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Breakfast commodities and global warming effects

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ABSTRACT

This paper investigates global warming in the breakfast index commodities by comparing the statistical properties of the prices of the commodities and their relationship with temperature from a regional perspective. Empirical results indicate that temperature deviations are individually mean reverting and display long memory behavior; however, in breakfast commodity prices mean reversion is only observed in the case of orange and wheat with the log prices. This evidence suggests that food commodities ares more vulnerable to shocks, with a higher exposure to the poorer population segments due to their high demand elasticity. Furthermore, the results of the cointegration analysis confirm the evidence of impact in prices of temperature deviations, especially for wheat and cocoa. For the rest of the cases, shock duration is expected to be short-lived with a smaller risk for the global economy.

1. Introduction

The Breakfast Index was initially created by Hard Assets Investor, a Van Eck-sponsored research-oriented online resource about commodity investing, started in 2009 and finishing in 2016. The breakfast index captures the food items mostly consumed as breakfast, these are cocoa, coffee, milk, wheat, butter, sugar, bacon and orange juice, monitoring its prices and comparing them with CPI indexes [1]. This breakfast index was followed by other large investment houses such as Bloomberg in 2017 or eToro in 2019 to estimate how well individuals with average wages are able to afford a typical breakfast, measuring both inflation and affordability of wholesale food prices. The increase of stock and demand in China, the deficit of dry climate of such as Brazil and trade export restrictions of other suppliers such as Russia or Argentina generated a price rally in 2020-2021 [2]. Furthermore, recent supply chain and energy bottlenecks in 2022 have raised inflation to levels that in some countries are double digit, pushing governments to strong measures to control inflation.

The impact of basic food commodities, as breakfast ones, might very large especially for the poor layers of the population, since income is a main determinant of the affordability of healthy diets [3]. Growth in food consumption has more closely followed population growth, particularly for grains. In addition, income elasticities vary with per capita income levels [4], especially at low levels of income, where elasticities of demand for commodities are high (in some cases well above unity). As per capita income levels rise, the marginal income elasticities fall. Thus, the question of the temporal length of tshocks is very important, defining a shock as an exogenous event that produces abrupt changes in the behaviour of the data.

The topic of mean reversion in financial markets has been a recurrent topic that started in the 80's decade [5-7] and is still investigated nowadays ([8-12]; etc.) specially in the financial markets, where investors look for stock market predictability and investment opportunities. However, in the specific field of commodities, the price behavior is different as it depends on its own supply and demand. A continuous increase in prices is something not observed in commodity markets, in contrast to runs that eventually "crash" [13]. The arguments for commodity bubbles are generally related with inelastic supply and demand

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in the short term [14], as the production function of these commodities is very capital intensive and it takes time to build capital [15] causing their respective supply not to respond demand increases. Therefore, while slumps in industrial commodities have been mainly related with declines in global economic growth, shocks in agricultural commodities are mostly associated with its specific supply or policy shocks and less with aggregate demand shocks [16].

Therefore, due to the recent post-Covid inflation peak this paper contributes to this specific field by studying the role of breakfast commodities, investigating if the commodities prices are reverting to the mean, in which case the increase of supply would compensate the increasing demand and recover the initial price. If, on the other hand commodities prices are not mean reverting, the increase of supply (if there were), would be small and prices would not recover the initial level.

Thus, in this paper we are interested in understanding two main issues. Firstly, if the behavior of food commodities related to the breakfast index exhibit mean reversion, that would help poorer layers of the population to recover from sharp rises. For this purpose, we investigate their degree of persistence and resilience to shocks [17], in order to know if this recent pricing rally might be controlled without additional policies. Secondly, to evaluate their long-term relationships with temperatures and to check if these commodities might be affected by global warming risks. It is clear that mean global land temperatures have risen nearly 1°C since 1970 [18] but countries have not warmed equally. Dell et al. [19] analyzed the annual variation in temperature over the past 50 years to examine the impact of climatic changes on economic activity, finding that higher temperatures substantially reduce economic growth in poor countries. In particular, in poor countries, a 1°C rise in temperature in a given year reduces economic growth by 1.3 % points on average. Therefore, we would like to extend this type of analysis in the particular case of basic food commodities.

The novelty of this paper is to study the degree of persistence in food commodities with fractional integration and the usage of fractional cointegration techniques to evaluate the relationship with temperature deviations. The understanding of the order of integration, i.e., the number of differences required to render the series stationary I(0), would help to understand if shocks are expected to have a transitory nature I(0) or if the series are I(1) and shocks are expected to have a permanent effect with no mean reversion properties. In this latter case, strong policy measures must be implemented to recover the original levels in the series after the shocks. Furthermore, the study of cointegration or a "long-run equilibrium" relationship [20], will help to understand if there is a direct contribution between these two factors.

The results reported in this work will show that most of the food commodities follow orders of integration close to 1 and the unit root null hypothesis cannot be rejected in any case; thus, food commodities appear now to be more vulnerable to shocks and their effects are expected to be permanent. Moreover, the cointegration results will confirm the evidence of impact in prices of temperature deviations, especially for wheat and cocoa. The remainder of the paper is organized as follows. Section 2 presents a literature review focused on persistence on food commodity prices, impacts of global warming in agriculture and specific studies of fractional integration in food commodities. Section 3 introduces the methodology on fractional integration and cointegration, while Section 4 presents the data and provides descriptive statistics. Section 5 displays the main results and discusses some of their implications with regards to understanding the potential evolution of these food commodities in the future. Finally, Section 6 summarizes the main conclusions of the paper.

2. Literature review

Early articles relating to breakfast indexes date back to Morgan et al. [21], Gejdenson and Schumer [22] or Ai et al. [23]. In general lines, these studies focused on prices, purchasing behavior, consumer behavior or co-movements among agriculture commodities. However, because of climate change concerns, during the past decade much more studies have arisen linking temperature effects with food commodities. Essentially, most of these papers forecasted severe impacts for agriculture commodities under climate change, when surpassing an optimum temperature as the crop productivity would tend to drop. Some examples are Schlenker and Roberts [24] with corn, soybeans and cotton production; Welch et al. [25] with impacts on rice crops or Lobell et al. [26] that analyzed global maize and wheat production. Dupuis [27] analyzed US forecast temperatures with price temperature derivatives. Ubilava [28] analyzed the ENSO effect and coffee price dynamics, in vegetable oils [29], and in wheat prices [30].

