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Multiscale entropy analysis of Brazilian agricultural commodities price dynamics

Análise de entropia multiescala da dinâmica de preços de commodities agrícolas brasileiras

Análisis de entropía multiescala de la dinámica de precios de productos agrícolas brasileños

Received: 11/06/2020 | Reviewed: 11/15/2020 | Accept: 11/17/2020 | Published: 11/22/2020

Djalma Beltrão da Costa Farias
ORCID: https://orcid.org/0000-0002-8442-8818
Universidade Federal Rural de Pernambuco, Brazil
E-mail: djalmabel@yahoo.com.br
Antonio Samuel Alves da Silva
ORCID: https://orcid.org/0000-0002-8759-0036
Universidade Federal Rural de Pernambuco, Brazil
E-mail: antonio.sasilva@ufrpe.br
Tatijana Stosic
ORCID: https://orcid.org/0000-0002-5691-945X
Universidade Federal Rural de Pernambuco, Brazil
E-mail: tastosic@gmail.com
Borko Stosic
ORCID: https://orcid.org/0000-0001-5031-6968
Universidade Federal Rural de Pernambuco, Brazil
E-mail: borkostosic@gmail.com

Abstract

During the last decade there were several consecutive periods of upsurge and decline of commodity prices. Price formation in agricultural markets is the result of many factors such as crude oil prices, exchange rates, biofuel demand, speculation in commodity futures markets, countries' aggressive stockpiling policies, trade restrictions and economic growth. The diversity of these factors as well as the occurrence of extreme socio-political events yields a market with complex price evolution. This paper uses time dependent multiscale entropy method to analyze the evolution of Brazilian agricultural commodities prices movements at different temporal scales during the period from March 2006 to March 2016.

We found that the entropy of both volatility and return series decreases as the temporal scale increases, indicating more regular price fluctuations and the loss of pattern diversity in long term trends. In general, volatilities series are more regular than return series as indicated by lower entropy values. By applying multiscale entropy in moving windows, we found that during the crisis the entropy of price fluctuations decreases indicating higher regularity and consequently lower efficiency in agricultural commodities market. The effect is more pronounced for volatility series and for higher temporal scales.
Keywords: Agricultural market; Multiscale entropy; Food crisis.

Resumo

Durante a última década, houve vários períodos consecutivos de aumento e queda dos preços das commodities. A formação de preços nos mercados agrícolas é o resultado de muitos fatores, como preços do petróleo, taxas de câmbio, demanda de biocombustíveis, especulação nos mercados futuros de commodities, políticas agressivas de estocagem dos países, restrições comerciais e crescimento econômico. A diversidade desses fatores, bem como a ocorrência de eventos sócio-políticos extremos, produzem um mercado com evolução complexa de preços. Este trabalho utiliza o método de entropia multiescala para analisar a evolução dos movimentos dos preços de commodities agrícolas brasileiras em diferentes escalas temporais durante o período de março de 2006 a março de 2016. Foi descoberto que a entropia das séries de volatilidade e retorno diminui à medida que a escala temporal aumenta, indicando flutuações mais regulares dos preços e a perda da diversidade de padrões nas tendências de longo prazo. Ao aplicar a entropia em maiores escalas em janelas móveis, descobrimos que durante a crise a entropia das flutuações de preços diminui, indicando maior regularidade e consequentemente menor eficiência no mercado de commodities agrícolas. O efeito é mais pronunciado para séries de volatilidade e para maiores escalas temporais.
Palavras-chave: Mercado agrícola, Entropia multiescala, Crise alimentar.

Resumen

Durante la última década, ha habido varios períodos consecutivos de aumento y disminución de los precios de los productos básicos. La formación de precios en los mercados agrícolas es el resultado de muchos factores, como los precios del petróleo crudo, los tipos de cambio, la demanda de biocombustibles, la especulación en los mercados de futuros de productos básicos, las políticas agresivas de almacenamiento de los países, las restricciones comerciales y el crecimiento económico. La diversidad de estos factores, así como la ocurrencia de eventos sociopolíticos extremos, producen un mercado con una evolución de precios compleja. Este documento utiliza el método de entropía multiescala dependiente del tiempo para analizar la evolución de los movimientos de los precios de produtos agrícolas en Brasil en diferentes escalas temporales durante el período comprendido entre marzo de 2006 y marzo de 2016. Descubrimos que la entropía de las series de volatilidad y rendimiento disminuye a medida que aumenta la escala temporal, lo que indica fluctuaciones de precios más regulares y la pérdida de diversidad de patrones en las tendencias a largo plazo. Al aplicar la entropía de escala múltiple en ventanas móviles descubrimos que durante la crisis la entropía de las fluctuaciones de precios disminuye, lo que indica una mayor regularidad y, en consecuencia, una menor eficiencia en el mercado de productos agrícolas. El efecto es más pronunciado para series de volatilidad y para escalas temporales más altas.

Palabras clave: Mercado agricola, Entropía multiescala, Crisis alimentaria.

