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Spatial price dependence by time scale: Empirical evidence from the international butter markets

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ABSTRACT

The objective of the present work is to investigate price dependence (co-movement) in the international butter markets. This is pursued using monthly wholesale prices from Oceania and the European Union and two non-parametric tools, namely, the copulas and the wavelets. The empirical results suggest that: (a) The price linkages in the two butter-producing regions are weak in the short-run but they become much stronger in the long-run. (b) The time horizon (time scale) is relevant not only for the intensity but for the structure of price co-movement as well; in the long-run, there is an asymmetry in price dependence in the sense that strong positive shocks are transmitted with a higher intensity compared to strong negative ones.

1. Introduction

The linkages between agricultural and food commodity prices in geographically separated markets have long attracted the attention of economists and policy makers. The interest in the topic is rooted in the recognition that the intensity and the pattern of price relationships may provide information about market integration (globalization) or segmentation (regionalization). Well-functioning (integrated) spatial markets are characterized by strong price co-movement (dependence); that means, price shocks in one of 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 assessment of spatial price linkages has been conducted with a large variety of quantitative tools and it has focussed both on the strength as well as on the structure of dependence. Among the most commonly employed approaches have been the linear and non-linear integration and cointegration, and the non-parametric regression (Goodwin and Piggott, 2001; Ghoshray, 2010; Emmanouilides and Fousekis, 2012; Hassouneh et al., 2012). In recent years, however, a tool that has become increasingly popular in the analysis of co-movement between stochastic processes such as prices in the physical or in the product quality space has been that of copulas (e.g. Reboredo, 2011, 2012; Serra and Gil, 2012; Chi and Goodwin, 2012; Emmanouilides et al., 2014; and Emmanouilides and Fousekis, 2015). A salient feature of copulas is that they can deal with non-linearity, asymmetry, and heavy tails of the marginal and the joint distributions of prices. Moreover, they allow the joint behaviour of random processes to be modelled independently (separately) of their marginal distributions offering, thus, considerable flexibility in empirical research (e.g. Nelsen, 2006; Patton, 2013; Brutti Righ and Ceretta, 2013; Panagiotou and Stavrakoudis, 2015).

A limitation of the commonly used approaches and of the copulas as well is that they do not properly account for the role the time scale (time horizon) plays in the dependence between prices. The realization of a price at a given point of time is the outcome of actions of agents who make decisions with reference to different horizons (in the sense that some operate on short time scales, some on medium time scales, while others operate on much longer views). As noted by Ramsey and Lampart (1998) and Ramsey (2014) differences in agents' time horizons may render the relationships between economic time series scale-(frequency-) dependent.[1] With regard to spatial market integration, frequency-dependence implies that the strength and the mode of price linkages may differ by time scale.

Applied researchers had been long aware that working with series averaged over all time scales or adopting the simple dichotomy "long-" vs "short-run", where the latter is largely dominated by noise, may lead to erroneous conclusions about the relationships between economic variables. A more realistic approach would involve separating out different time scales of the variation in the data and assessing linkages by scale level. This has been achieved since the early 1990s with the

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[1] Scale and frequency are inversely related; a high (low) scale is associated with a low (high) frequency. Therefore, the terms frequency and scale are used here interchangeably.

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wavelets analysis. The first fruitful applications of it were in geophysics, in engineering, and in medicine. Following the pioneering work of Ramsey and Lampart (1998), however, there has been a number empirical economic studies using wavelets over the last years especially in the fields of macroeconomics and finance (e.g. Aguiar-Conraria et al., 2008; Rua and Nunes, 2009; Fernandez-Macho, 2012; Caraiani, 2012; Gallegati et al., 2014; Crowley and Hughes-Hallett, 2014).

Against this background, the objective of the present paper is to assess the strength and the pattern of price co-movement in the international butter markets. The international trade of dairy products has gained momentum in the last 20 years as a result of food trade liberalization, innovations in milk processing, rising per capita incomes, changing demographics and dietary patterns in a number of countries facing natural handicaps in dairy production (e.g. Beghin, 2005; Dong, 2006). An investigation, therefore, into the degree of integration of geographically separated dairy commodity markets is timely. To the best of our knowledge there are no earlier empirical published works on the topic.

The assessment of price linkages relies on monthly wholesale prices from the Oceania and from the European Union (two major players in the international butter markets), on wavelets and on copulas. In particular, the non-parametric tool of wavelets is applied initially to analyse the activity of the individual time series into a cascade of components where each component is associated with a time scale. Then, the tool of copulas is employed to extract information about dependence by scale level.

Oceania, in general, and New Zealand, in particular, enjoy a comparative advantage in milk production and, as a result, the countries in the region are strong supporters of free trade. The EU, however, still employs trade-distorting policy instruments such an intervention price for the domestically produced butter. At the same time, the bulk of the EU butter imports come from Oceania. It would be, therefore, interesting to investigate whether the differences in trade policies have an impact on the strength and, more importantly, on the mode of price co-movement. As known, the symmetry or the asymmetry of price transmission has implications about the distribution of trade benefits not only between the trading regions but among economic agents such as producers and consumers within each region as well (Meyer and von Cramon-Taubadel, 2004; Serra et al., 2006; Emmanouilides and Fousekis, 2012).

