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Price co-movement in the principal skim milk powder producing regions: a wavelet analysis

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Abstract

This paper investigates price co-movement in the principal skim milk powder (SMP) producing regions (the EU, Oceania, and the USA) using wavelet analysis and monthly data over 2001 to 2015. The empirical results suggest: First, the price linkages at the high frequencies are weak but they become progressively stronger as one considers longer time horizons. Second, the pair of regions (EU, Oceania) is more integrated than the pairs (EU, USA), and (Oceania, USA). Third, the SMP prices in the EU and in Oceania move together and lead prices in the USA.

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1. Introduction

The linkages between commodity prices in geographically separated markets have long attracted the attention of economists and policy makers. The interest in the topic stems from the understanding that the intensity and the mode of price relationships may provide information about market integration or segmentation. Well-performing (integrated) spatial markets are characterized by strong price co-movement (dependence); that means, price shocks in one them evoke response to the others. Price transmission is a necessary condition for economic efficiency and maximization of benefits from spatial arbitrage (e.g. Meyer and von Cramon Taubadel, 2004; Serra *et al*., 2006).

The investigation of price linkages in the physical or in the product quality space has been conducted with a large variety of quantitative approaches. The overwhelming majority of empirical studies have relied on tools suitable for analysis in the time domain such as the models of integration, cointegration, threshold or smooth transmission, and their variants (e.g. Abdulai, 2002; Dawson and Dey, 2002; Serra *et al*., 2006; Emmanouilides and Fousekis, 2012; Hassouneh, *et al*. 2012). Very few works have relied on tools suitable for analysis in the frequency domain (spectral analysis) (e.g. Miller and Hayenga, 2001)[1]. Both types of analysis have strengths and weaknesses. The analysis in the time domain offers an excellent time-localization (resolution); it assumes, however, that every point in the time-domain contains information about all frequencies. As a result, frequency information is completely lost and there is no way for a researcher to determine how the different periodic components of a given series change over time or how two or more time series are related to each other at different frequencies. The analysis in the frequency domain (spectral analysis) offers an excellent frequency-localization; it assumes, however, that every point in the frequency domain contains information from all points in the time domain. As a result, time information is completely lost and there is no way for a researcher to determine how two or more time series are related at different time periods (e.g. Ramsey and Lampart, 1998; Crowley, 2007).

A quantitative tool which reconciles the analysis in the time domain with that in the frequency domain is the wavelet analysis. Its theoretical foundations were laid in the 1980s and it was introduced in applied science in the early 1990s. The wavelet analysis allows unveiling relationships among time series in the time-frequency domain (that means, assessing how time series are related at different frequencies and how those relationships evolve over time). It has found fruitful applications in geophysics, in medicine, and in engineering. Following the pioneering work of Ramsey and Lampart (1998), there has been a number of empirical studies using wavelet analysis mostly in Finance and Macroeconomics[2].

Against this background the objective of the present paper is to investigate price co-movement in the principal skim milk powder (SMP) markets. This is pursued using wavelet analysis and monthly wholesale prices from the three principal SMP-producing regions (EU, USA, and Oceania) The international trade of dairy products has acquired considerable momentum in the last 20 years due to liberalization of food trade, innovations in milk processing, rising per capita incomes, and changing dietary patterns in a number of developing countries (e.g. Beghin, 2005; Dong, 2006). The SMP market is considered to be the most competitive among all international dairy commodity markets (AgriHQ Academy, 2014); therefore, it presents a particular interest with regard to the investigation of spatial price co-movement. In what follows, Section 2 presents the analytical framework and Section 3 the data, the empirical models and the empirical results. Section 4 offers conclusions.

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[1] The works of Granger and Hatanaka (1964) and Labys and Granger (1970) were among the early applications of spectral analysis to price time series.

[2] Surveys are available in Crowley (2007), and in Aguiar-Conraria and Soares (2014).

2. Wavelet analysis of co-movement between time-series

Let $x(t)$ be a time series. The *continuous wavelet transform* (CWT) maps $x(t)$ into a function of two variables, namely, time and scale[3]. This is achieved through the use of local basis functions called *wavelets*. A real or a complex-valued function $\psi(t) \in L^2(R)$ qualifies as a *mother wavelet* if it satisfies the *admissibility condition*[4]

$$0 < C_\Psi = \int_{-\infty}^{\infty} \frac{\Psi(\omega)}{|\omega|} d\omega < \infty \qquad (1),$$

where $\Psi(\omega)$ is the Fourier transform of $\psi(t)$, ω is an angular(radian) frequency, and C_Ψ is an *admissibility constant* (e.g. Farge, 1992; Daubechies, 1992). Starting with a mother wavelet one may obtain a family of *daughter wavelets* by scaling and translating $\psi(t)$ as

$$\psi_{\tau,s} = \frac{1}{\sqrt{|s|}} \psi(\frac{t-\tau}{s}) \qquad (2).$$

In (2), $s \in R - \{0\}$ is the *scaling* (*dilation*) parameter and $\tau \in R$ is the *translation* (shift) parameter. The former controls the wavelet's width (support); $|s| > 1$ implies stretching and $|s| < 1$ implies compressing. The latter indicates where the wavelet is centered; changes in τ shift the position of the wavelet in time.