A second group of studies, linked food commodities with both rainfall and temperature but with similar purposes. Dell et al. [19] compared economic aggregates, concluding that higher temperatures would reduce agricultural, industrial output and the aggregate investment. Lewis and Witham [31], for wheat and barley, pointed negative impacts from high temperatures and the increase in drought frequencies. Merener [32] studied soybean supply shocks finding a linear negative response between future prices and daily rain, while Oko-Isu et al. [33] analyzed the reaction of coffee output to climate in Nigeria.

A third group is the one that links climate change and macroeconomics. Changnon [34] pointed that climate conditions generate uncertainties of 1 %-2 % of US GDP depending on extreme or mild conditions. Legg and Huang [35] analyzed negative climate impacts but suggesting an agriculture opportunity because of improving its policies, emissions, and fertilizers. Nelson and Shively [36] analyzed crop productivity, land requirements and energy impacts. Lanzafame [37] analyzed economic growth in Africa, finding evidence of short- and long-run relations between temperature and GDP growth per-capita. Mauger et al. [38] analyzed the US milk industry, estimating that climate impacts would imply losses to 6.3 % by the end of the 21st century. Smith and Ubilava [39] analyzed the economic growth in terms of ENSO shocks, suggesting that different impacts would depend across climatic zones. Balvers et al. [40] analyzed temperature shocks and the cost of equity, suggesting that temperature impacts might imply a loss in the present value of nearly 8 %. More recently, Benzie and Persson [41] and Ercin et al. [42] focused into European Union cross-border climate vulnerabilities, as many countries would be exposed to water dependency, trade openness or globalization risks.

In the specific field of the fractional integration and cointegration methodologies used on this research, very few papers can be mentioned. Power [43] analyzed daily live cattle futures prices over the period (1991-2014), estimating an integration factor of 0.951; however, the null hypothesis of a unit root could not be rejected, implying permanency of shocks. Regarding FCVAR models, Xu et al. [44] analyzed soybeans, wheat and oats plus some other Canadian commodities, finding evidence of backwardation behavior for wheat, and neither backwardation nor contango behavior for soybeans and contango behavior for oats. Some other related FCVAR models but for non-agriculture commodities can be found in Yaya and Gil-Alana [45] or Dolatabadi et al. [46,47]. Finally, with regards to related co-movements studies in agricultural fields, it can be mentioned Jiang and Fortenberry [48] that examined links between U.S. soybean prices and the Dow Jones U.S. Water Index; Yuan et al. [49] that found evidence of contagion effects among agricultural during extreme events; Algieri and Leccadito [50] that identified possible transmission channels between coffee, cocoa, maize, rice, soybeans, sugar and wheat, and Flori et al. [51], that investigated the nexus between climate-related variables, commodity price co-movements and financial stability.

3. Methodology

3.1. Fractional integration

We use fractional integration and cointegration methods, which belong to the category of long memory processes. A process is said to be long memory if the infinite sum of its autocovariances (γ_u, or pseudo-covariances in case of nonstationarity) is infinite, i.e.,

$$\sum_{u=-\infty}^{\infty} \gamma_u = \infty. \tag{1}$$

Within this category, a very commonly-used model is the one based on fractional integration that is characterized because the number of differences required to render it short memory or I(0) is a fractional value. In other words, x_t is said to be integrated of order d or I(d) if it can be expressed as:

$$(1-L)^d x_t = u_t, t = 1, 2, ..., \tag{2}$$

where L is the lag operator and u_t is I(0), which is defined as a process where the infinite sum of its autocovariances is finite, i.e.,

$$\sum_{u=-\infty}^{\infty} \gamma_u < \infty. \tag{3}$$

Note that the polynomial in L in (2) can be expressed in terms of its Binomial expansion such that

$$(1-L)^d = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - dL + \frac{d(d-1)}{2} L^2 - \ldots \tag{4}$$

and thus, Eq. (2) can be represented as

$$x_t = d x_{t-1} - \frac{d(d-1)}{2} x_{t-2} + \ldots + u_t. \tag{5}$$

According to Eq. (5), if d is a non-integer value, x_t will depend on all its past history and d can be taken as the relevant parameter to measure the degree of persistence in the data as the higher the value of d is, the higher the level of association is between the observations and thus, the level of persistence in the data. In addition, values of d smaller than 1 support the hypothesis of mean reversion with shocks having temporary effects, while $d \geq 1$ implies lack of mean reversion and permanency of shocks. The estimation of the differencing parameter is based on a frequency domain version of the Whittle function by using a simple version of a testing procedure developed in Robinson [52] and widely used in empirical applications of fractional integration [53].

The use of fractional integration allows that the number of differences may be a fractional value, showing then a greater flexibility in the specification of the series. In essence, comparing with traditional unit root testing, this approach circumvents the dichotomy between stationary I(0) and non-stationary I(1) series. It does so by allowing the integration parameter to adopt any real value, including fractional ones, as opposed to integer values only. Additionally, it successfully avoids erroneous unit root outputs, particularly in instances where the differencing parameter approaches to one ($0.5 < d < 1$). In this context, the series is not I(1) though exhibits long memory and is non-stationary but still mean-reverting at a low pace (see Diebold and Rudebush, [54-56]). Consequently, a broader range of dynamic processes can be taken into consideration, and valuable information can be obtained on the persistence and mean reversion properties of the series. The integration parameter can be interpreted as a measure of the degree of persistence in terms of its d value. Long memory is very much related with the concept of self-affinity. Thus, self-affine time series display power-law and hence scale-invariant correlations. In fact, Mandelbrot [57] characterizes self-affine processes as having long memory [58]. Seminal works in this context of long memory, self-affinity and fractional integration include among others Gil-Alana and Robinson [53], Barkoulas and Baum [59], Mandelbrot [57] and Cont [60,61].

3.2. Fractionally cointegrated vector autoregressive model

Johansen [62] introduced, in a multivariate context, the fractionally cointegrated vector autoregressive model (FCVAR). It was subsequently further developed by Johansen and Nielsen [63,64]. It is basically an extension of the Cointegrated Vector AutoRegressive (CVAR) approach in Johansen [65] to the fractional case, allowing both the orders of integration of the individual series and the cointegrating relations to be fractional values.