Bringing together the advantages of wavelets and of copulas enables a researcher to determine the extent to which the intensity and the pattern of price linkages change by the time horizon (i.e. short-, medium-, and long-run). Information about differences in price co-movement under transitory and permanent price shocks is potentially useful for traders in formulating strategies such as building and releasing stocks in order to keep their competitors out of the market. It appears that the work of Brutti Righ and Ceretta (2011) on the linkages between stock market indexes in Brazil, in Germany, in Hong-Kong, and in the U.S.A. has been the only earlier study which has utilized both wavelets and copulas. In that work the authors considered a number of parametric copula families. Here, in contrast, the copulas are estimated with a non-parametric approach which allows the data "*to speak for themselves*" avoiding in this way potential misspecification bias.

In what follows, Section 2 presents the analytical framework (copulas and wavelets) and Section 3 the data, the empirical implementation and the results. Section 4 offers conclusions and economic implications.

2. Analytical framework

2.1. Discrete wavelet transforms and multiresolution decomposition

Let $x(t)$ be a Tx1 time series. The discrete *wavelet transform* (DWT) maps $x(t)$ into a function of two variables, namely, time and scale. This is achieved through the use of local-basis functions called *wavelets*. The wavelets have two genders; the *mother* wavelet is a sequence of rescaleable functions defined as

$$\psi_{j,k}(t) = 2^{-j/2}\psi\left(\frac{t-2^j k}{2^j}\right), \tag{1}$$

where $j=1,2,\ldots,J$ indexes scale so that 2^j stands for the scale (*dilation*) parameter and $k=1,2,3,\ldots,N/2^j$ indexes shift so that $2^j k$ stands for the shift (*translation*) parameter; the *father* wavelet is a scaling function defined as

$$\phi_{J,k}(t) = 2^{-J/2}\phi\left(\frac{t-2^J k}{2^J}\right) \tag{2}$$

(e.g. Ramsey and Lampart, 1998; Crowley, 2005; Martin-Barragan et al., 2015). The dilation parameter controls the wavelet's width; with high (low) values of it one focusses on the low (high) frequency components of $x(t)$. The translation parameter indicates where the wavelet is centred; changes in it, shifts the position of the wavelet in time.

Projections of $x(t)$ on mother wavelets obtain the *transform coefficients* vectors.

$$d_{j,k}(t) = \int x(t)\psi_{j,k}(t)dt, \tag{3}$$

$j=1,2,\ldots,J$, while projection of $x(t)$ on the father wavelet obtains the *scaling coefficients* vector

$$s_{J,k}(t) = \int x(t)\phi_{J,k}(t)dt \tag{4}$$

(e.g. Crowley, 2005; Gallegati et al., 2014). The scaling coefficients $s_{J,k}$ correspond to the smooth behaviour of $x(t)$ at the coarse scale capturing in this way the low frequency oscillations; the transform coefficients $d_{Jk},\ldots,\ d_{1k}$ represent progressively finer scale deviations from the smooth behaviour, thus, capturing higher frequency oscillations (Ramsey, 2014).

The mother and the father wavelets when are multiplied with their respective transform and scaling coefficients give the *atoms* $D_{j,k}$ and $S_{J,k}$ (i.e. $D_{j,k}(t)=\psi_{j,k}(t)d_{j,k}(t)$ and $S_{J,k}(t)=\phi_{J,k}(t)s_{J,k}(t)$). The sums of atoms over all k and at a certain scale level j give the *crystals*

$$S_J(t) = \sum_k S_{J,k}(t) \tag{5a}$$

and

$$D_j(t) = \sum_k D_{j,k}(t), \tag{5b}$$

for $j=1,2,\ldots,J$.

The multiresolution decomposition (MRD) of $x(t)$ is

$$x(t) = S_J(t) + D_J(t) + D_{J-1}(t) + \ldots + D_1(t), \tag{6}$$

where the crystal $S_J(t)$ is the *smooth* and the crystals $D_j(t), j=1,2,\ldots,J$ are the *details* (e.g. Crowley, 2005; Ramsey, 2014). The sequence $S_J, D_J, D_{J-1},\ldots,\ D_1$ stands for the components of the original time series $x(t)$ at different scales and at an increasingly finer resolution level.

The MRD provides information about the time horizon at which activity in $x(t)$ takes place; specifically, with the monthly data used here, D_1 represents the activity at (or the component of) $x(t)$ in a time scale from 2 to 4 months, D_j represents the activity at a time scale from 2^j to 2^{j+1} months, while S_J represent the activity beyond the time scale of 2^{J+1} months (e.g. Fernandez-Macho, 2012; Gallegati et al., 2014).

The DWT has two limitations. First, it can be applied to dyadic time series (those with number of observations equal to a power of 2) only; second, it is not shift-invariant (that means, it is sensitive to