The continuous wavelet transform of $x(t)$ with respect to wavelet $\psi(t)$ is given by

$$W_{x,\psi}(\tau, s) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{|s|}} \psi^*(\frac{t-\tau}{s}) dt \qquad (3)$$

where * denotes complex conjugate. Being a function of two parameters (s and τ) the continuous wavelet transform offers a localization of $x(t)$ in both the time and in the scale domains. The precision of localization, however, is limited by *Heisenberg's uncertainty principle* (derived from quantum mechanics) according to which certain pairs of physical quantities cannot be known simultaneously with arbitrary high precision. For the parameters s and τ, in particular, it is impossible to know the exact scale and the exact time of occurrence of that scale. That means, there is a trade-off between precision in time and precision in scale; the higher precision in time comes at the expense of a lower precision in scale (and vice versa). For empirical applications, therefore, one has to select wavelets which yield small levels of total uncertainty and achieve a good compromise between time uncertainty and scale uncertainty (Rua, 2012; Aguiar-Conraria and Soares, 2014; Aguiar-Conraria *et al.*, 2014)[5].

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[3] An alternative to CWT is the so-called Discrete Wavelet Transform (DWT). Relative to the DWT, the CWT is computationally intensive. The results of the CWT, however, are easier to interpret relative to those of the DWT (Aguiar-Conraria and Soares, 2014; Aguiar-Conraria *et a*l., 2014). In the field of agricultural economics the DWT has been applied by Davidson *et al.* (1998) to investigate cyclical behaviour in the prices of 21 internationally traded commodities and by Bowden and Zhu (2008) to decompose the farmer terms of trade in New Zealand into trend and cyclical components and to examine causal influences with regard to exchange rate, output prices, and input prices. In none of the above mentioned works price co-movement and spatial market integration was an issue.

[4] $L^2(R)$ is the set of squared integral functions. These are defined on the real line and they satisfy $\int_{-\infty}^{\infty} \psi(t) dt < \infty$ and $\int_{-\infty}^{\infty} |\Psi(t)^2| dt < \infty$. Functions in $L^2(R)$ have finite energy.

[5] The lower bound of the total uncertainty, defined as the product the standard deviation in time and of the standard deviation in scale, equals 0.5 (Aguiar-Conraria *et al.*, 2008).

The *wavelet power spectrum*, which represents the local (at any pair s and τ) variance of $x(t)$ is defined as the amplitude of the continuous wavelet transform,

$$WPS_{x,\psi}(\tau,s) = \left|W_{x,\psi}(\tau,s)\right| \qquad (4).$$

When the time-scale relationship between the two time series $x(t)$ and $y(t)$ is of interest, it can be measured by the *cross-wavelet spectrum* (it represents the local covariance) as

$$WPS_{xy,\psi}(\tau,s) = W_{x,\psi}(\tau,s)W^{*}_{y,\psi}(\tau,s) \qquad (5)$$

(Hudgins *et al.*, 1993). From the cross-wavelet power spectrum one may obtain the *complex wavelet coherency*, the *real wavelet coherency*, and the *phase difference* (phase lead of $x(t)$ over $y(t)$). The first, is defined as

$$\rho_{xy,\psi}(\tau,s) = \frac{S(WPS_{xy,\psi}(\tau,s))}{[S(\left|WPS_{x,\psi}\right|^{2})S(\left|WPS_{y,\psi}\right|^{2})]^{0.5}} \qquad (6),$$

where *S* denotes a smoothing operator in both time and scale (e.g. Cazelles *et al.*, 2008; Aguiar-Conraria *et al.*, 2014). The cross-wavelet spectrum enters directly formula (6). Therefore, $\rho_{xy,\psi}$ is (for complex-valued wavelets) complex-valued as well and, thus, it is difficult to interpret. For this reason, the real wavelet coherency, defined as

$$R_{xy,\psi}(\tau,s) = \frac{\left|S(WPS_{xy,\psi}(\tau,s))\right|}{[S(\left|WPS_{x,\psi}\right|^{2})S(\left|WPS_{y,\psi}\right|^{2})]^{0.5}} \qquad (7)$$

is used in practice (Rua, 2012; Marczak and Gomez, 2015). $R_{xy,\psi}$ takes values between 0 and 1 with a high (low) value indicating a strong (weak) co-movement between the two time series. By plotting $R_{xy,\psi}$ in the time-scale space one can distinguish regions where the link is stronger and to identify varying patterns in time and/or in scale.