Following these research papers, we use their multivariate Fractional Cointegrated VAR (FCVAR) model to check the relationship of the variables in the long term.

The FCVAR model is described in the next equation:

$$\Delta^d X_t = \alpha\beta' L_b \Delta^{d-b} X_t + \sum_{i=1}^{k} \Gamma_i \Delta^b L_b^i Y_t + \varepsilon_t, \tag{6}$$

where ε_t is an error term with mean zero and variance-covariance matrix Ω that is p-dimensional, independent and identically distributed; α and β are $p \times r$ matrices where $0 \leq r \leq p$. The relationship in the long-term equilibria in terms of cointegration in the system is due to the matrix β. Controlling the short-term behavior of the variables is due to parameter Γ_i. Finally, the deviations from the equilibria and their speed in the adjustment is due to parameter α.

4. Data

To apply the methodologies referred to in the above section, we use as a climate proxy for the climate change impacts the temperature deviations [66]. Some authors have examined the available data in an attempt to identify any empirical evidence of the relationship between variations in temperature and climate change. The results of this research indicate a direct relationship between local temperature volatility and climate change-related tweets [67]. As Sisco and Weber [68] also point out, there is a correlation between temperature anomalies and an increase in internet searches related to climate change. Researchers in the field of climate change have indeed employed the absolute temperature as a metric for climate change, as evidenced by studies such as those by Wittenborn et al. [69] on the Baltic Sea and Cerrato et al. [70] on the Alps. Alternatively, Arnell et al. [71] conducted research that specifically examines the impacts of climate change at varying levels of global temperature increase. However, in recent times, some other authors specializing in social sciences have used the temperature variation as a proxy for climate change. These include Song and Tong [72] for monetary policy; Chen and Fang [73] for foreign direct investment, and Ngepah and Regina [74] for gender inequality and climate change. In any event, regarding our study, the use of temperature or temperature anomalies (we used global deviations with respect to the 1901-2000, and average regional temperature anomalies with respect to the 1910-2000 average) does not affect the estimation of the integration factor since we use the following regression model:

$$y_t = \alpha + \beta t + x_t, \quad (1-L)^d x_t = u_t, \quad u_t = \rho u_{t-12} + \varepsilon_t \tag{7}$$

In particular, we use three different estimations: in the absence of deterministic terms (i.e., with $\alpha = \beta = 0$); with a constant ($\beta = 0$), and with a constant and a linear trend, in the latter case with the two parameters (α and β) being estimated. Consequently, there is a decoupling of the average value of the temperature for the estimation of the integration factor, and therefore the value will be equal for absolute temperatures and for temperature deviations.

We have chosen temperature deviation data from NOAA Global time series (1895-2021) on a monthly basis, https://www.ncdc.noaa.gov/cag/global/time-series. As different regions were expected to lead the production of these food commodities, we use regional temperature patterns in the commodity where it is produced. Thus, specific deviations of North America, South America, Asia and Africa were taken into consideration. Full data is shown in Fig. 1a and 1b (zooming data after 1990) for temperature deviations with linear trends of these deviations. It can be seen that this trend tends to be faster (higher slope) in Asia than in the rest of regions.

Regarding food commodities, different monthly datasheets were examined, depending on the data available. In particular, the data chosen were the following:

- Sugar: “SB1 Comdty” from Bloomberg (1961-2021), USD
- Wheat: “W1 COMB Comdty”, from Bloomberg (1959-2021), USD
- Orange: “JO1 Comdty”, from Bloomberg (1967-2021), USD
- Milk: “WPS016”, Producer Price Index by Commodity: Farm Products: Raw Milk, from St. Louis FRED (1967-2021), Index 1982=100
- Coffee: “PCOFFOTMUSDM”, Global price of Coffee, Other Mild Arabica, from St. Louis FRED (1990-2021), U.S. Cents per Pound
- Coccoa: “PCOCOUSDM”, Global price of Cocoa, St. Louis FRED (1990-2021), U.S. Cents per Pound
- Bacon: “APU0000704111”, Average Price: Bacon, Sliced in U.S. City Average, St. Louis FRED (1980-2021), U.S. Cents per Pound

To discount the inflation effect, the CPIAUCNT index was used (Consumer Price Index for All Urban Consumers 1982-1984=100) from St. Louis FRED. Main statistics of both time series (natural values and CPI adjusted) are reported in Table 1 Food commodity series are displayed in Fig. 2.

Fig. 3 shows the nominal and CPI adjusted price on base year 2000 for these commodities in terms of the temperature deviation for both longer series (Fig. 3a, sugar, wheat, orange, milk and bacon dated between 1960s and 1980s) and for all small series with selected data starting in 1990s (Fig. 3b). A grade 2 polynomial regression line was introduced, finding evidence of a clear negative-slope behavior in most longer time series, that is flattening in recent times (after 1990s), indicating a smaller price variation for these commodity series in terms of the temperature deviation. This issue could indicate that in the long term, productivity gains were still compensating for the worsening effect of climate change. However, as the slopes for the same commodities tend to have a clear decrease in the mid-term series (after the onset of the 1990s), the increase of temperature deviations in recent times might be impacting more negatively over the productivity gains than before.

Table 2 compares both groups of results. As commodities are traded in global markets, it has been chosen as temperature proxy the region of the commodity producer global leader as it can be seen on this table. For longer series dated in 1960s (sugar, wheat, orange and milk), it can be clearly seen that the slope is negative but clearly higher [-0.47, -0.60] than recent times starting in 1990s [-0.05, -0.31]. Bacon is an exception having positive slope that tends to grow in recent times 0.05 vs 0.44. As temperature deviations tended to grow in recent times (see Fig. 1), this result might show that the commodity price reduction trend that shows longer time series has been reduced in recent times.

5. Results

The persistence of the series is estimated using fractional integration methods allowing the order of integration (say d) to take fractional as well as integer values. This is a more general and flexible approach than the standard methods based on the I(0) versus I(1) dichotomy, and it encompasses a variety of cases, namely: short-memory series ($d = 0$); long-memory stationary series ($0 < d < 0.5$); mean-reverting nonstationary series ($0.5 \leq d < 1$); unit roots ($d = 1$) or explosive patterns ($d > 1$). The estimation of the differencing parameter is based on an approximation to the likelihood function (Whittle function) formulated in the frequency domain, and uses a simple version of the tests of Robinson [52] to determine the confidence bands for the values of d.