1. Introduction

During the last decade there were several consecutive periods of upsurge and decline of commodity prices. The prices of nearly all food commodities rose in excess of 50% in 2007, then fell during the global crisis in 2008, rose again in 2010, 2011, and 2012, fell between 2014 and early 2016, and again started increasing since the second quarter of 2016 (Tiwari et al., 2018). The increasing food price volatility is a main concern for policymakers as it adversely affects food security in developing countries, since their population, especially those living in urban areas, spend a relatively high share of their household income for food consumption. The resulting frustration is often followed by social unrest (described as food riots), political instability and socio-political conflicts (Bellemare, 2015; Smith, 2014; Sternberg, 2012). Various factors such as crude oil prices, biofuel demand, speculation in commodity futures markets, countries' aggressive stockpiling policies, trade restrictions, macroeconomic shocks to money supply, exchange rates, and economic growth affect food prices volatility (Nazlioglu & Soytas, 2011; Tadesse et al., 2014). Agricultural markets were extensively studied with econometric methods that produced useful results about commodities price variation such as volatility spilover (Mensi et al., 2013; Xiarchos & Burnett, 2018), price co movement and causality relationship (Cai et al., 2020; Nazlioglu & Soytas, 2012). Recently, agricultural markets have attracted the attention from researchers from related fields such as econophysics, revealing novel aspects of price dynamics such as

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fractal and multifractal properties (He & Chen, 2011; Lima et al., 2019; L. Liu, 2014; Pal & Mitra, 2018), information content (Albarracín. et al., 2019; Kristoufek & Vosvrda, 2014; Zunino et al., 2011), and network structure (Kristoufek et al., 2012; Tabak et al., 2010). In this work we contribute to the existing literature by analyzing the complexity of Brazilian agricultural commodities prices during the period from March 2006 to March 2016. We use time depended multiscale entropy (MSE) method which allows to compare time evolution of price regularity at different temporal scales. Recently MSE was applied to study efficiency of financial markets. Alvarez-Ramirez et al. (2012) applied this method on US stock market and found that market was most efficient at around 1990 in the last 70 years, and that the efficiency is strongly affected by cyclic dynamics with dominant periods of about 4.5 and 23 years. Martina et al. (2011) applied MSE on crude oil prices and found that the economic recession coincides with the decline of entropy, suggesting that the crude oil market regularity has been strongly affected by the economic downturn and that the recovery of previous recessions has been reflected as long-term entropy increases. Albarracín. et al. (2019) used MSE to analyze Brazilian biofuel and food market. They found that that ethanol prices are characterized by higher complexity and lower regularity, and this effect was more notable during the global economic crisis. In this work we analyze the complexity of price dynamics of Brazilian agricultural commodities sugar, cotton, rice, coffee, corn and wheat. We calculate MSE in in moving windows to investigate the time evolution of entropy values that indicate the degree of market regularity (inefficiency) at different temporal scales and evaluate the impact of 2007/2008 and 2010-2012 food crisis.