The real wavelet coherency is a non negative number in all frequencies and it should not be interpreted separately from the *phase difference* (angle) which gives the relative position of the two series in the pseudo-cycle as a function of time and frequency. The phase difference can be computed as

$$\varphi_{xy,\psi}(\tau,s) = \mathrm{Arctan}\left(\frac{\mathrm{Im}(WPS_{xy,\psi}(\tau,s))}{\mathrm{Re}(WPS_{xy,\psi}(\tau,s))}\right) \qquad (8),$$

where *Im* stands for imaginary and *Re* for real part of the cross-wavelet spectrum, respectively[6] (e.g. Torrrence and Compo, 1997; Aguiar-Conraria and Soares, 2014; Marczak and Gomez, 2015); it can be positive or negative and it lies between $-\pi$ and π. If $\phi_{xy,\psi}(\tau,s) = 0$, the time series move together in the specified frequency; if $\phi_{xy,\psi}(\tau,s) \in (0,\pi/2)$, they move in-phase with *x* leading; $\phi_{xy,\psi}(\tau,s) \in (-\pi/2,0)$, they move in-phase with *y* leading; a phase difference of π (or of $-\pi$) suggests an anti-phase relationship; if $\phi_{xy,\psi}(\tau,s) \in (\pi/2,\pi)$, the two series move out-of-phase with *y* leading; and if $\phi_{xy,\psi}(\tau,s) \in (-\pi,-\pi/2)$, they move out of phase with *x* leading. Moves in- (out-) of-phase imply positive (negative) correlation (Agterberg, 2014). Figure 1 presents the interpretation of the wavelet phase angle. The examination of phase differences may yield useful insights

[6] Economic data are real-valued. The use of real-value wavelets, therefore, to compute cross-wavelet spectrums will imply a zero phase angle. For this reason, complex-valued wavelets are typically employed for economic analysis.

about the timing (leading, lagging, or synchronic) of the price linkages as well as on the existence of a fixed or a changing relationship.

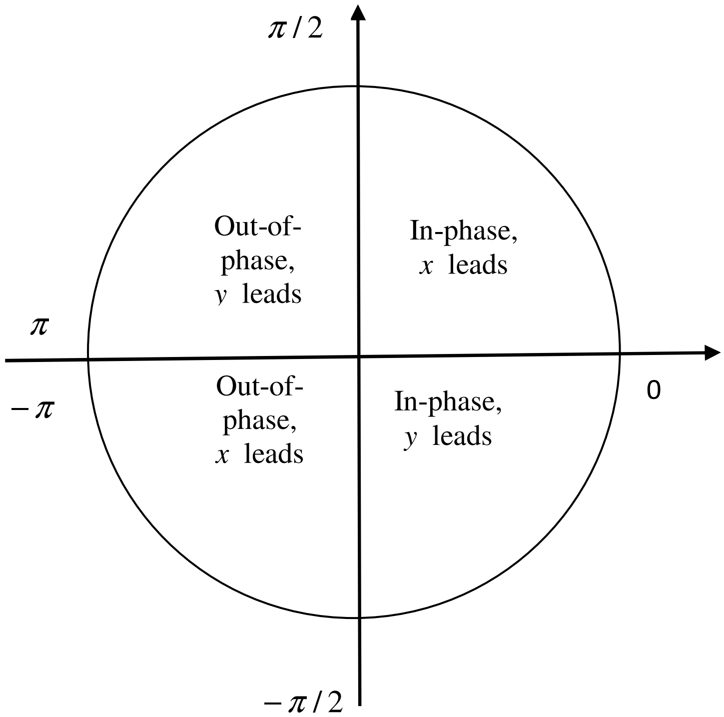

Figure 1. Phase difference between two time series

When more than two series are available, one may be interested in the *partial complex wavelet coherency* which captures the co-movement of two time series, conditional on the influence of a third series. The complex partial wavelet coherency between, say, series x and y, conditional on series z is computed as

$$\rho_{xy.z,\psi}(\tau,s)=\frac{\rho_{xy,\psi}-\rho_{xz,\psi}\rho^{*}_{yz,\psi}}{[(1-R^{2}_{xz,\psi})(1-R^{2}_{yz,\psi})]^{0.5}} \qquad (9).$$

Again, because $\rho_{xy.z,\psi}$ is complex and difficult to interpret, its absolute value (the real partial wavelet coherency) is used in practice. The partial phase delay between x and y may be obtained by replacing the wavelet spectrum in (7) by its respective conditional (on z) one (e.g. Aguiar-Conraria and Soares, 2014). A finding that controlling reduces coherency in some region of the scale-time space will imply that part of the strength of co-movement between x and y is due to the presence of z; an opposite finding will imply that z works towards clouding the relationship between the x and the y series.

There is a number of functions that can be used for continuous wavelet transforms; the most common choice, however, is the Morlet wavelet (Goupillaud *et al.*, 1984) defined as

$$\psi_{\omega_0}(t)=\pi^{-0.25}e^{i\omega_0 t}e^{-t^2/2} \qquad (10).$$

The Morlet wavelet has a number of advantages: (a) it is complex-valued (suitable, therefore, for the study of phase differences); (b) it has optimal joint time-scale concentration (its total uncertainty reaches the lower bound, 0.5); (c) it achieves an excellent compromise between time uncertainty and scale uncertainty (each equals to $1/\sqrt{2}$); (d) it facilitates the conversion from scale to the usual Fourier frequency f (cycles per unit of time). As known, the relationship between f and s is $f(s)=\frac{\omega_0}{2\pi s}$; setting $\omega_0=6$ (a very common choice in economic applications) one gets $f=\frac{6}{2\pi s}\approx\frac{1}{s}$. Because of the last relationship, the terms scale and frequency will be used here interchangeably; high (low) frequency will imply small (large) scale.

