlling for macroeconomic variables. He uses OLS regressions to estimate the pass-through of changes in the oil price to the prices of other commodities. Lescaroux (2009) uses a market-oriented approach to identify common macroeconomic shocks by taking the role of inventories into account. He argues that macroeconomic shocks affect the inventory levels of commodities, the cost of storage and through this channel also the prices of commodities. After controlling for changes in inventory levels Lescaroux does not find strong evidence for excess co-movement. Vansteenkiste (2009) derives similar results using a dynamic factor model, finding that various common macroeconomic factors cause the prices of the commodities to oscillate together.

As a consequence of their analytical approaches, all these papers provide important insights into the co-movement between different commodity prices in the short and medium run. Yet they do not take the long run into account. In the long run the production of biofuel can be an explanation for the co-movement especially between the prices of energy and food commodities (Arshad/Hameed 2009; Serra/Zilbermann 2013), and the current state of the economic cycle might arguably be quite irrelevant. With the rising importance of biofuel production the agricultural and energy markets became more connected and prices might move together over longer periods.

Some other empirical studies try to filter out the long-run component performing co-integration tests and VECM. Arshad/Hameed (2009) and Harri et al. (2009) show that there is a link between the oil price and the prices of other commodities in the long-run. However, Harri et al. (2009) do not find evidence for such a link in the case of wheat. Saghainan's (2010) results are mixed, he shows that the considered series are co-integrated but does not find any causal link when applying a test of contemporaneous causal structures. In contrast, Zhang et al. (2010) do not find evidence for a long-run co-movement between the prices of oil and agricultural commodities at all. McPhail et al. (2012) derive similar results and show that oil and corn prices are not co-integrated, but based on an impulse response analysis they conclude that oil prices do have a long-run effect on corn prices. The impulse response analysis however covers only the effect of a shock from impact up to 10 month. While these co-integrated VAR models give some information about the sources of the co-movement, they provide no clear definition of "short-run" and "long-run". In particular what is meant by long-run in each specific model depends on the characteristics of the unobserved stochastic trend. In contrast, the frequency domain Granger causality test of Breitung/Candelon (2006) offers an intuitive interpretation of short- and long-run co-movement because it provides the length of the cycle for each test-statistic.

3. Testing procedure

Most empirical results on the link between oil and food commodity prices are generated using Granger Causality tests in the time domain. Therefore, we present results of this test as a starting point of our analysis. This allows us to compare our results directly with the findings of other studies.

A variable Y_t is said to Granger cause X_t, if Y_t contains information to predict X_t that is not available otherwise (e.g. Lütkepohl 2005: 41pp.). The idea of testing for Granger causality in the time domain can be illustrated in the following VAR model of order p.

$$X_t = \theta_{11,1} X_{t-1} + ... + \theta_{11,p} X_{t-p} + \theta_{12,1} Y_{t-1} + ... + \theta_{12,p} Y_{t-p} \tag{1}$$

$$Y_t = \theta_{21,1} X_{t-1} + ... + \theta_{21,p} X_{t-p} + \theta_{22,1} Y_{t-1} + ... + \theta_{22,p} Y_{t-p} \tag{2}$$

Using the lag operator (L) this model can be written in matrix notation as

$$\Theta(L) \begin{pmatrix} X_t \\ Y_t \end{pmatrix} = \begin{pmatrix} \theta_{11}(L) & \theta_{12}(L) \\ \theta_{21}(L) & \theta_{22}(L) \end{pmatrix} \begin{pmatrix} X_t \\ Y_t \end{pmatrix} = \varepsilon_t \tag{3}$$

where $\Theta(L) = I - \Theta_1 L - ... - \Theta_p L^p$ is the lag polynomial and Θ_k are 2×2 coefficient matricies. Under certain conditions Y_t does not Granger cause X_t if $\Theta_{12}(L) = 0$, which means that past values of Y_t are not related to X_t. This can be tested by using an F-Test for the coefficients $\Theta_{12,i}$ for i = 1, … , p. Due to the fact that Granger causality tests in most cases are based on one period ahead predictions it is not well suited to distinguish short and long run effects[3].

To get a more precise picture of the short- and long-run effects we use a frequency domain Granger causality test (Ding et al. 2006).