2. Methodology

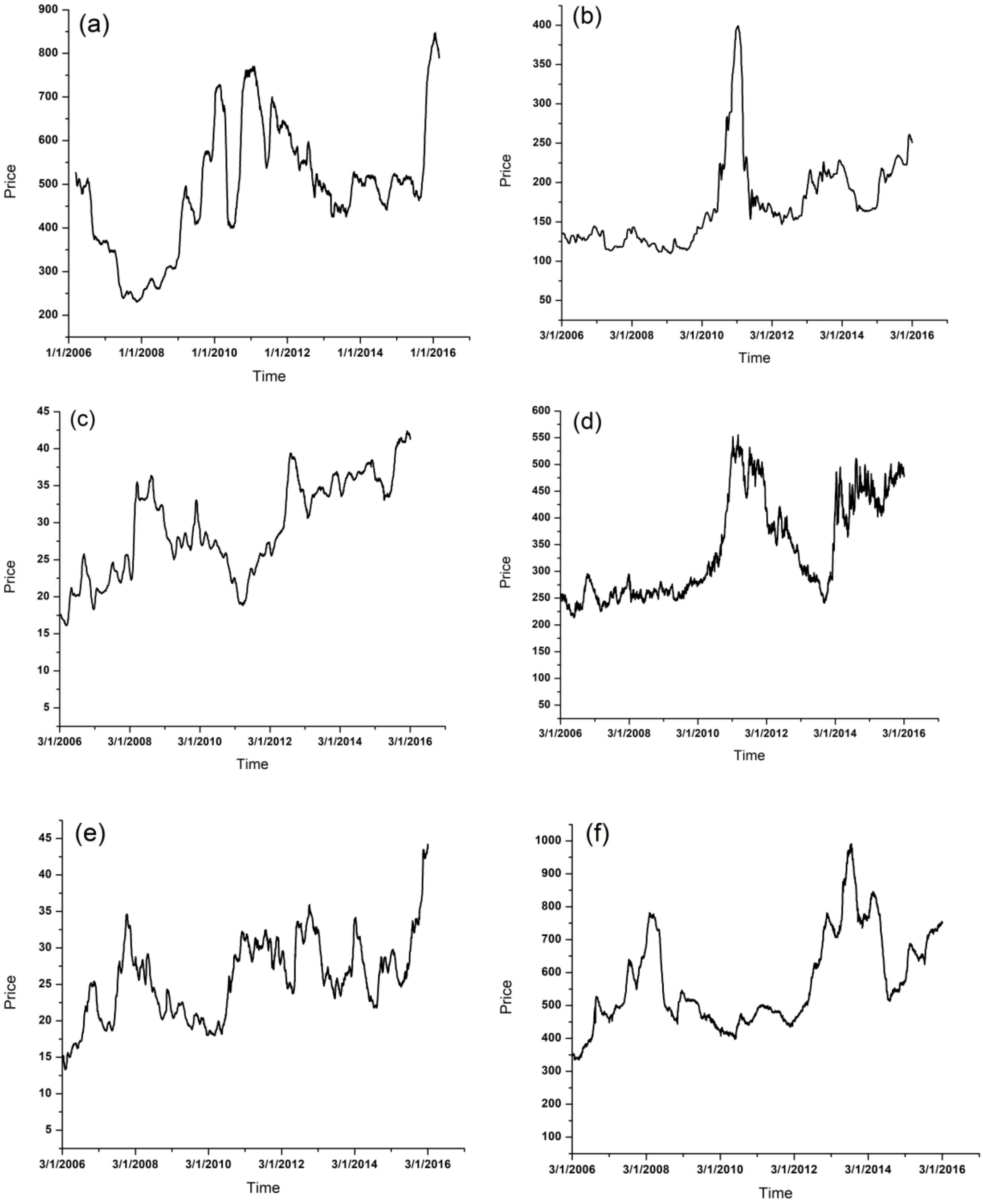
2.1 Data

This is a quantitative research (Pereira et al., 2018). The data used in this work are daily prices of Brazilian agricultural commodities (sugar, cotton, rice, coffee, corn and wheat) obtained from Center for Advanced Studies in Applied Economics/Luiz de Queiroz College of Agriculture/University of São Paulo — CEPEA/ESALQ / USP and are available at electronic address https://www.cepea.esalq.usp.br/br. We analyzed the daily returns $R_t = \ln(P_t) - \ln(P_{t-1})$ where P_t is the price at day t and daily volatility returns $V_t = |R_t|$

where P_t is the price at day t. The original, return and volatilities series recorded between

01/03/2006 and 13/03/2016, are shown on Figure 1, Figure 2 and Figure 3, respectively, where it is seen that prices of Brazilian agricultural commodities follow global increasing trend during 2007/2008 and 2010-2012 food crisis.

Figure 1. Time series of daily prices P for (a) sugar, (b) cotton, (c) rice, (d) coffee, (e) corn and (f) wheat.



Source: Authors.