3. The Data, the models, and the empirical results

The data for the empirical investigation are monthly nominal wholesale prices of SMP (in \$1000 per ton). They have been obtained from DairyCo and they refer to the period 2001:1 to 2015:3[7]. The EU, the USA, and Oceania are, in this order, the three principal SMP-producing regions in the World. They are at the same time the three major exporters; taken together, they accounted for more than 82% of the World exports in 2011-13 (OECD-FAO, 2015). The most important import markets for SMP are Mexico, China, Indonesia, Algeria, Russian Federation, Middle East, Malaysia, Pakistan, and Egypt. The demand for SMP in developed countries have been stagnating in recent years; therefore, the growth in SMP production has been bound to come from exports to countries where not enough freshly produced milk is available. Trade flows of SMP among the USA, the EU, and Oceania are negligible; market integration in this case may be achieved indirectly, that means, from the fact that the three principal producing regions compete for customers in the international SMP market.

All earlier works which have used the CWT to study linkages between economic time series have focussed their attention on the relationship between rates of change (e.g. Aguiar-Conraria *et al*., 2008; Addo *et al*., 2014; Aguiar-Conraria *et al*., 2014; Marczak and Gomez, 2015). This applies to the present study as well; the variables of interest here are the logarithmic price ratios, $\ln(p_{i,t}/p_{i,t-1})$ where p_{it} is the wholesale price in time *t*=2001:2, …, 2015:3, and in region *i*=Oceania, EU, and USA. We denote the logarithmic price ratios as *deu*, *doc*, and *dus*.

Figure 2 presents the real wavelet coherency for the SMP prices in Oceania and in the USA[8]. The vertical axis presents the scale (in months) while the horizontal axis presents points in time. The inverted U-shaped red line indicates the cone of influence (COI), that is, the region of the real wavelet coherency affected by the edge effects[9]. The black contours designate the 5% level of significance estimated from Monte Carlo simulations using phase randomized surrogate series[10]. The colour code for the values of the real wavelet coherency ranges from red (very high) to blue (very low); warmer colours indicate higher values. The statistically significant real wavelet coherencies are predominantly associated with low frequencies (scales above 12 months) and with the most recent years of the sample (roughly

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[7] www.dairyco.org.uk/market-information

[8] All estimations have been carried out using the GWPackage developed by Aguiar-Conraria and Soares. Accessible at https://sites.google.com/site/aguiarconraria/joanasoares-wavelets.

[9] As it is the case with other transforms, the CWT when applied to series with finite lengths suffers from border distortions which increase with the scale (e.g. Cazzelles *et al*., 2008; Aguiar-Conraria and Soares, 2014). Results such as real wavelet coherencies, therefore, falling within the CIO should be interpreted with care.

[10] Surrogate is a non parametric randomized linear version of the original data which preserves the mean, the standard deviation, the autocorrelation, the partial autocorrelation function, and the power spectrum (e.g. Addo *et al*., 2014). Here, as in Aguiar-Conraria *et al*. (2008) and Aguiar-Conraria and Soares (2014) the surrogates are constructed fitting an ARMA(1,1) model to the original data and building new samples by drawing errors from a Gaussian distribution.

after 2006); it is noteworthy that prior to 2006 one can hardly identify a region with statistically significant coherencies even at the very high scales. Table 1 presents descriptive statistics of the real wavelet coherencies for Oceania and the USA computed over all scales as well as over two scale bands; namely, the scale band 2-12 months and the scale band over 12 months.

Figure 3 presents the phase differences for two scale bands, again (the 2-12 months and the over 12 months); the "*x*" series is *doc* and the "*y*" series is *dus*. Note that there are no statistical tests for the significance of phase angles. Ge (2008) showed that under the null hypothesis of no linear relationship between two time series the phase difference will be distributed uniformly on $[\pi, -\pi]$. The information from phase difference graphs, therefore,