Tables 3–7 display the estimated values of d in a model given by the following regression:

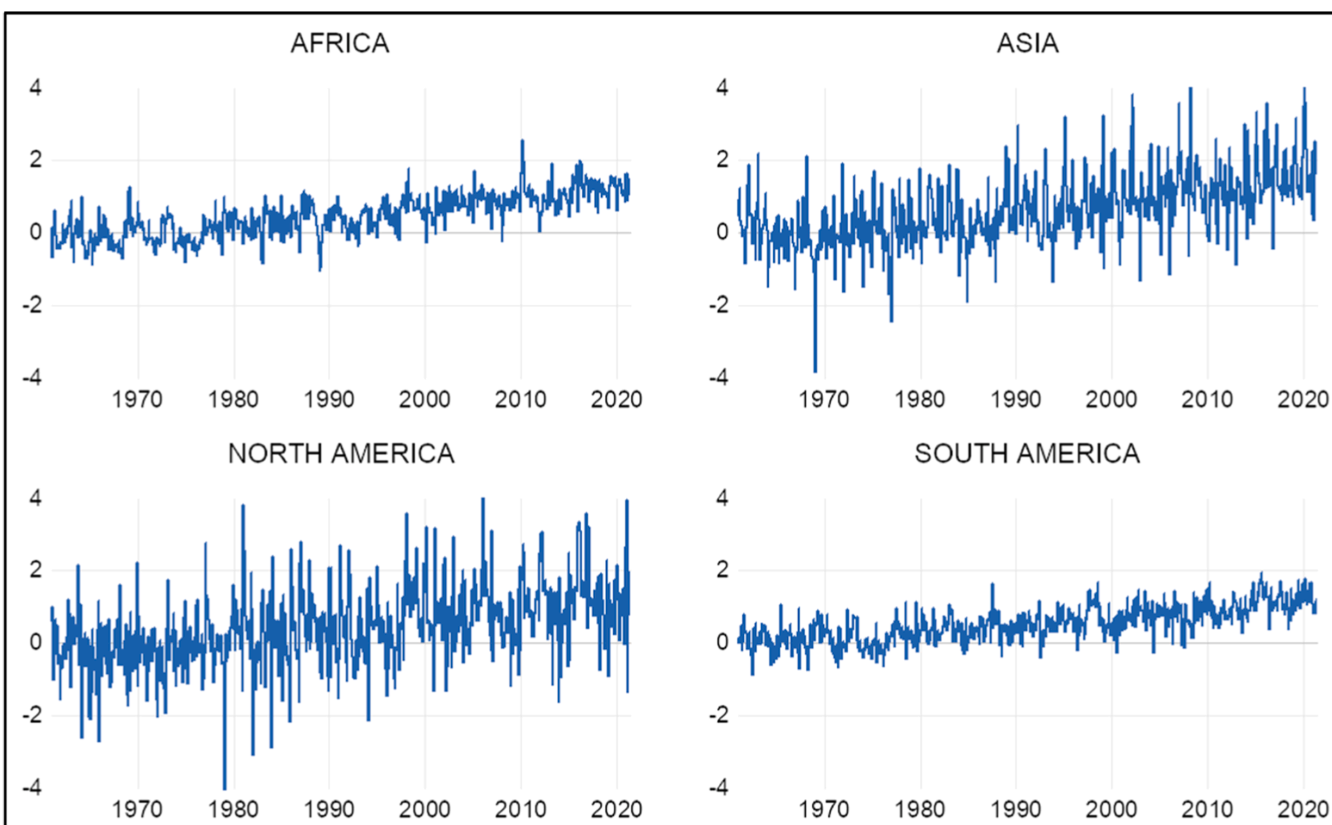

Fig. 1. Temperature deviation (1960-2021) per global region. Data source: NOAA.

Table 1
Descriptive statistics. Original data and CPI adjusted (year 2000 = base 100).

Original data							
	Beef	Coccoa	Coffee	Milk	Orange	Sugar	Wheat
Mean	3.26	1,944.09	130.77	98.22	108.40	10.92	369.40
Median	3.07	1,727.33	128.56	97.90	108.63	9.68	348.25
Maximum	6.37	3,522.10	302.71	194.60	221.95	53.20	1,073.00
Minimum	1.27	860.74	52.02	-	29.00	1.32	116.50
Std.Dev.	1.41	706.68	51.22	32.71	40.94	6.98	164.84
Volatility(Stdev/Mean)	0.46	0.41	0.40	0.33	0.38	0.72	0.47
Skewness	0.63	0.41	0.70	-0.01	0.20	1.75	0.94
Kurtosis	2.05	2.04	3.48	3.04	2.44	8.09	4.07
Jarque-Bera	51.70	25.15	33.99	0.05	12.84	1,151.92	142.41
CPI adjusted (year 2000)							
	Beef	Coccoa	Coffee	Milk	Orange	Sugar	Wheat
Mean	3.19	1,700.53	116.50	138.55	157.44	18.44	612.25
Median	3.10	1,637.74	110.25	123.63	142.71	12.92	529.80
Maximum	4.52	2,852.16	289.28	237.48	363.56	179.49	2,131.06
Minimum	2.18	879.01	50.41	68.88	51.78	3.82	242.41
Std.Dev.	0.53	404.46	41.28	43.72	71.28	17.91	316.47
Volatility(Stdev/Mean)	0.17	0.25	0.37	0.35	0.50	1.39	0.60
Skewness	0.31	0.44	1.17	0.45	0.63	4.18	1.47
Kurtosis	2.49	2.96	4.57	1.85	2.47	27.22	5.73
Jarque-Bera	13.45	12.43	124.88	56.70	50.95	19,807.00	484.80
Observations	377	377	377	640	652	725	725

$$y_t = \alpha + \beta t + x_t\ ,\ \ (1-L)^d x_t\ = u_t\ ,\ \ u_t\ = \rho u_{t-12}\ + \varepsilon_t \tag{8}$$

where y_t refers the observed data; α and β are unknown coefficients, namely the intercept (constant) and the linear time trend coefficient; L indicates the lag operator; x_t stands for the regression errors, assumed to be integrated of order d or I(d), meaning that u_t is integrated of order 0; moreover, given the seasonal nature inherent to the data, a seasonal (monthly) AR(1) process is assumed for the I(0) disturbances u_t, where ρ is the seasonality indicator, and ε_t is a white noise process.