Several proposals have been made to construct such tests in the frequency domain (Geweke 1982; Hosoya 1991; Breitung, Candelon 2006; Lemmens et al. 2008). In what follows we use the test proposed by Breitung/Candelon (2006). They construct a Wald-test for the coefficients $\Theta_{12}(L)$ at different frequencies by imposing an additional restriction. To get an idea where this restriction comes from we write system (3) in the following moving average representation

$$\Psi(L)\eta_t = \begin{pmatrix} \Psi_{11}(L) & \Psi_{12}(L) \\ \Psi_{21}(L) & \Psi_{22}(L) \end{pmatrix} \begin{pmatrix} \eta_{1t} \\ \eta_{2t} \end{pmatrix} \tag{4}$$

where $\Psi(L) = [\Theta(L)G]^{-1}$ and G is the lower triangular matrix of the Cholesky decomposition $G'G = \Sigma^{-1}$ such that $G\varepsilon_t = \eta_t$ and $E(\eta_t \eta_t') = I$. Fourier transforming this system we get the following spectral density of X_t which consists of two parts

$$f_X(\omega) = \frac{1}{2\pi} \left\{ \left| \Psi_{11}\left(e^{-i\omega}\right) \right|^2 + \left| \Psi_{12}\left(e^{-i\omega}\right) \right|^2 \right\}. \tag{5}$$

The first element in equation (6) which is related to the autoregressive coefficients of equation (1) is called the “intrinsic” term (Barnett/Seth 2011). The second element is related to the exogenous variable in equation (1) and is called the “causal” term of the spectrum. Breitung/Candelon (2006) use this causal $\Psi_{12}(L)$ element to construct their frequency domain Granger causality test. Due to the fact that

$$\Psi_{12}(L) = -\frac{g^{22}\Theta_{12}(L)}{|\Theta(L)|} \tag{6}$$

[3] Dufour et al. (2006) propose an approach to distinguish short and long-run causality based on several period ahead predictions.

Where g^{22} is the lower diagonal element of G^{-1} it is possible construct a test on the coefficients at each frequency by transforming $\Theta_{12}(L)$ into the frequency domain: $\Theta_{12}(e^{-i\omega})$. It follows from De Moivre's theorem (Hamilton 1994) that

$$\Theta_{12}(e^{-i\omega}) = \sum_{k=1}^{p} \theta_{12,k} \cos(k\omega) - \sum_{k=1}^{p} \theta_{12,k} \sin(k\omega) i \,. \tag{7}$$

Therefore, $\left|\Theta_{12}(e^{-i\omega})\right| = 0$ implies that

$$\sum_{k=1}^{p} \theta_{12,k} \cos(k\omega) = 0 \tag{8}$$

and

$$\sum_{k=1}^{p} \theta_{12,k} \sin(k\omega) = 0 \,. \tag{9}$$

The null hypothesis of no Granger Causality at frequency ω can be tested by using a standard Wald-test on a set of coefficients of equation (1).

$$H_0 : R(\omega)\Theta_{12}(L) = 0 \tag{10}$$

with

$$R(\omega) = \begin{bmatrix} \cos(\omega) & \cos(2\omega) & \ldots & \cos(p\omega) \\ \sin(\omega) & \sin(2\omega) & \ldots & \sin(p\omega) \end{bmatrix} \tag{11}$$

This test has a χ_2^2 distribution. It can also be applied to VAR models with more than two variables. A crucial step in this testing procedure is to determine the lag order of the VAR because it determines the dynamic structure of the model (Lemmens et al. 2008). To get sufficient dynamic structure in the model to perform the frequency decomposition it is necessary to include at least three lags in the VAR.[4]

[4] We are grateful to Jörg Breitung for this hint.

4. Empirical Results

Before we perform Granger Causality tests we first examine whether the considered variables are stationary. As shown in table 1 the ADF tests indicate that most variables have a unit root in levels but are stationary in first differences. Only for palm oil and EU sugar we can detect stationarity in both cases, but at a lower significance level in the case of levels. As all variables are stationary at the 1% significance level in the models in first differences our analysis will focus on variables in their first differences.