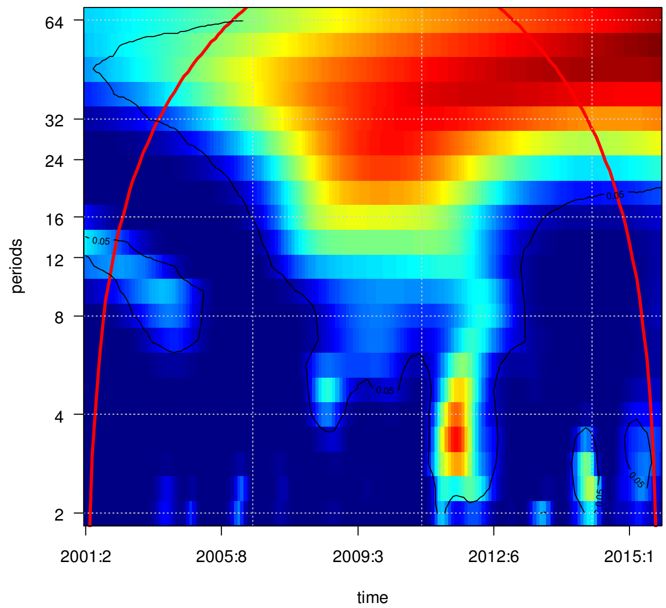


Figure 2. Oceania and the USA: Real wavelet coherency

Table 1. Oceania and the USA:
Descriptive statistics for the real wavelet coherency

	Quantile				
Scales	0%	25%	50%	75%	100%
all	0.015	0.558	0.801	0.904	0.960
2 to 12 months	0.015	0.466	0.638	0.908	0.947
more than 12 months	0.267	0.859	0.912	0.939	0.960

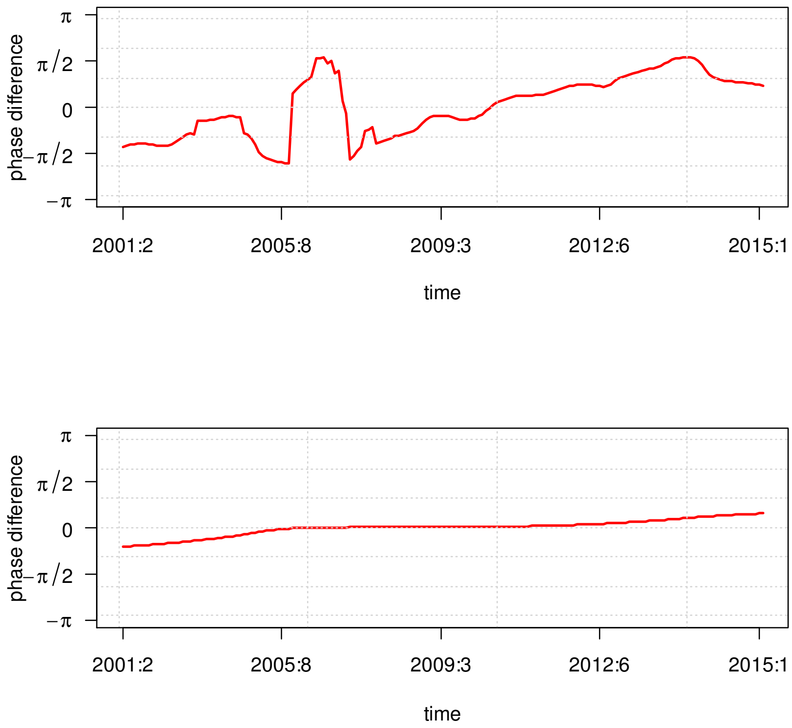


Figure 3. Oceania and the USA: Phase Difference, by Scale
(upper part, 2- 12 months; lower part, over 12 months)

should be always considered with reference to the statistical significance of coherency at the different scales and to the cone of influence. The phase angle for the scale 2-12 months exhibits an erratic behaviour prior to 2007 and after 2012 where, however, coherency at that band is generally not statistically significant. Between 2007 and 2011, the angle difference is initially in $(-\pi/2,0)$ suggesting that there is a positive relationship between the price changes in the two regions with price shocks in the USA leading those in Oceania. Then, the angle difference lies in $(0,\pi/2)$ suggesting again an in-phase movement of prices with Oceania as the leader. For scales over 12 months and for the sample intervals where coherency is statistically significant (this happens largely after 2006) the phase difference lies in $(0,\pi/2)$ suggesting that the Oceania market leads the USA market.

Figure 4 presents the real wavelet coherency for the SMP prices in the EU and in the USA. As it was the case for the rates of price change in Oceania and the USA, the statistically significant coherencies are predominantly associated with the low frequencies and with the most recent years of the sample. Table 2 presents the relevant descriptive statistics. The similarity in the coherency patterns of the pairs (*doc*, *dus*) and (*deu*, *dus*) carries over to their respective phase differences (Figure 5); there is an erratic behaviour at scales where coherency is not statistically significant and evidence of positive co-movement at the low frequencies with EU (the "*x*" series) being the leader.