Table 3 displays the estimates of d in Eq. (8) under three potential scenarios with respect to the first equality in (8). Thus, the values in the second column refer to the estimates based on the assumption that $\alpha = \beta = 0$, i.e., $y_t = x_t$, and there are no deterministic terms. In column 3 we suppose that only $\beta = 0$ and thus, we include an intercept, while those in column 4 refer to the model with the two coefficients (for the constant and the linear trend) being estimated from the data. If both coefficients are statistically significant, we choose the model with both coefficients, and if only the intercept is statistically significant, we choose the model with an intercept. The selected models are those where the values of d appear in bold in Table 3, and based on that, the estimated coefficients are reported in Table 4.

Regarding the temperature deviations we observe that the time trend coefficient is statistically significant in all cases, with clear evidence that the estimated value of d is above 0 and below 0.5, implying stationarity though with long memory behavior. Looking at the AR coefficients, in Table 4, it seems that seasonality is not much relevant in any of the series under examination. The long memory evidence is in line with many other papers investigating the climate change and the temperature deviations persistence with fractional integration ([75,76]; etc.); and with some others that found evidence of of long-range dependence and nonlinear warming trends [77], or a significant warming under an long-range dependence null hypothesis [78]

Empirical results of the food commodity series show mixed patterns: mean reversion only takes place in the case of orange, however with a close to the one-interval (0.83, 0.94) that would imply a low mean reverting pattern. On the other hand, the unit root null hypothesis cannot be rejected for wheat (0.93, 1.09), and this hypothesis is rejected in favor of d > 1 in the remaining five series (cocoa, bacon, coffee, milk and sugar). As part of our ongoing sensitivity checks, we have compared nominal and real prices in Table 5, confirming that there are no significant variations. In general, the results are very similar, with the I(d) characteristic being maintained in all cases except for the wheat case. In this case, we find that the d-value decays from 1.00 to 0.90 and the confidence interval moves from I(1) to I(d), with 0.5 < d < 1. However, as this result belongs to the upper end of the interval, the expected behavior would be a very slow mean reverting process.

Taking logs in these commodity prices (Tables 6 and 7) the estimates of d are slightly smaller, and mean reversion but with slow patterns occurs now in the cases of orange (0.85, 0.97) and wheat (0.88, 0.99). The I(1) hypothesis cannot be rejected for sugar (0.97, 1.09), and d is significantly higher than 1 for bacon, cocoa, coffee and milk. Results are in line with those from Power [43] for cattle futures where the I(1) hypothesis cannot be rejected.

Consequently, this analysis suggests that prices of food commodities appear to be very vulnerable to shocks as they are expected to remain permanent in most commodity prices, with transitory effects only expected in the cases of orange and wheat but with slow mean reverting patterns. Thus, from an economic perspective, external shocks events as periods of larger inflation (2021-2022) might have a long-lasting impact on food commodities and therefore, further policies should be required to restore previous pricing levels. These results would also provide empirical support to the study of Baes and Nagle [4], that points major vulnerabilities to the poorer population segments due to their high demand elasticity. To complete the empirical analysis, we have included the results of Bai-Perron's [79] methodology (Table 8), testing for the presence of structural breaks in the data. We find evidence of these breaks in 1999 for bacon (when EU ban US beef imports); for coffee in 1997 (when coffee production has exceeded demand [80]); for orange in 1990 (Florida winter cold waves); for sugar in 1974 (Laurel-Langley Agreement expiration) and 1983 (Caribbean sugar crisis); and for wheat in 2010 (severe drought and wildfires in Russia). Therefore, these empirical results show that these breaks were mainly motivated by supply problems.

In order to understand production cycles, geographic sensitivity, crop yields, and supply-demand dynamics in response to climate events, we try to analyse these factors in the crops under study, before studying their temperature interactions. Starting with oranges, it appears that this is the least vulnerable crop, as it is the only one that has demonstrated mean reversion. Orange trees are perennial crops with 9 year maturity with annual cycles [82] and a concentrated production (Brazil, Florida