Table 1: Augmented Dickey-Fuller Test

	T-statistic Levels	**T-statistic 1st differences**
Food Index	-0.994	-10.675***
Barley	-1.801	-17.796***
Maize	-2.084	-14.874***
Palm Oil	-2.624*	-7.960***
Rice	-2.034	-13.070***
Soybean Oil	-2.203	-14.380***
Sugar EU	-3.284**	-11.915***

All variables are in logs; * significant at 10% level, **significant at 5% level, *** significant at 1% level

To perform the Granger causality tests we first estimate bivariate VAR models for oil prices and several food price indices. In a next step we furthermore include industrial production into to the VAR models to control for business cycle developments that could have led to a co-movement of the oil price and the considered food prices. For oil and food prices we use monthly commodity price indices from the IMF primary commodity prices database. The studied commodities are crude oil (US-Dollar per barrel), the overall food index, soybean oil (US-Dollar per metric ton), maize (US-Dollar per metric ton), barley (US-Dollar per metric ton), EU sugar (US cents per pound), rice (US-Dollar per metric ton), and palm oil (US-Dollar per metric ton). The sample depends on the data availability. In most cases it ranges from January 1980 to September 2013. For the overall food index and EU sugar we use data from January 1991 to September 2013. In addition, we use industrial production data from the International Financial Statistics database of the IMF which we seasonally adjust before using them in the testing procedure. To determine the lag length we use the LR criterion.

Before using the frequency domain Granger causality test of Breitung/Candelon (2006) we perform simple Granger causality tests in the time domain to gain first insights into the effect of the oil price on the prices of the other commodities.

Table 2: Granger Causality Tests (Oil → Food)

	Bivariate			Trivariate		
	Test statistic	**P-Value**	**# Lags (LR)**	**Test statistic**	**P-Value**	**# Lags (LR)**
Food Index	13.26	0.428	13	14.75	0.323	13
Barley	9.66	0.140	6	14.03	0.727	18
Maize	6.17	0.290	5	14.44	0.757	19
Palm Oil	14.20**	0.027	6	22.64	0.253	19
Rice	15.33	0.428	15	18.98	0.393	18
Soybean Oil	8.70	0.191	6	19.09	0.451	19
Sugar EU	21.61***	0.001	6	22.76**	0.012	10

chi-square values, * significant at 10% level, **significant at 5% level, *** significant at 1% level.

As can be seen in Table 2, the oil price Granger causes only two of the considered food commodities in the bivariate and only one in the trivariate model. In the case of palm oil the link vanishes when controlling for global economic activity, indicating that the co-movement was established by common business cycle developments. For EU Sugar we can detect Granger causality also in the trivariate model. This implies that there seems to be other factors than common macroeconomic shocks that drive the co-movement. For the other food commodities we cannot detect any Granger causality in the time domain, but the oil price could still Granger cause these commodities at certain frequencies. To derive further insights into the possible causes of the co-movement we therefore perform the frequency domain Granger causality test of Breitung/Candelon (2006) to disentangle short- and long-run effects[5]. Three graphs are shown for each commodity: the first depicts the results of the bivariate system, the second the results of the trivariate system that includes industrial production besides crude oil and the studied commodity. Finally, the third graph shows the test results of the trivariate model for the pre-crisis period ranging from January 1980, 1991 respectively, until December 2006. Comparing the results of the pre-crisis period to those of the whole period should give some indication about what have changed during the crisis. The test statistics for 314 frequencies as well as the 5 percent critical values (dashed line) are shown for each food price index in Figure 2.The frequencies on the horizontal axis range from 0 to 3.2. They can be translated into periodicities of T months by T=2 π/ω. This means that

[5] The GAUSS code can be downloaded from Jörg Breitung's homepage.

frequencies smaller than 0.05 corresponds to cycles longer than 10 years. Business cycles are typically assumed to last between 2 ½ and 7 years. The respective frequencies are roughly 0.2 and 0.07. Frequencies around 0.5 belong to cycles of 12 months which capture seasonal effects (Hamilton 1994: 167-170) and a frequency of two corresponds to cycles of three months.