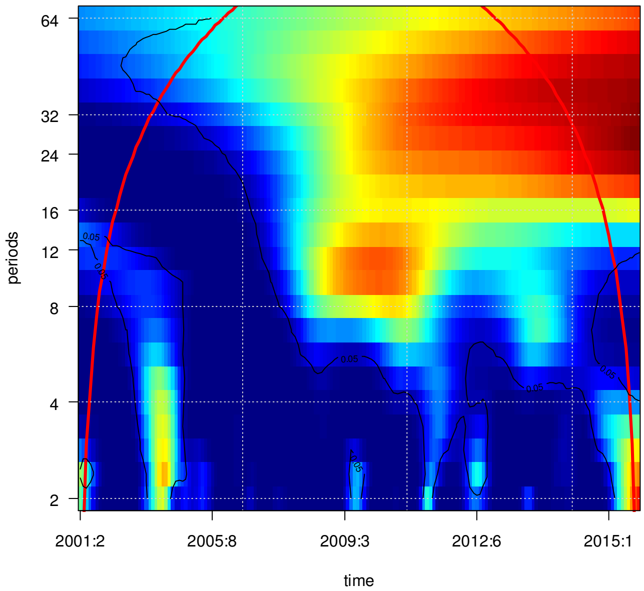


Figure 4. The EU and the USA: Real wavelet coherency

Table 2. The EU and the USA:
Descriptive statistics for the real wavelet coherency

	Quantile				
Scales	0%	25%	50%	75%	100%
all	0.019	0.649	0.848	0.933	0.984
2 to 12 months	0.019	0.534	0.754	0.864	0.969
more than 12 months	0.138	0.864	0.932	0.959	0.984

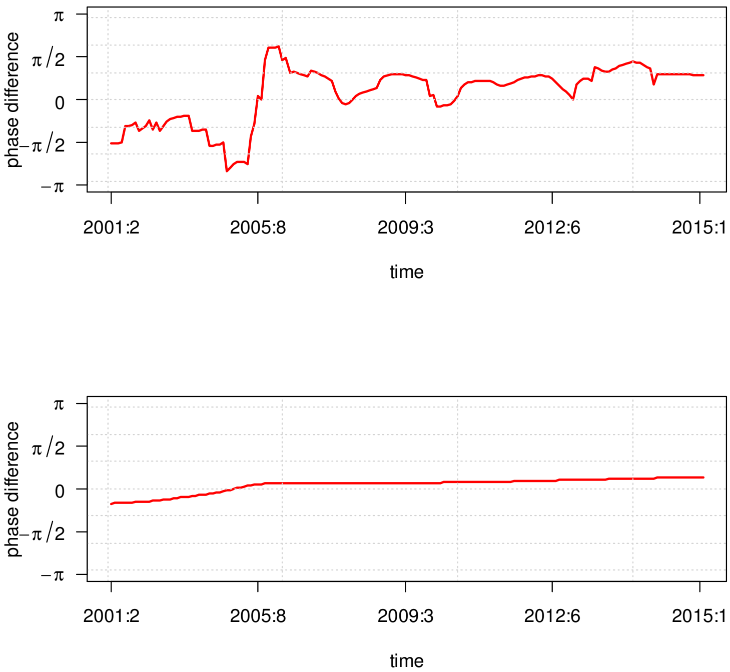


Figure 5. The EU and the USA: Phase Difference, by Scale
(upper part, 2- 12 months; lower part, over months)

Figure 6 presents the real wavelet coherency for SMP prices in the EU and in Oceania. The price changes in this pair of regions are far more strongly associated compared to the other two pairs considered. The real wavelet coherencies are statistically significant at the large scales over the entire period 2001 to 2015. Moreover, the regions where coherency is not statistically significant are largely located at the bottom left part of Figure 6 (at the high frequencies and prior to 2009). Table 3 presents the relevant descriptive statistics. Given that coherencies are to a great extent statistically significant, it is now safer to draw conclusions about potential lead-lag relationships. The phase difference for the scale band 2-12 months evolves around zero but most of the times it lies $(0, \pi/2)$ implying that it is the "*x*" series (*deu*) rather the "*y*" (*doc*) series that leads. The values of the phase angle for scales over 12 months are almost everywhere very close to zero suggesting that prices in the EU and in Oceania move together (Figure 7).

The results from the wavelet analysis appear to be in line with the developments in the SMP trade during the period considered in this study. In particular, in the first years of the sample, the EU and Oceania were the main competitors in the global SMP market. The USA production of SMP was consumed domestically and/or it was exported to the country's neighbours (notably Mexico). After the mid-2000s the USA, thanks to rather favourable international international prices, has become a very active exporter. It has increased considerably its export volumes and at the same time it, to a large extent, has differentiated its export markets; although still about one third of the USA exports head to Mexico, the markets of China, Philippines, Indonesia, Vietnam, and Malaysia have become increasingly important for the USA. On those latter markets, the US exporters of SMP have to compete with their counterparts from Oceania and from the EU. The USA's exposure to direct competition with the other two principal players in the international SMP market aligned, in a rather short time interval, the rate of change in wholesale prices in the US to those in Oceania and in the EU (the abrupt change/break in the intensity of price co-movement is evident in Figures 2 and 4 about 2006/7).