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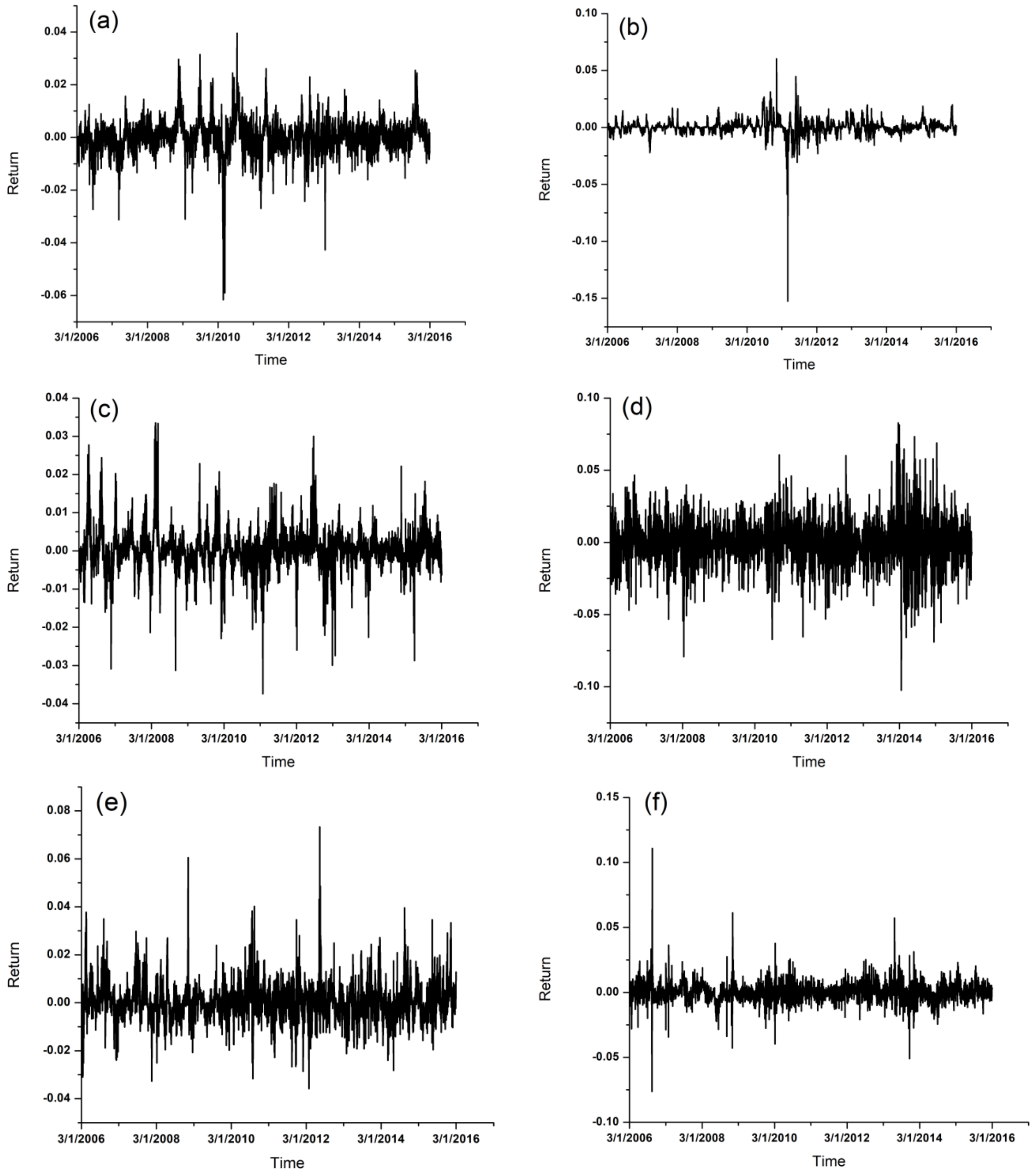
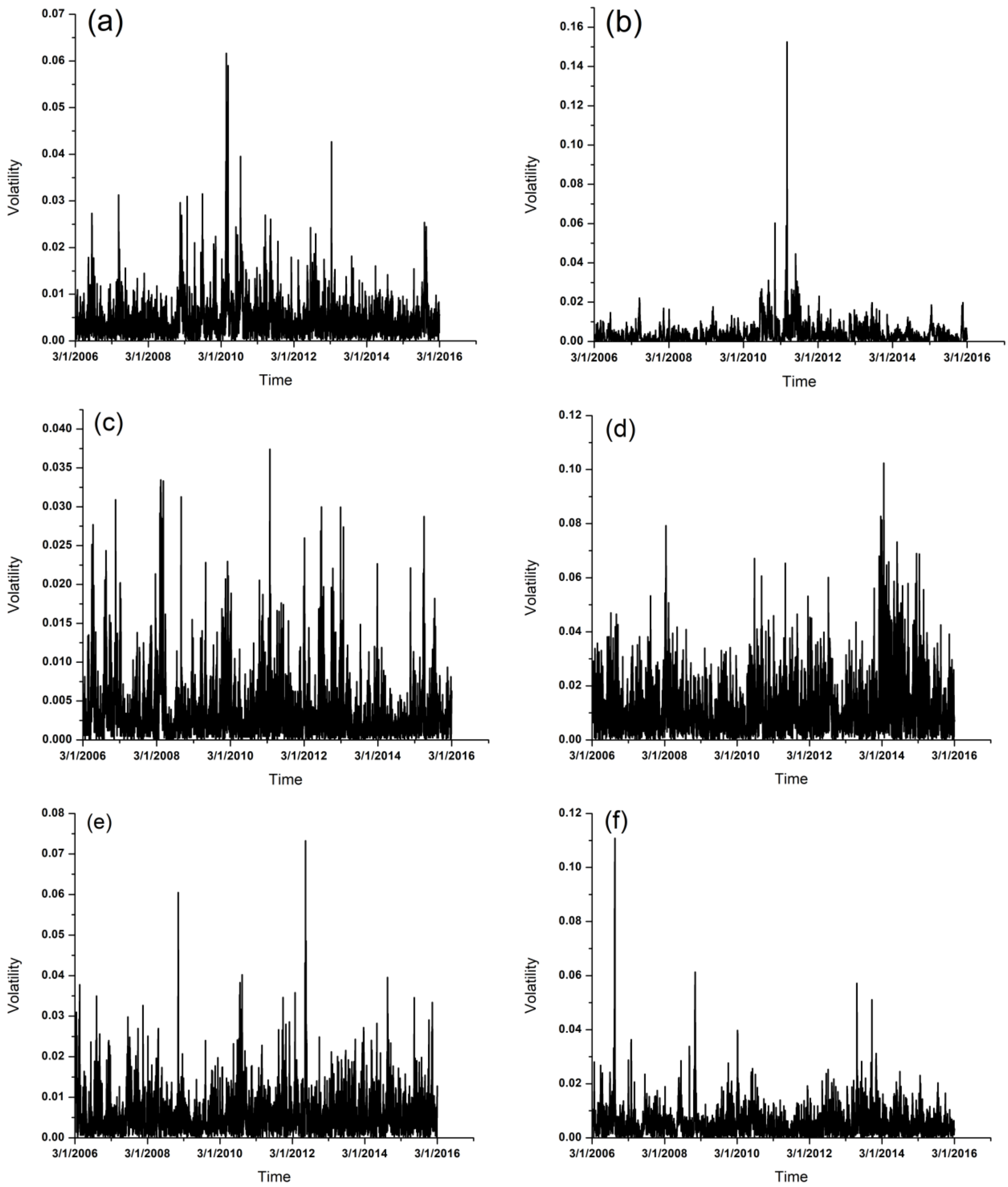
Figure 2. Time series of daily returns R for (a) sugar, (b)cotton, (c) rice, (d) coffee, (e) corn and (f) wheat.



Source: Authors.

Figure 3. Time series of daily volatility V for (a) sugar, (b)cotton (c) rice, (d) coffee, (e) corn and (f) wheat.



Source: Authors.