Figure 2: Causality tests between oil and food prices

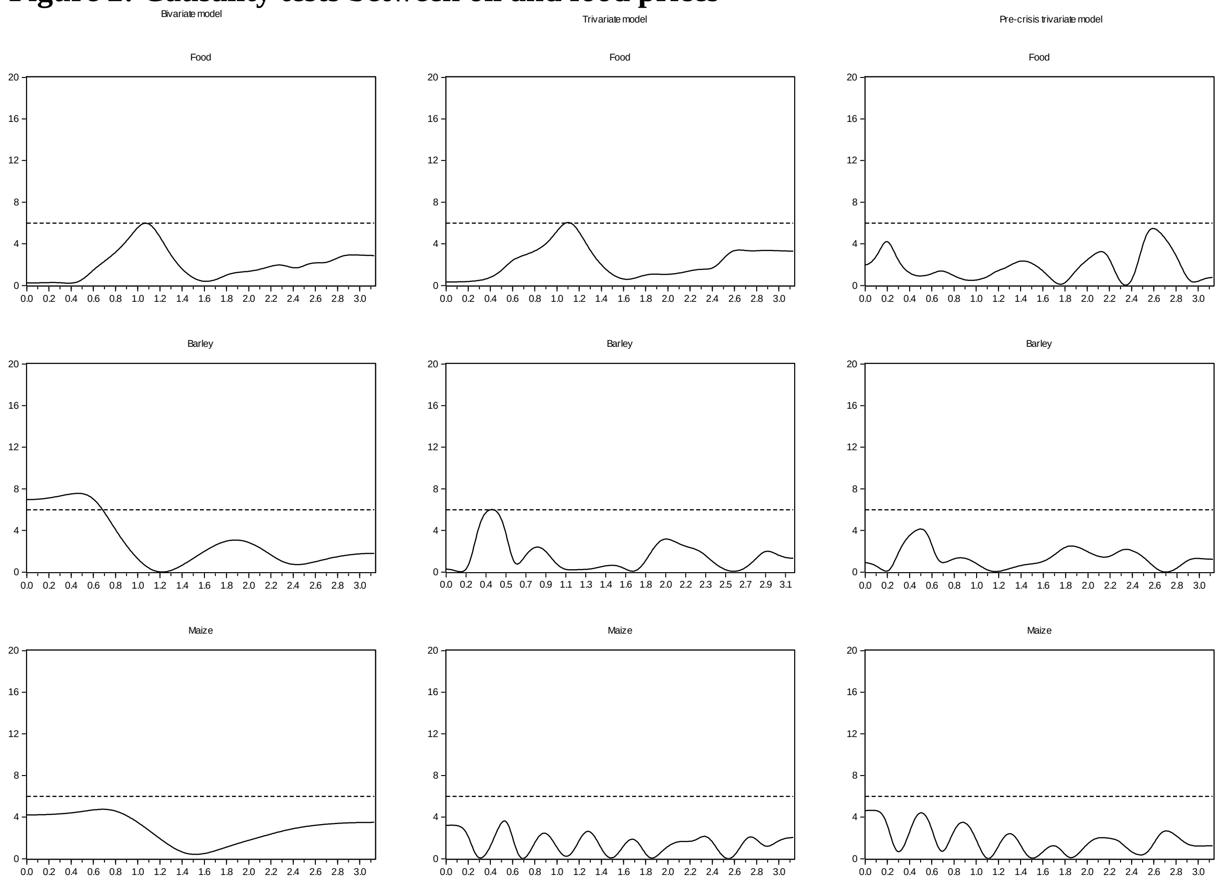
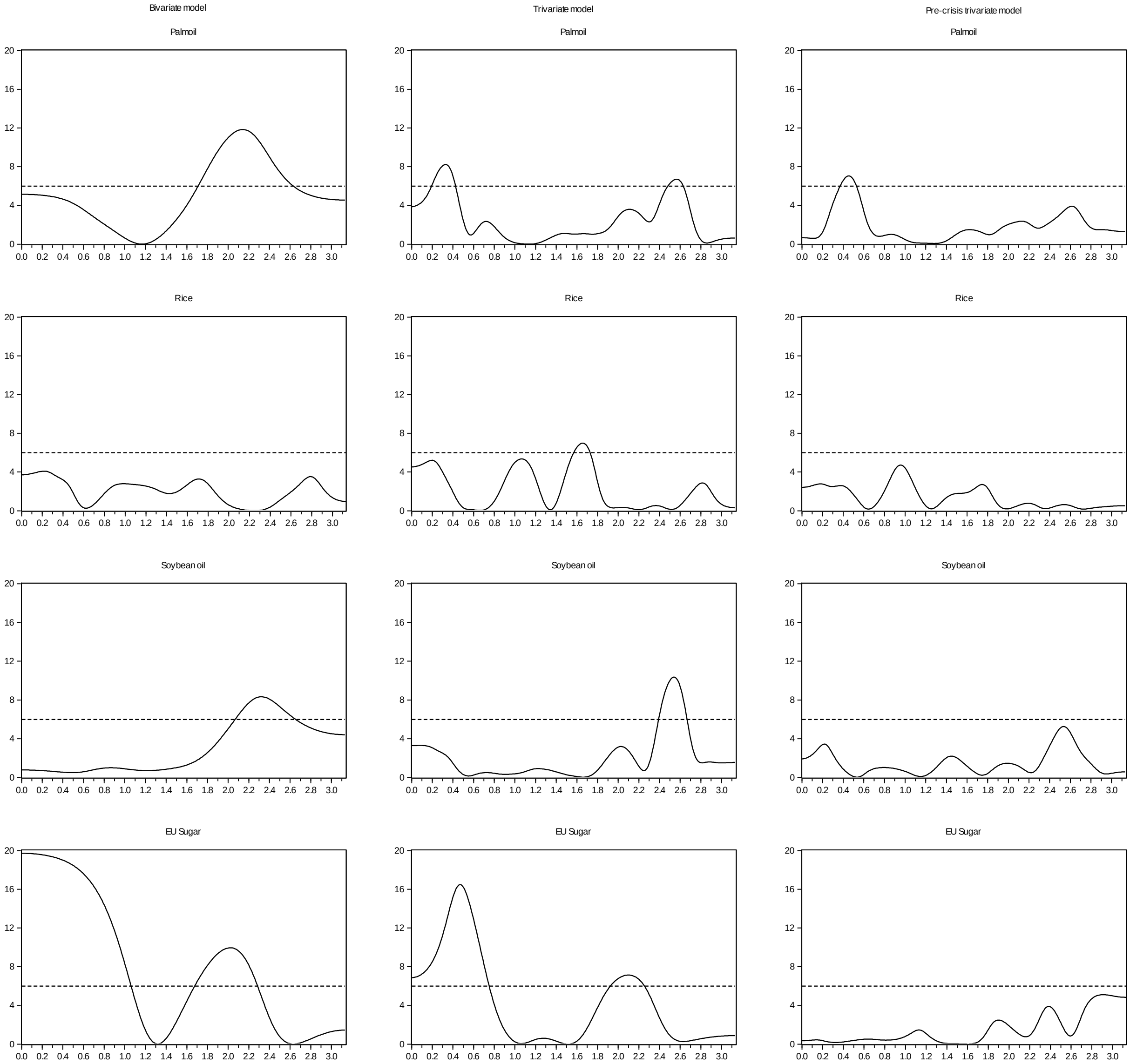


