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Breakfast in America: An analysis of cross-correlation of Class III milk futures prices

Derick Quintino[1], Paulo Ferreira[2,3,4]

Department of Economics, Administration and Sociology, University of São Paulo, Piracicaba 13418-900, Brazil[1]
VALORIZA—Research Center for Endogenous Resource Valorization, 7300 Portalegre, Portugal[2]
Instituto Politécnico de Portalegre, 7300 Portalegre, Portugal[3]
CEFAGE-UE, IIFA, Universidade de Évora, Largo dos Colegiais 2, 7000 Évora, Portugal[4]

ABSTRACT— In the agribusiness context, the milk market is an important economic sector. Therefore, this study aims to determine whether milk prices are correlated with prices of products apparently correlated, such as coffee, sugar and live cattle. We use a robust methodology, namely the correlation coefficient from the Detrended Cross-Correlation Analysis, with daily data between October 2011 and June 2020. We find there is significant correlation only between milk and coffee in the long run. Our results are of interest for agents involved in the dairy production chain, in terms of portfolio diversification strategies, as well as for policy-makers in this important sector of agribusiness and with a relevant consumer market.

KEYWORDS: Detrended Cross-Correlation Analysis; Econophysics; Class III milk prices.

1. INTRODUCTION

In recent years, it is important to highlight that world demand for milk and meat is expected to increase by 60% by 2050, due to a rising population, largely in emerging and developing countries, increasing the demand for meat and dairy products, with the income-elasticity of demand in such countries being in general greater than in developed ones [17]. According to the Diets for a Better Future report [5], it is essential to reduce the growth rate of consumption of red meat and dairy products to mitigate global warming, given that these products are responsible for major GHG emissions, in addition to bringing health benefits. Bearing this in mind, it is worth mentioning the scarcity of recent studies relating the prices of dairy products and other agricultural commodities, and the paper by [4] being an exception. The author relates the carbon emissions prices with butter prices in the European Union and finds evidence of a positive long-term relationship between the variables. The economic argument points out that higher emission prices are likely to increase the demand for vegetable oil, which could also affect the prices of close substitutes such as butter. In this paper we seek to increase the body of literature on correlation of dairy prices in different ways. From the point of view of the assets considered, we will investigate the relationship between the prices of milk and other agricultural commodities. In this sense, for better analysis of the results, in comparative terms, we also use the prices of assets with mature futures contracts which could be related to the dairy industry, such as sugar, coffee and cattle. Furthermore, we use a recent sample, starting in October 2011, with the beginning of the Class III milk future price series, and ending in June 2020, also including information about the recent market volatility after the global shock caused by COVID-19. In fact, in the most recent period included in our sample, the prices of commodities showed intense volatility, among which are the prices of milk price (see Figure 1). In addition, and compared to the paper of [4], we use data with a higher frequency, on a daily basis, of future markets that have a large volume of trading and are of interest to industry agents, investors and policy-makers, due to the signalling of market price expectations. The Class III milk futures contract traded on the Chicago Mercantile Exchange (CME) has historically been the most widely traded dairy product: Class I milk is used for beverages; Class II milk for soft products like cheese, yogurt and ice cream; Class III milk for cream and

hard manufactured cheeses, and, finally, Class IV milk for butter and dry milk. [3]. Although the milk futures markets are well developed, the Class III milk market is subject to government intervention, in the form of minimum prices, which generates an additional element of uncertainty, due to the higher basis risk (difference between future and spot prices) for US farmers [11].

Regarding the empirical strategy adopted, we will follow the work of [12]. The authors studied the relationship between oil and food price indices, from January 1990 to July 2016, including the dairy sub-index, using the correlation coefficient based on the detrended cross-correlation analysis (ρDCCA) proposed by [22]. Among the general results, they find that oil prices have a strong positive interdependence with dairy prices, in several sub-periods of analysis. In this sense, it is important to note that the ρDCCA methodological tool has several successful empirical applications, in various fields of knowledge. Among many examples in economics and finance, we can cite the recent investigation by [2], [18], [13], [1], [6]. The remainder of the text is organized as follows: after this introduction, section 2 describes the method and data, and section 3 analyzes the results and discusses them.

2. Material and Methods

For our purpose, we use the ρDCCA, a correlation coefficient proposed by [22], based on the assumptions of the DCCA proposed by [15]. This DCCA has the following steps. Considering two time series xi and yi, with equal length N, each time series is integrated, i.e., calculating $X_k = \sum_{i=1}^{k}(x_i - \langle x \rangle)$ and $Y_k = \sum_{i=1}^{k}(y_i - \langle y \rangle)$, $\langle x \rangle$ and $\langle y \rangle$ being the mean observed values of each series (with k=1, 2, … , N). These integrated series are then divided into (N-n) overlapping boxes of equal length n, with $4 \leq n \leq \frac{N}{4}$ and based on the ordinary least squares (OLS), local trends are calculated ($\tilde{X}_{k,i}$ and $\tilde{Y}_{k,i}$) in order to detrend previous time series and to calculate the covariance of the residuals for each box and given by $f_{xy}^2(n,i) = \frac{1}{(n+1)}\sum_{k=1}^{i+n}\left(X_k - \tilde{X}_{k,i}\right)\left(Y_k - \tilde{Y}_{k,i}\right)$. Considering the whole set of (N-n) boxes, the covariance of the residuals is averaged, i.e., calculating $F_{xy}^2(n) = \frac{1}{(N-n)}\sum_{i=1}^{N-n} f_{xy}^2(n,i)$.