2.2 Sample entropy ($SampEn$)

The sample entropy ($SampEn$) method was introduced by Richman et al. (2000) to analyze the dynamics of time series by evaluating its regularity and level of complexity. A greater regularity (lower complexity) produces lower values of $SampEn$, whereas for a series with higher complexity (lower regularity) the value of $SampEn$ statistic is higher. The applications of sample entropy include physiology (Weng et al., 2017), geophysics (Balasis et al., 2009) climatology (Shuangcheng et al., 2006), hydrology (Xavier et al., 2019) engineering (Zhao & Yang, 2012) and finances (Alvarez-Ramirez et al., 2012; Martina et al., 2011).

$SampEn\,(m,r,N)$ is defined as the negative natural logarithm of the conditional probability that two sequences that are similar (within a tolerance level r) for m points remain similar for $m\ +1$ points, where self-matches are excluded. An algorithm for calculating sample entropy can be described as follows. Given a time series of size N $X = x_1, x_2, \ldots, x_N$, first $N-m+1$ $\mathbf{x}_m(i)$ vectors of size m are constructed where $\mathbf{x}_m(i) = x_i, x_{i+1}, \ldots, x_{i+m-1}$, and $i = 1,\ldots,N-m+1$. The distance $d_{i,j}$ between the vectors $\mathbf{x}_m(i)$ and $\mathbf{x}_m(j)$ is calculated as $d_{i,j}[\mathbf{x}_m(i), \mathbf{x}_m(j)] = \max\{|x_{i+k} - x_{j+k}| : k = 0,\ldots,m-1\}$, for each $i = 1,\ldots,N-m$ and $j = 2,\ldots,N-m+1$, where $i \neq j$ and $j > i$ to exclude self-matches. Subsequently, $B_i^m(r) = \frac{B_i}{N-m-1}$ and $A_i^m(r) = \frac{A_i}{N-m-1}$ are calculated, where B_i is the number of vectors $\mathbf{x}_m(j)$ of size m that are similar to vectors $\mathbf{x}_m(i)$ within a tolerance r such that $d_{i,j}[\mathbf{x}_m(i), \mathbf{x}_m(j)] \leq r$, and A_i is the number of vectors $\mathbf{x}_{m+1}(j)$ that are similar to vectors $\mathbf{x}_{m+1}(i)$. From the probability values $B_i^m(r)$ and $A_i^m(r)$ we calculate the mean values $B^m(r) = \frac{1}{N-m}(\sum_{i=1}^{N-m} B_i^m(r))$ and $A^m(r) = \frac{1}{N-m}(\sum_{i=1}^{N-m} A_i^m(r))$, respectively, and then we obtain the statistic called sample entropy expressed in (1).

$$SampEn(m,r,N) = -ln\left(\frac{A^m(r)}{B^m(r)}\right) \qquad (1)$$

It can be shown that $A^m(r)/\ B^m(r)$= A/B where A is the number of forward matches of length *m+1* and B is the number of forward matches of length m. The quantity *A/B* is precisely the conditional probability that two sequences within a tolerance *r* for m points remain within *r* of each other at the next point. $SampEn\,(m,r,N)$ can be expressed as $-ln(A/B)$, which is the negative natural logarithm of the conditional probability that two sequences that are similar for *m* points remain similar at the next point, where self-matches are not included in calculating the probability (Richman et al., 2000).

2.3 Multiscale sample entropy (MSE)

Entropy is scale dependent, a pattern may look less or more regular depending on the timescale. In financial temporal series fluctuations are in general more complex (higher entropy) in smaller time scales and more regular (lower entropy) in higher timescales (Alvarez-Ramirez et al., 2012). Costa et al. (2002) introduced Multiscale entropy method to analyze scale dependent complexity of time series. They showed that uncorrelated random signals have, for larger scales, lower MSE values then correlated noise, making MSE more appropriate for quantifying complexity in short and noisy time series, then traditional entropy methods that evaluate pattern repetition on single temporal scale. The implementation of MSE algorithm can be described as follows. Given the time series $X = x_1, x_2, \dots, x_N$, the moving-average filter is applied to each timescale τ, obtaining a series $Y_\tau = \frac{1}{\tau}\sum_{j=0}^{\tau-1} x_{i+j}$, where $i = 1, \cdots, N - \tau + 1$. Thus, Y_τ holds the values of *X* for each timescale greater than τ or frequencies smaller than $f = \frac{1}{\tau}$, removing short-term fluctuations at higher values of τ which effectively reduces the complexity of the time series (Alvarez-Ramirez et al., 2012; Martina et al., 2011). MSE method was used physiology (C. Liu & Gao, 2017; Miskovic et al., 2019), geophysics (Hernández-Pérez et al., 2010), engineering (Gao et al., 2018), hydrology (Wang et al., 2018) and finances (Alvarez-Ramirez et al., 2012; Martina et al., 2011; Stosic et al., 2016).