Figure 2 (continued)



First of all, the results show that the crude oil price index Granger causes most of the considered food commodities at least at some frequencies either in the bivariate or in the trivariate cases. However, in some cases the test statistic surpasses the 5 per cent critical value of 5.99 only slightly.

Next, we take a closer look at each studied commodity. To start with, the oil price is estimated to Granger cause the overall food price index in the range [1.09,1.13] in the trivariate sytsem, corresponding to a cycle length of about 6 months. However, the test statistic is only slightly higher than the critical value in the respective range. In the bivariate case and in the pre-crisis period the oil price does not Granger cause the overall food index. We derive similar results for barley and maize. While the oil price does not Granger cause the maize price at all, we can detect Granger causality at lower frequencies for barley in the models that cover the whole period: In the range [0,0.69] in the bivariate and in the very small range [0.42,0.43] in the trivariate model. This implies that the link between the oil price and the price for barley is mostly established by common business cycle developments. Thus for the food index, maize and barley we find, if at all, only week evidence for Granger causality which correspond to the results of the Granger causality test in the time domain. It contrasts, however, with the findings of other empirical studied. Arshad/Hameed (2009), Harri et al. (2009) and McPhail et al. (2012) e.g. find a long-run relationship between the petroleum price and the price for maize. They explain this long-run link by the production of biofuels and the increasing importance of petroleum derived inputs in agricultural production. Saghaian (2010) show that the oil price Granger causes corn prices but does not find any causal link between oil and corn prices when applying a test of contemporaneous causal structures. The results of Qui et al. (2012) indicate that an oil supply shock leads to a substantial increase in the corn price in the short-run. McPhail et al. (2012) however conclude that index trading in maize did not lead to the build-up of a bubble in this market, which correspond to our finding that the oil price does not Granger cause maize prices at high frequencies.