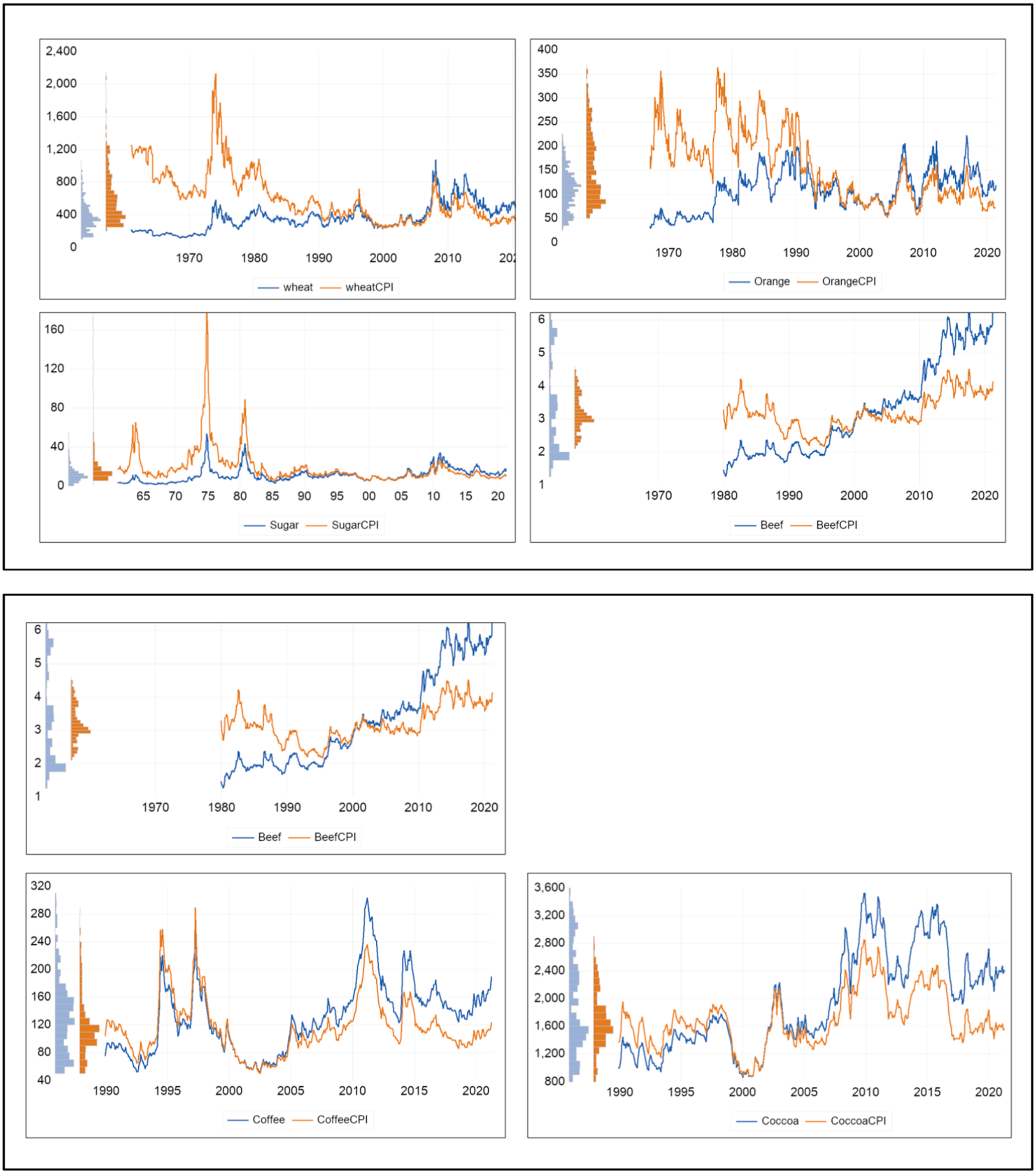

Fig. 2. Food commodity prices selected, nominal and CPI base 2000 adjusted

Note: Sugar data from "SB1 Comdty" from Bloomberg (1961-2021), USD. Wheat price, data from "W1 COMB Comdty", from Bloomberg (1959-2021), USD. Orange price data from "JO1 Comdty", from Bloomberg (1967-2021), USD. Milk price data from Producer Price Index by Commodity: Farm Products: Raw Milk, from St. Louis FRED (1967-2021), Index 1982=100. Coffee price, data from "PCOFFOTMUSDM", Global price of Coffee, Other Mild Arabica, St. Louis FRED (1990-2021), U.S. Cents per Pound. Cocoa price, data from "PCOCOUSDM", Global price of Cocoa, St. Louis FRED (1990-2021), U.S. Cents per Pound. Bacon price, data from "APU0000704111", Average Price: Bacon, Sliced in U.S. City Average, St. Louis FRED (1980-2021), U.S. Cents per Pound.

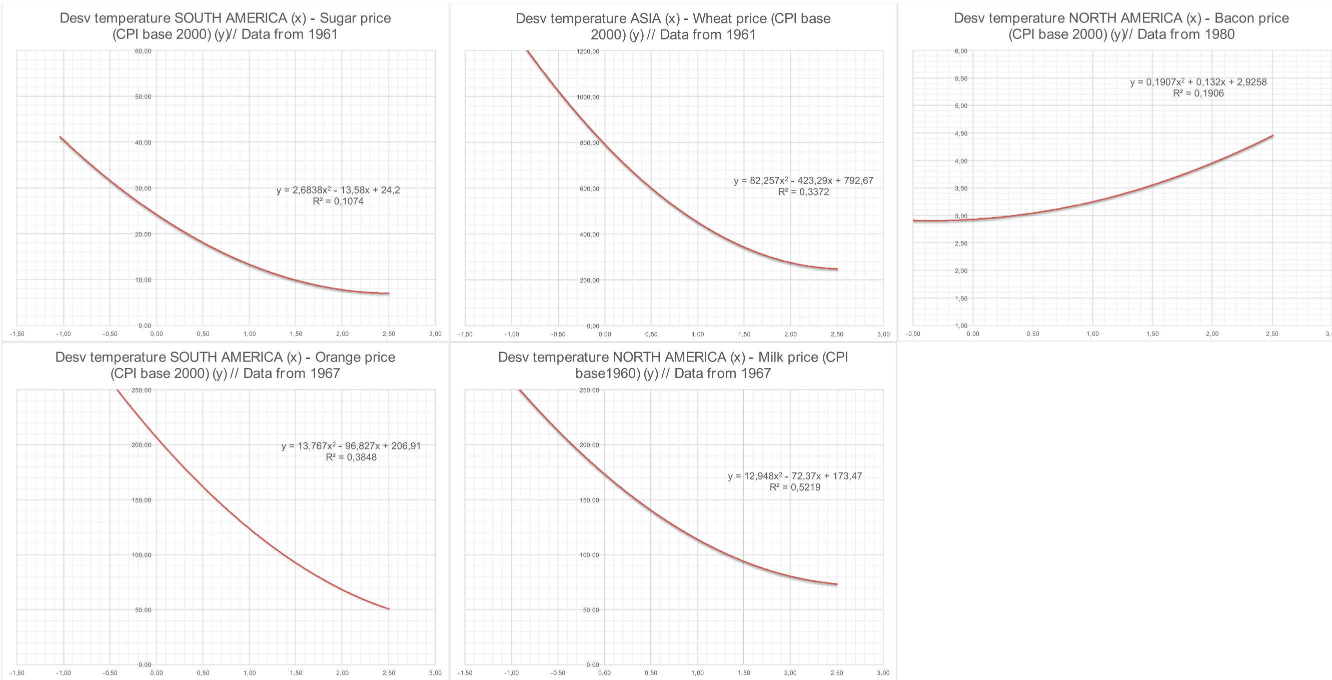

Fig. 3a. Temperature deviation versus price in constant prices (CPI base 2000); with data from inception on longer series (sugar, wheat, orange, milk and bacon).