3. Results and Discussion

The results of multiscale sample entropy (MSE) analysis for the series of daily returns R_t and daily volatility V_t are shown on Figure 4. It is seen from Figure 4 that: (i) For both, returns and volatility the entropy value decreases as the timescale increases, the long-term trend of the time series looses pattern diversity and fluctuations become more regular (ii) The entropy of volatility is generally lower (or approximately equal for some scales) than the entropy of returns indicating that the volatility dynamics is more regular than the returns dynamics (iii) Sugar, rice and corn show similar behavior: at smaller time scales the entropy of volatility series is lower than entropy of return series while the difference vanishes for higher timescales iv) Cotton shows opposite behavior: both returns and volatility have same entropy for smaller time scales, while for higher time scales the entropy of volatility is lower

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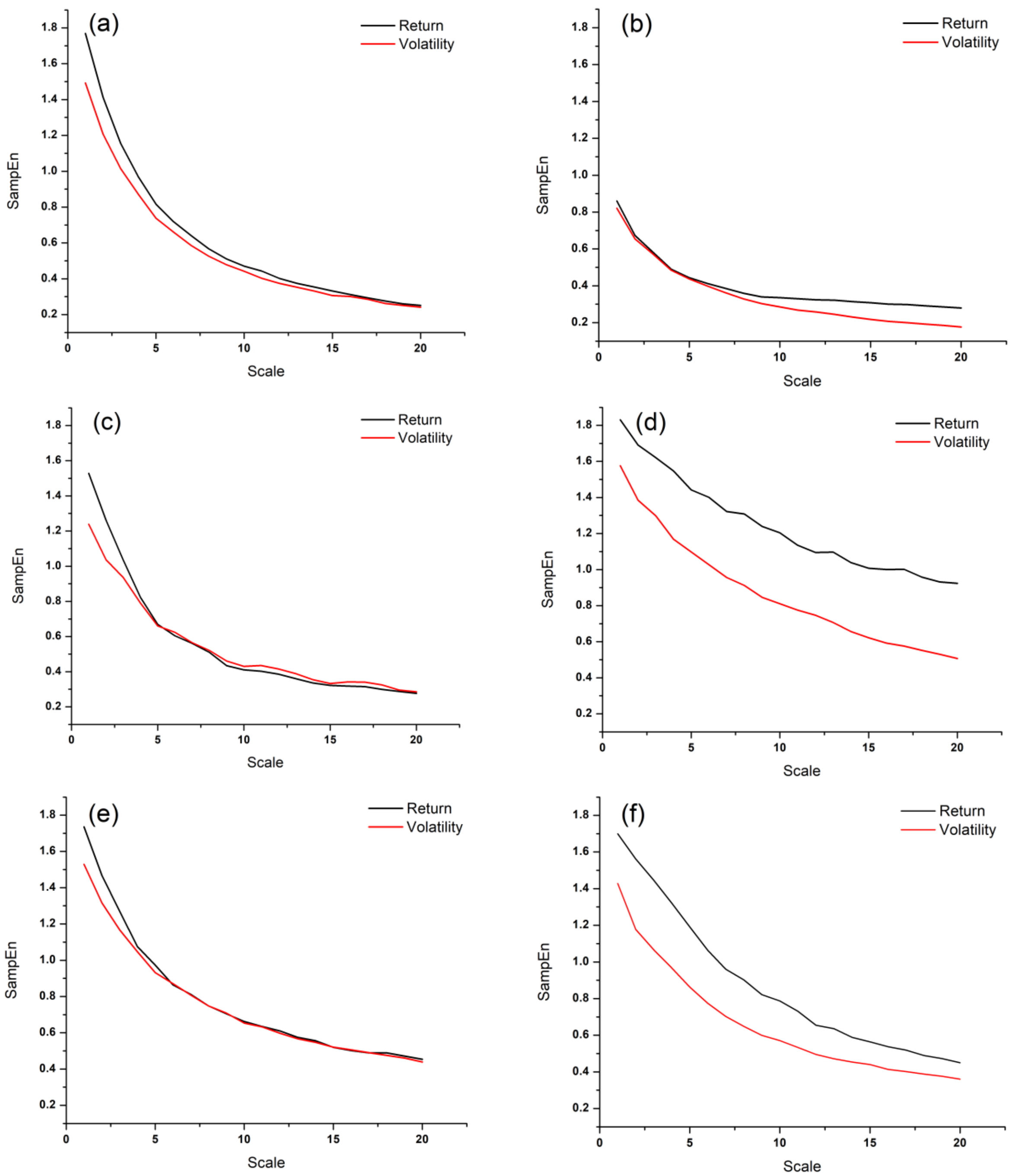
that the entropy of returns v) For coffee and wheat volatility exhibits lower entropy values for all time scales.

Figure 4. Multiscale $SampEn$ statistics (MSE) for the series of daily returns R and volatility V of (a) sugar, (b) cotton (c) rice, (d) coffee, (e) corn and (f) wheat.



Source: Authors.