The DCCA correlation coefficient is given by $\rho_{DCCA} = \frac{F_{xy}^2(n)}{F_{xx}(n)F_{yy}(n)}$ and is composed of the value of $F_{xy}^2(n)$, previously defined, and by $F_{xx}(n)$ and $F_{yy}(n)$ with the root mean square fluctuation functions of each individual time series xi and yi, being derived from the Detrended Fluctuation Analysis (DFA) proposed by [14], used to analyse serial dependence.

The correlation coefficient given by ρ_{DCCA} has the desirable property of $-1 \leq \rho_{DCCA}(n) \leq 1$, it is robust to non-stationarity and is useful to distinguish between different time scales, allowing, for example, differences between the short and long run to be studied (for more details about the properties of the coefficient, see [19], [9], [10], [23] For this purpose, we use Class III milk and live cattle (both CME Exchange), as well as the sugar and coffee (both from ICE Exchange) futures prices. All prices are freely accessible from the Quandl platform (https://www.quandl.com/). The period of analysis is between 2011/10/05, the beginning of the Class III milk futures prices series, and 2020/06/30, totalling 2143 observations.

3. Results and Discussion

We start our analysis with a quick view of the descriptive statistics of the returns of the assets used. We can see (Table 1) that the average return is very close to zero for all assets, as expected, with coffee having the highest volatility (standard deviation), while milk does not have a representative different volatility compared to other goods. However, it is interesting to note that, in the extreme movements of maximum and minimum,

milk prices are highlighted. Furthermore, and related to that result, milk shows strong positive asymmetry, with mean that positive returns are more frequent than negative ones, contrasting with live cattle. Finally, milk has high kurtosis values, which indicates that the returns do not follow a normal distribution. Although the kurtosis of milk returns has the highest value, the remaining assets analysed also have high kurtosis levels, which allow us to conclude that the respective distributions are platicurtik, a usual result in financial data.

Table 1. Summary statistics

Commodities	Mean	Std Dev	Min	Max	Skewness	Kurtosis
Milk	0.0001	0.0172	-0.2049	0.4890	9.7009	331.6094
Cattle	-0.0004	0.0129	-0.1565	0.0679	-1.6549	19.9256
Coffee	-0.0003	0.0206	-0.0732	0.1179	0.2754	4.5582
Sugar	-0.0003	0.0191	-0.1829	0.1661	0.4180	11.8581

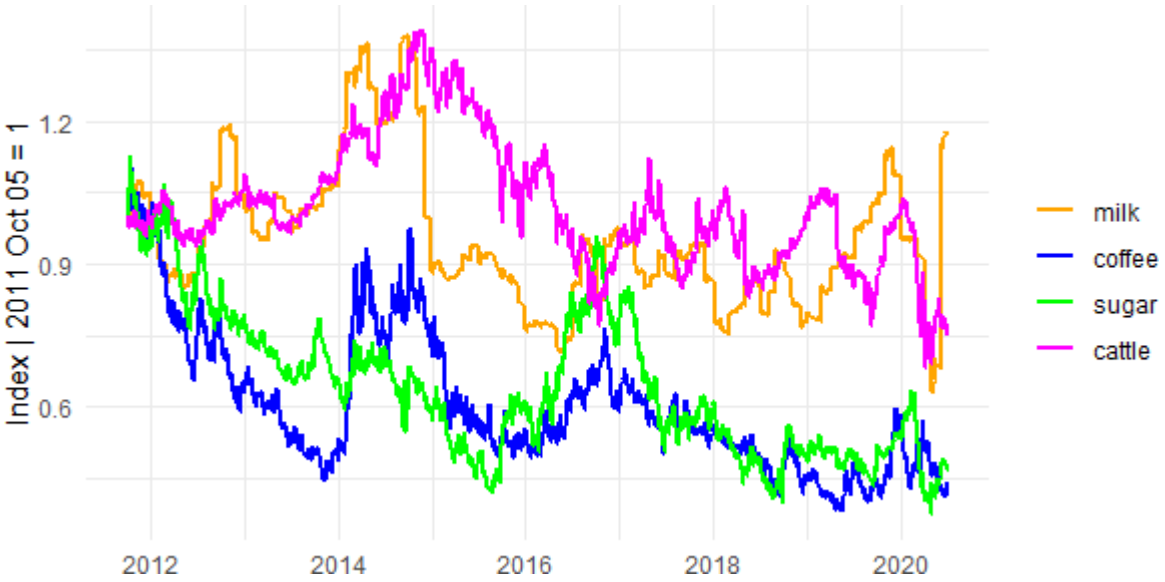

Figure 1. Price index normalized for 1 in the first observation of each series.