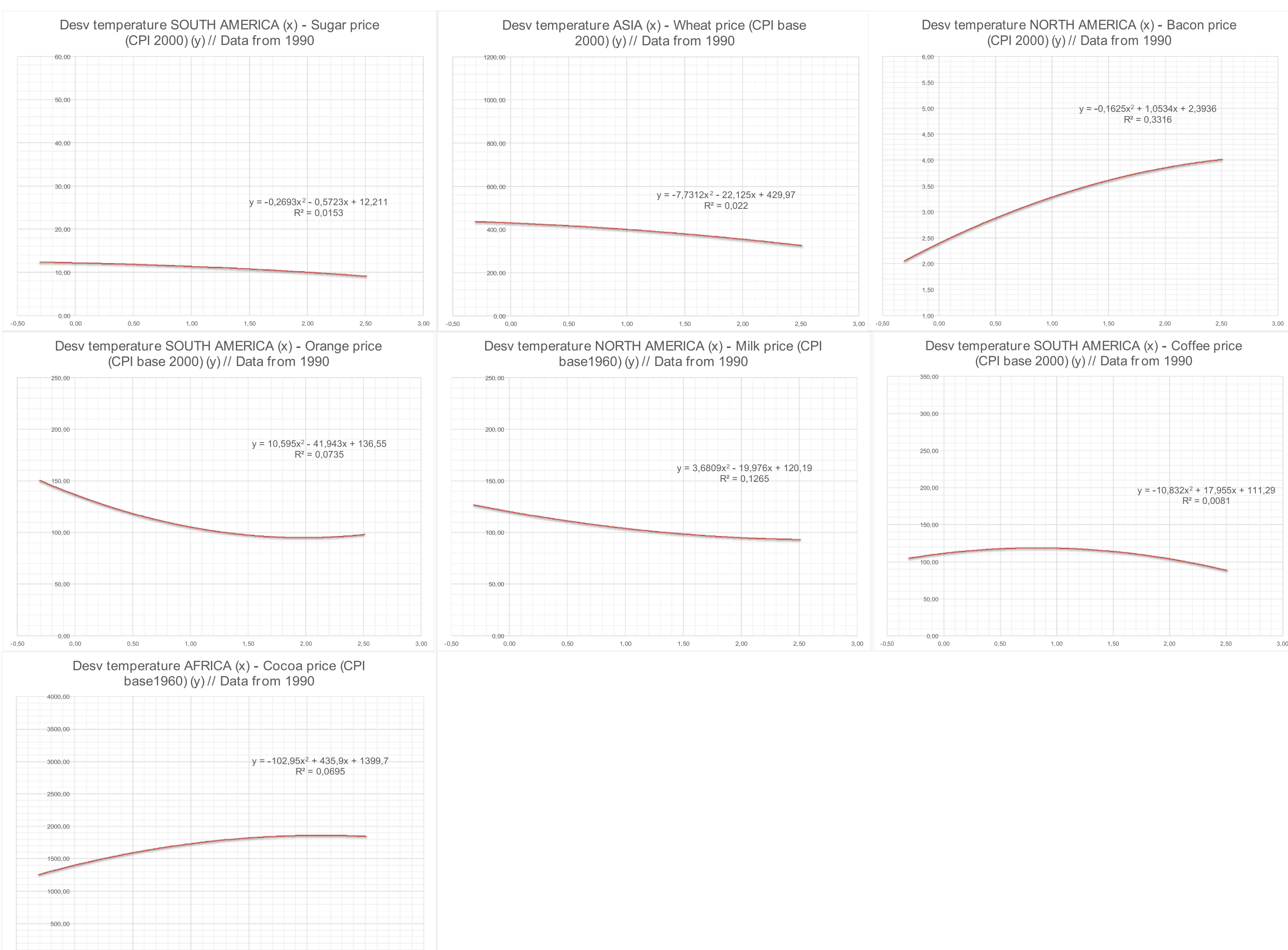

Fig. 3b. Temperature deviation versus price in constant prices (CPI base 2000); with data from 1990 in all series.

Table 2
Quadratic regressions, between prices (CPI base 2000) and temperature deviation $\left(Price = \alpha \cdot TD^2 + \beta \cdot TD + \gamma\right)$ for longer series (sugar, wheat, orange, milk and bacon) and all series starting in 1990.

	Proxy Temp	Data from	α	β	γ (TD=0)	Price (TD=1)	Slope β/γ
Sugar	S. America	1961	2,68	-13,58	24,20	13,30	-0,56
Wheat	Asia	1961	82,26	-423,29	792,67	451,64	-0,53
Orange	S. America	1967	13,77	-96,83	206,91	123,85	-0,47
Milk	N. America	1967	12,95	-72,37	120,19	60,77	-0,60
Bacon	N. America	1980	0,19	0,13	2,93	3,25	0,05
Average			22,37	-121,19	229,38	130,56	-0,53
			α	β	γ (TD=0)	Price (TD=1)	Slope β/γ
Sugar	S. America	1990	-0,26	-0,57	12,21	11,37	-0,05
Wheat	Asia	1990	-7,73	-22,13	429,97	400,11	-0,05
Orange	S. America	1990	10,60	-41,94	136,55	105,20	-0,31
Milk	N. America	1990	3,68	-19,98	120,19	103,89	-0,17
Bacon	N. America	1990	-0,16	1,05	2,39	3,28	0,44
Average			1,22	-16,71	140,26	124,77	-0,12
Coffee	S. America	1990	-10,83	18,00	111,29	118,45	0,16
Cocoa	Africa	1990	-102,95	435,90	1399,70	1732,65	0,31

Table 3
Estimates of d (fractional integration factor): Original time series.

Series	No terms	A constant	A constant + trend
Temperatures	0.42 (0.38, 0.45)	0.44 (0.40, 0.49)	**0.37 (0.31, 0.44)**
N. America	0.23 (0.20, 0.27)	0.24 (0.21, 0.27)	**0.20 (0.16, 0.24)**
S. America	0.38 (0.35, 0.40)	0.38 (0.35, 0.40)	**0.30 (0.27, 0.35)**
Asia	0.32 (0.28, 0.36)	0.32 (0.29, 0.36)	**0.27 (0.23, 0.32)**
Africa	0.45 (0.41, 0.49)	0.45 (0.41, 0.48)	**0.42 (0.38, 0.48)**
Prec. N. America	0.13 (0.10, 0.17)	0.13 (0.10, 0.17)	**0.12 (0.09, 0.17)**
Bacon	1.02 (0.96, 1.10)	**1.22 (1.12, 1.34)**	1.22 (1.12, 1.34)
Cocoa	1.08 (1.00, 1.18)	**1.10 (1.02, 1.21)**	1.10 (1.01, 1.21)
Coffee	1.13 (1.05, 1.23)	**1.12 (1.03, 1.21)**	1.12 (1.03, 1.21)
Milk	1.06 (1.00, 1.13)	**1.32 (1.22, 1.44)**	1.32 (1.22, 1.44)
Orange	0.92 (0.87, 0.98)	**0.88 (0.83, 0.94)**	0.88 (0.83, 0.94)
Sugar	1.26 (1.18, 1.35)	**1.26 (1.18, 1.36)**	1.26 (1.18, 1.36)
Wheat	1.01 (0.94, 1.08)	**1.00 (0.93, 1.09)**	1.00 (0.93, 1.09)

The values in bold are those referring to the selected specification. The values in parenthesis are the 95 % confidence bands.