For the other considered food commodities we find more evidence for Granger causality, but, similar to the overall food index, the test statistics exceed the critical value only slightly in the cases of palm oil and rice in the trivariate model. For palm we can detect Granger causality in all the considered models, but there are differences with respect to the frequencies involved. While the oil price Granger causes the price for palm oil only at higher frequencies in the bivariate case, this link is established at low and high frequencies in the trivariate model. This means that in the bivariate approach the correlation of oil prices and industrial production hides the link between oil and palm oil at lower frequencies. In the pre-crisis period we can detect Granger causality only at low frequencies.

In the case of rice we can detect Granger causality only in the trivariate model that covers the whole period in the range [1.58, 1.73], corresponding to a cycle length of about 4 month. In contrast, Arshad/Hameed (2009) find a long-run relationship between oil and rice prices. Similar to rice the oil price Granger causes the price for soybean oil at higher frequencies in the trivariate model that covers the whole period but not in the pre-crisis model. We can furthermore detect Granger causality at higher frequencies in the bivariate model. A possible explanation for this short-run link between oil and soybean oil could be herd behavior or speculation (UN 2009; Silvennoinen/Thorp 2010). Gilbert (2008) however does not find evidence that index trading has a significant effect on the price of soybean oil. In the case of EU sugar our results indicate a short-run as well as a long-run relationship between the oil price and the price for EU sugar in both models that cover the whole period, but no relationship in the pre-crisis period.

These results offer some important insights into the co-movement between oil and food prices. For the food index, barley and maize we find only week evidence for Granger causality which contrasts the findings of other empirical studies. In the cases of palm oil and EU sugar there seem to exist a long-run relationship between the oil price and the two food commodities. This link was already established in the pre-crisis period in the case of palm oil but exists only in the models that cover the whole period in the case of EU sugar. A possible explanation for this long-run relationship might be the production of biofuels, as palm oil and sugar are intensively used to produce biofuels. Since maize and soybean oil are also main input factors in the production of biofuels we would also expect some long-run relationship between oil and the two series. However, for maize we cannot detect any Granger causality at all and in the case of soybean oil our results indicate only a short-run relationship. These results, though, correspond to the findings of the Granger causality test in the time domain, where we can only find a link between the oil price and EU sugar/palm oil. For both of these commodities we can furthermore detect Granger causality at higher frequencies in the trivariate model indicating that also short-term factors seem to matter for the co-movement of the series.

Moreover, the oil price does not Granger cause rice, soybean oil and EU sugar in the pre-crisis period, but we can detect Granger causality at higher frequencies in the trivariate models that cover the whole period. We derive similar results for palm oil. While the oil price Granger causes palm oil only at low frequencies in the pre-crisis period this link is also established at higher frequencies in the trivariate model that covers the whole period. This indicates that after 2006 the oil price and the prices of the considered food commodities started to move together over shorter cycles. This result is roughly in line with Nazlioglu et al. (2013) who find that volatility transmission between oil and agricultural commodity markets only occurred in the post-crisis period.

5. Conclusions

The high correlation between oil and food prices is well established in the literature. However, it is an important question whether this relation arises from the long-run waves, business cycles or very short-run fluctuations. So far empirical studies use cointegration tests and VECM to distinguish short-run and long-run causality. A drawback of this approach is that it is difficult to see what short-run and long-run exactly means. In this paper we use the relatively new frequency domain Granger causality test by Breitung/Candelon (2006). This allows us to test Granger causality at specific frequencies which can be translated into the associated cycle length. We apply this test to an overall food price index as well as to several indices of food commodity prices.

For the food index, barley and maize we find only week evidence for Granger causality. In the cases of EU sugar and palm oil our results indicate that the production of biofuel might be an explanation for the co-movement between the oil price and the two series. Furthermore the oil price does not Granger cause the prices for palm oil, rice, EU sugar and soybean oil at high frequencies in the pre-crisis period but does so in the trivariate models that cover the whole period. Thus there might have been some changes during/after the food price crisis in 2007/2008 that led to a co-movement between the oil price and the prices of the studied commodities over shorter cycles. A possible explanation for this could be the financialization of commodity markets.

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