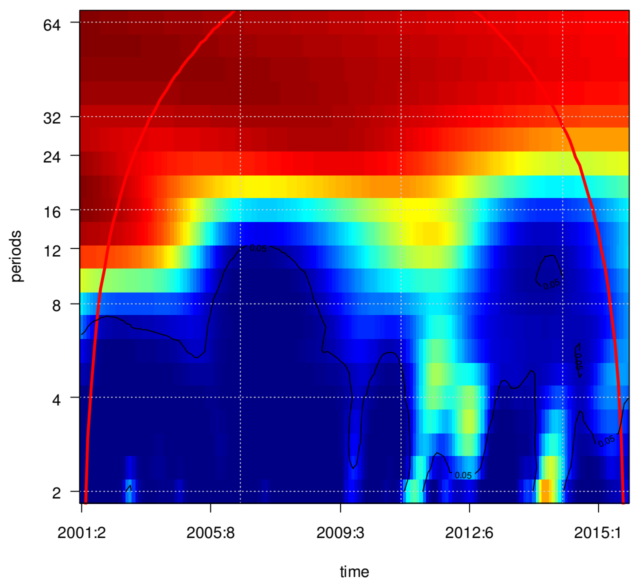


Figure 6. The EU and Oceania: Real wavelet coherency

Table 3. The EU and Oceania:
Descriptive statistics for the real wavelet coherency

	Quantile				
Scales	0%	25%	50%	75%	100%
all	0.02	0.729	0.892	0.981	0.992
2 to 12 months	0.02	0.577	0.751	0.854	0.987
more than 12 months	0.826	0.968	0.982	0.987	0.992

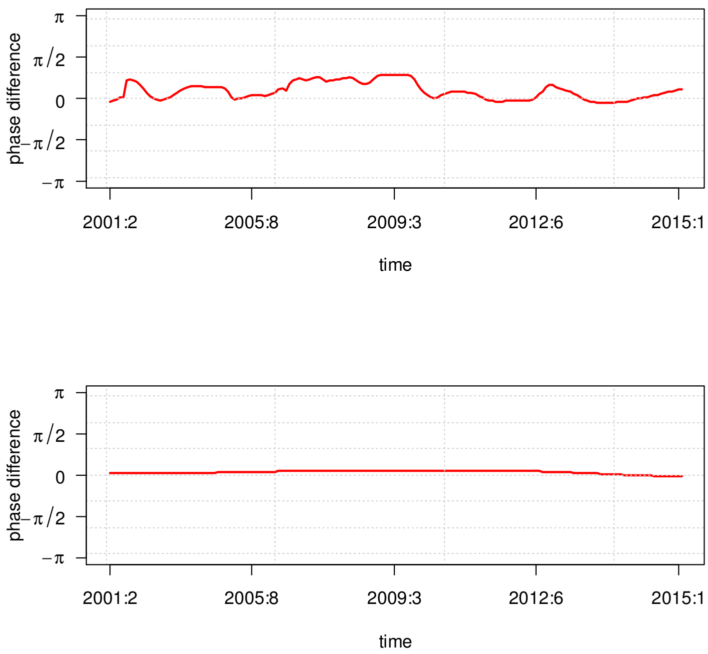
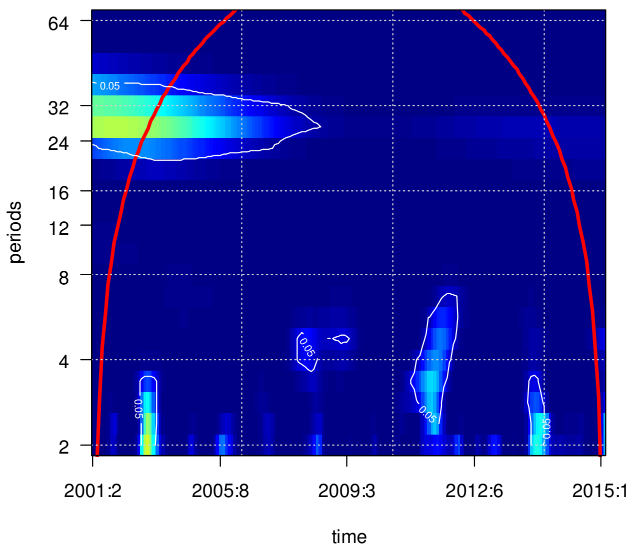
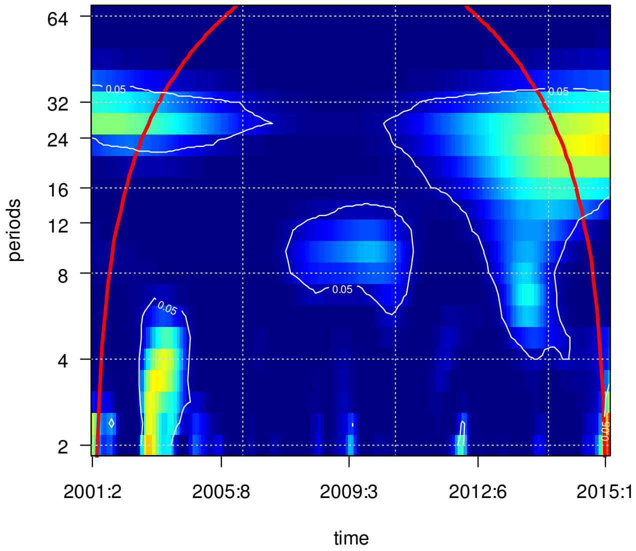