We employed multiscale $SampEn$ statistics in overlapping sliding windows to analyses temporal evolution of regularity of returns and volatility series at different temporal scales. Figure 5 shows the results obtained for returns with window size $w = 200$ and $\tau = 1{,}5{,}10, 21$ (coarse grained series at scales of 1 day, 1 week, 2 weeks and 1 month). The corresponding results for volatility series are shown on Figure 6. The general behavior observed in MSE graphs (Figure 4) that volatility series are more regular than return series indicated by lower entropies values stands for all temporal scales and for sliding windows (Figure 5, Figure 6). However, time evolution of MSE reveals some new otherwise hidden properties of analyzed series, particularly the effect of food crisis. During the first crisis 2008 the entropy of sugar, corn and wheat series decreases (Figure 5(a), 5(e), 5(f,) 6(a), 6(e), 6(f)) indicating higher regularity of price dynamics, while while cotton, coffee and rice show opposite tendency, the price become more irregular ,characterized by higher entropy values (Figure 5(b), 5(c), 5(d), 6(b), 6(c), 6(d)). The effect is more pronounced for volatility series and for higher temporal scales. For all commodities we observed the decrease in entropy (higher regularity) during the second crisis in 2010. Lower entropy (higher regularity) related with financial crisis indicates lower market efficiency which was also observed for other financial markets (Bellemare, 2015; Smith, 2014; Sternberg, 2012; Tadesse et al., 2014; Tiwari et al., 2018).

Figure 5. Time-dependent $SampEn$ of daily returns R of (a) sugar, (b)cotton (c) rice, (d) coffee, (e) corn and (f) wheat for timescale τ =1 ,5,10,21 day and window size 252 days.