The results of the correlation coefficients between the assets analysed are presented in Figure 2. We can see that milk returns do not show strong correlations with others possible related commodities in the short run. The only asset showing a significant correlation with milk is coffee, in the long run, corresponding to the 256-day time scale, approximately one year considering trading days.

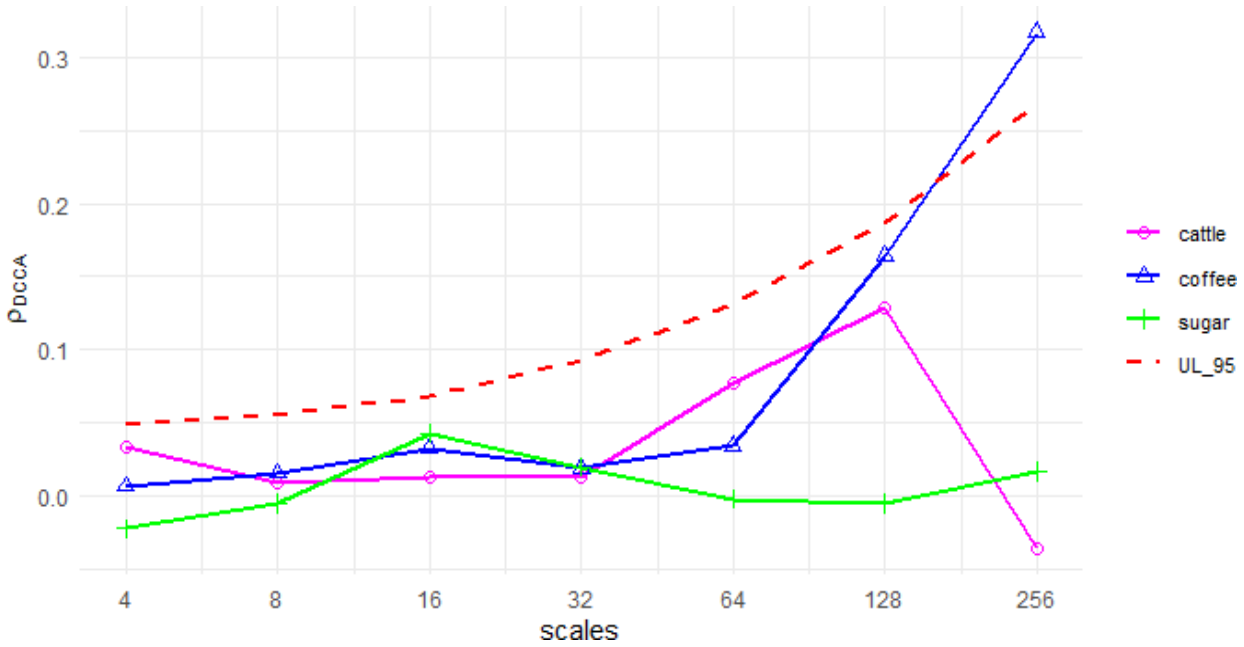

Figure 2. Detrended cross-correlation analysis coefficient - $\rho DCCA$ - between Class III milk prices and cattle, coffee and sugar prices, depending on k (time scales, in days). Dashed lines are upper limits of the confidence interval, as values below them are not statistically significant according to the critical values from [16].

Our results from cross-correlating milk prices are in line with recent studies. [7], [11] highlight that both the American and European markets have changed their dairy price management policy many times, and these policies generate greater price volatility with increased uncertainty and making cross-hedge strategies with milk-related agricultural commodities more difficult. Just as the Class III milk market has its specificities, coffee prices also have sui generis characteristics. In addition to being a seasonal crop with regionalized production, which makes price prediction more complex, it has experienced many periods of high volatility, including the formation of price bubbles [20]. In this aspect, future research may deepen the price relationship between Class III milk and coffee, in order to compare the evidence, found in the present study. Important to note that live cattle prices also evidenced recent formation of bubbles [21], and sugar prices are affected by recent global financial uncertainty [8], and these facts may alter the strength of correlation with other commodites, including milk prices. Finally, our results are important to assist policy-makers in decision-making, particularly as milk prices are not fully determined by the market, but also subject to US government policies. They are also of interest to private sector agents who aim to manage the risk of milk prices, relating not only to the traditional agricultural commodities analyzed here, but also to energy commodities with issues related to oil and GHG emissions mitigation as carbon emissions prices. Therefore, it is essential to understand the price correlations of Class III milk, and the new assets that are gaining maturity in the energy commodities market, in addition to traditional agricultural commodities and traditional econometric methods such as VAR- and VECM-family models.

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