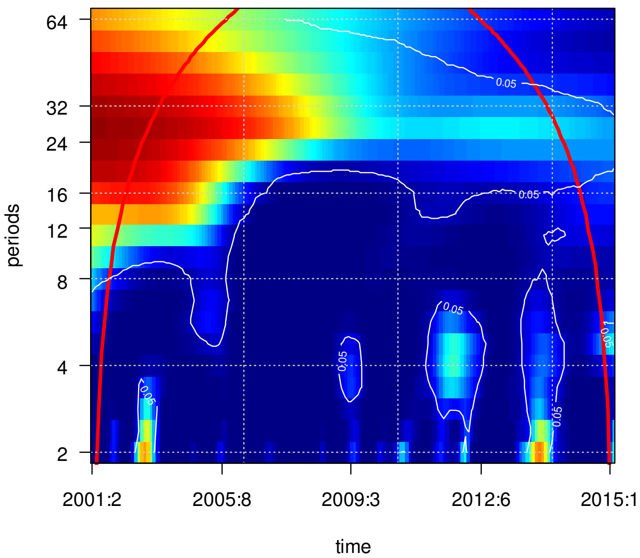
Figure 7. The EU and Oceania: Phase Difference, by Scale
(upper part, 2- 12 months; lower part, over 12 months)



(a) Oceania and the USA



(b) The EU and the USA



(c) The EU and Oceania

Figure 8. Real Partial wavelet coherency

Figure 8 (panels (a), (b) and (c)) presents the partial wavelet coherencies. In general, these are considerably lower than the corresponding (at the same time period and frequency band) unconditional ones even at the large scales[11]. The only noteworthy exception appears in the upper left part of Figure 8 (panel (c)) where the coherency between the price changes in Oceania and the in EU is unaffected by the price changes in the USA. The decrease in the high and statistically significant coherencies at the low frequencies with conditioning has an interesting economic interpretation. The three SMP-producing regions at the large scales have formed, in recent years, a great pool within which prices move together; changes in just one price contain much of the information relevant to the changes in the other two prices. The exception in the upper left part of Figure 8 (panel (c)) substantiates the claim. In the first years of the sample, the USA was not well integrated with the other two producing regions (that means, price changes in the US prices were not really informative about price changes in the EU and in Oceania); as result, conditioning on the US price changes had no effect whatsoever on the strength of the relationship between price changes in the EU and in Oceania.

4. Conclusions

The objective of the present paper has been to analyse price linkages in the principal SMP producing regions. This has been pursued using wavelet analysis and monthly wholesale prices from the EU, Oceania, and the USA. The continuous wavelets transforms by mapping stochastic processes into the time and into the frequency domains are capable of revealing potentially interesting patterns of spatial price dependence which cannot be detected by alternative approaches focussing exclusively either on the time or on the frequency domain.

According to the empirical results:

(a) The price linkages at the high frequencies are generally weak over the entire span of the data. They become, however, progressively stronger as one considers longer time horizons. This indicates a low speed of price transmission; full transmission of a price shock from one of the SMP region to the other is likely to require considerable (more than 12 months) amount of time.

(b) The pair of regions EU and Oceania exhibit over the total period considered here a higher degree of integration compared to the pairs USA and EU, and USA and Oceania. The rate of price changes in the USA, however, has shown a strong tendency to align with those in the other two regions after 2006/7 when the country started expanding its volume of SMP exports and diversifying its export markets.

(c) At the low frequencies, price changes in both the EU and Oceania have been leading price changes in the USA. At the high frequencies, price changes in the EU largely lead those in Oceania; at the low frequencies, however, there is no such lag-lead relationship; prices in the EU and in Oceania move together. This is an indication that not only the strength but the timing of a spatial price relationship can be frequency-dependent.

The intensification of trade is expected to strengthen the price linkages and the integration of the SMP-producing regions. According to the OECD-FAO (2015) the trade of SMP will exhibit an annual growth rate at about 2% in the next 10 years. Underlying that forecast is the assumption of strong growth in incomes among developing countries, especially in the Middle East, North Africa, South East Asia, and China. Nevertheless, there are uncertainties and challenges as well. First, is the outcome of various Free Trade Agreements and Regional Trade Agreements currently under discussion. Second, is the efforts of major importers (e.g. China) to increase their degree of self-sufficiency in dairy

[11] Given that the overwhelming majority of partial coherencies are not significant, it does not make much sense to purse an analysis of lead-lad relationships through the phase difference graphs.

commodities, in general, and in SMP, in particular. Third, is the impact of the removal since April 2015, of the EU quota on the production of milk and dairy commodities. Fourth, the environmental issues associated with dairy production activities (e.g. greenhouse-gas emissions, water access and manure management) may result into binding constraints (e.g. stringent environmental legislation) for certain important SMP exporters such as New Zealand.

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