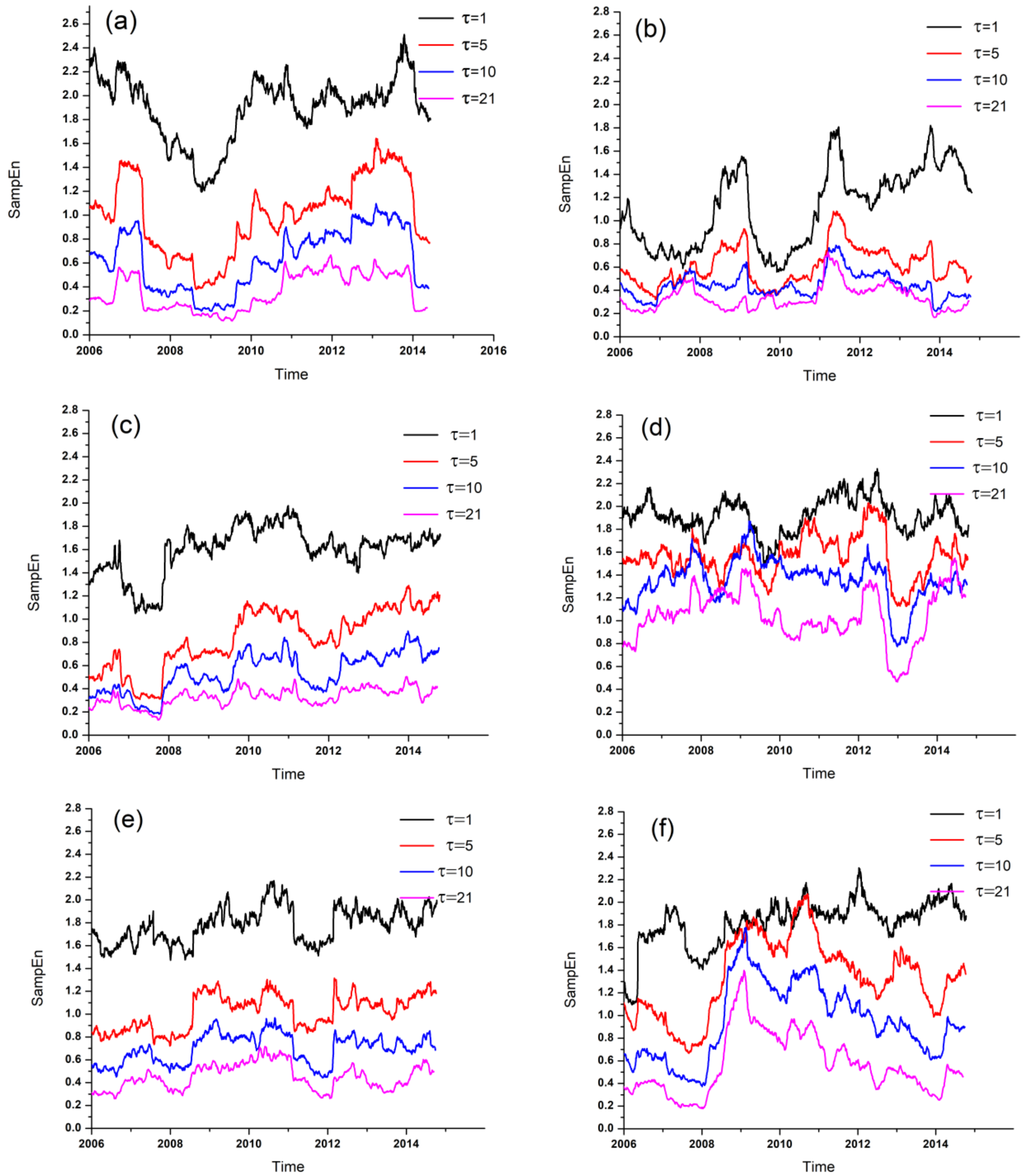


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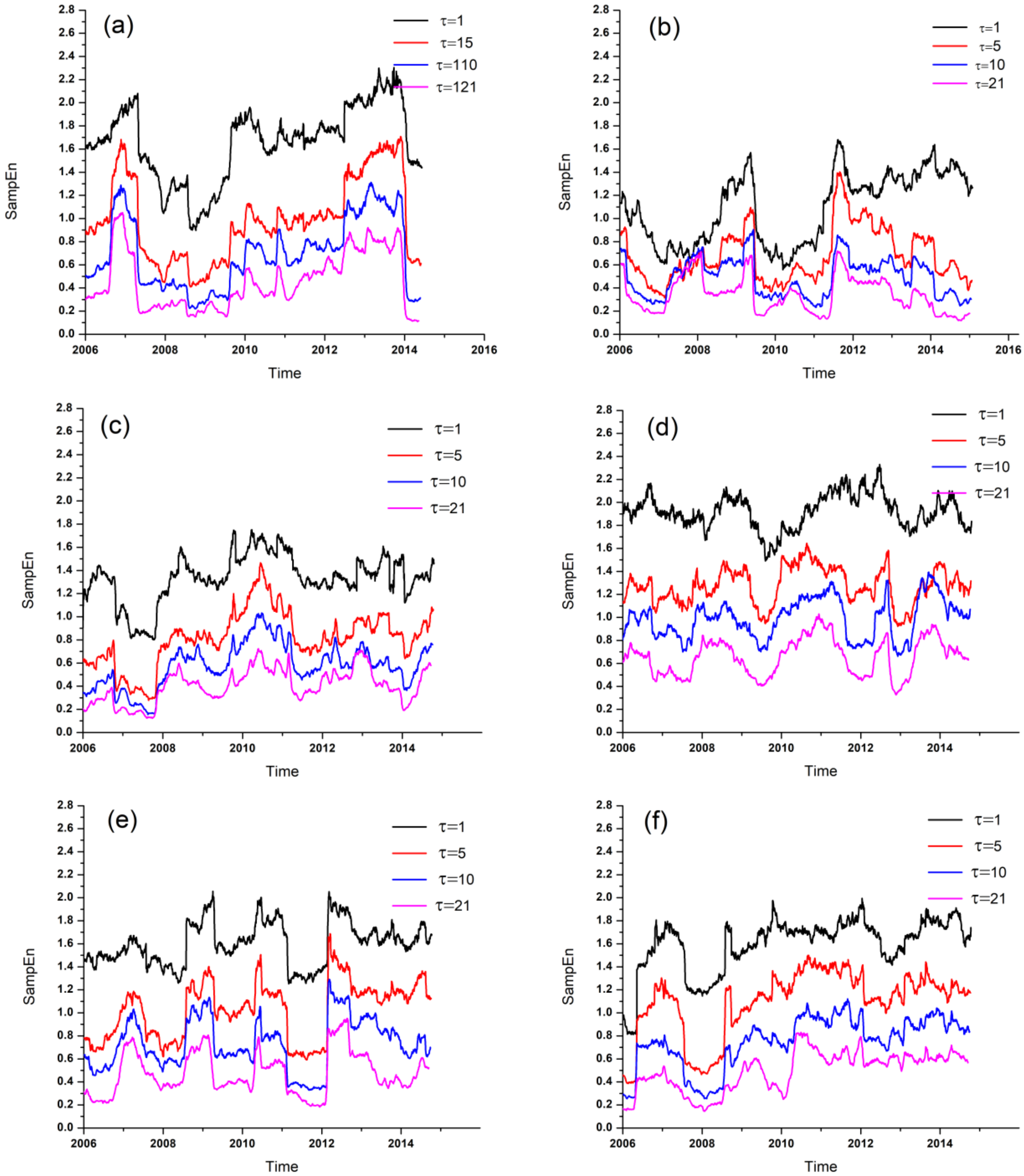
Figure 6. Time-dependent $SampEn$ of daily volatility V of (a) sugar, (b)cotton (c) rice, (d) coffee, (e) corn and (f) wheat for timescale $\tau = 1, 5, 10, 21$ day and window size 252 days.



Source: Authors.

4. Final Considerations

We found that for both returns and volatility the entropy values decrease as the temporal scale increases, indicating more regular price fluctuations and the loss of pattern diversity in long term trends. In general, volatilities series are more regular than return series as indicated by lower entropy values. This behavior persists when coarse grained series are analyzed in sliding windows. However, this novel approach permits closer view to entropy (price regularity) temporal variation and evaluation of the impact of recent food crises. We found that during the crisis the entropy of price fluctuations decreases indicating higher regularity and consequently lower efficiency in agricultural commodities market. The effect is more pronounced for volatility series and for higher temporal scales. Our conclusions have practical implications for commodity portfolio management, forecasting commodity market volatility shocks, and hedging agricultural commodity market risks. During the periods of higher degree of market efficiency (higher entropy) the agricultural commodities can be viewed as the good opportunity for portfolio diversification and capital allocation, while the periods of lower market efficiencies (lower entropy) give rise to exploitable opportunities and significant speculative activities in agricultural commodity market. Overall, our results showed that entropy methods implemented within a time depended multiscale framework, have good capacity to monitor the evolution of the agricultural market for different time scales, and detect different market phases which, in some cases, can be related to macroeconomic events.

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Percentage of contribution of each author in the manuscript

Djalma Beltrão da Costa Farias – 25%

Antonio Samuel Alves da Silva – 25%

Tatijana Stosic – 25%

Borko Stosic – 25%