Table 4
Summary of estimated coefficients for the fractional integration factor in the selected models estimated in Table 2.

Series	No terms	A constant	A constant + trend	—
Temperatures	0.37 (0.31, 0.44)	-0.0660 (-2.54)	0.0019 (6.49)	0.067
N. America	0.20 (0.16, 0.24)	-0.5276 (-3.36)	0.00114 (5.67)	0.016
S. America	0.30 (0.27, 0.35)	-0.5585 (-6.49)	0.00117 (10.64)	-0.001
Asia	0.27 (0.23, 0.32)	-0.6690 (-3.80)	0.00141 (6.55)	0.049
Africa	0.42 (0.38, 0.48)	-0.4617 (-3.20)	0.00109 (5.25)	-0.025
Prec. N. America	0.13 (0.10, 0.17)	0.11267 (2.29)	-0.00013 (-2.37)	
Bacon	1.22 (1.12, 1.34)	3.3061 (29.16)	—	0.181
Cocoa	1.10 (1.02, 1.21)	230.419 (14.22)	—	-0.014
Coffee	1.12 (1.03, 1.21)	74.574 (6.93)	—	-0.035
Milk	1.32 (1.22, 1.44)	31.141 (50.27)	—	-0.185
Orange	0.88 (0.83, 0.94)	27.146 (9.70)	—	-0.014
Sugar	1.26 (1.18, 1.36)	2.885 (4.23)	—	-0.084
Wheat	1.00 (0.93, 1.09)	213.25 (20.77)	—	-0.005

The values in parenthesis in the third and fourth columns are their corresponding t-values. The last column report the seasonal AR coefficients.

and the Mediterranean). As a tree, the timing and success of each stage is highly sensitive to temperature and rainfall, affecting the acidity and quality [83]. Furthermore, extended maturation cycles have resulted in production shortages that cannot be rectified in the immediate future due to the large tree maturity. A similar situation is found with cacao, as it is also a perennial crop with trees that follow a 8 year growth cycle before reaching peak production [84]. In addition, its production cycle is highly sensitive to environmental conditions (consistent tropical temperatures, high humidity, and regular rainfall) leading to a 70 % of production based in West Africa. In recent times, ENSO (El Niño–Southern Oscillation) events have caused immediate yield reductions in production, followed by several years of increased output as trees recover due to the natural cycle of tree maturity [85]. Given that both crops are traded on global markets with large maturity cycles, the main difference between them is that cacao looks more concentrated in terms of production causing that its price is more vulnerable to shocks, with a higher d-value.

On the other hand we have coffee and sugar. Coffee plants are small in stature and reach maturity more quickly, at around 18 to 24 months [86]. However, as orange and cacao, its cultivation is highly climate-dependent, with temperatures ranging from 18° to 22° for Arabica and from 22° to 28° for Robusta. Beyond their optimal temperature ranges, the quality and yield of both species decline [87]. Consequently, climate change is expected to reduce global coffee production and to decrease the area of suitable coffee-growing land by 2050 [88]. Even though it is currently produced in several regions, including Central America and the Caribbean, South America, Africa and Asia, it is expected future production losses if climate forces shift in coffee cultivation from presently cultivated areas to new areas [87]. Moreover, as coffee demand still increases, so too does its price volatility [89]. All these factors are causing a d-value that does not follow a mean reversion pattern with a d-value larger than 1. Similarly, the sugar cane is cultivated in tropical regions and requires a 12-month growth cycle with an optimal growth temperature of 24°C, and a consistent water supply [90], being highly sensitive to temperature extremes. For example, a 1 % rise in maximum temperature can cause a 61.2 % decrease in yield [91]. Therefore, main producers of this crop are located in the tropical belts, including Brazil, India and Thailand. Furthermore, in this crop, its global

Table 5
Comparison of results between original series and CPI adjusted, for the selected model estimated in Table 2.

	NON-CPI ADJUSTED		CPI-ADJUSTED	
	No terms	A constant	No terms	A constant
Bacon	1.15 (1.09, 1.21)	0.0092 (0.94)	1.22 (1.12, 1.34)	3.3061 (29.16)
Cocoa	1.14 (1.08, 1.20)	3.8858 (0.35)	1.10 (1.02, 1.21)	230.419 (14.22)
Coffee	1.11 (1.07, 1.15)	0.3646 (0.27)	1.12 (1.03, 1.21)	74.574 (6.93)
Milk	1.29 (1.22, 1.36)	-0.7604 (-0.20)	1.32 (1.22, 1.44)	31.141 (50.27)
Orange	0.94 (0.88, 0.99)	0.1282 (0.45)	0.88 (0.83, 0.94)	27.146 (9.70)
Sugar	1.17 (1.14, 1.19)	0.0240 (0.12)	1.26 (1.18, 1.36)	2.885 (4.23)
Wheat	0.90 (0.87, 0.94)	0.6056 (0.56)	1.00 (0.93, 1.09)	213.25 (20.77)

The values in parenthesis in the second and fourth columns are the 95 % confidence bands, while the third and fourth columns are their corresponding t-values.

Table 6
Estimates of d (fractional integration factor): log-transform time series.

Series	No terms	A constant	A constant + tren
Bacon	1.01 (0.95, 1.08)	**1.22 (1.12, 1.34)**	1.22 (1.12, 1.34)
Cocoa	1.01 (0.94, 1.09)	**1.10 (1.01, 1.20)**	1.10 (1.01, 1.20)
Coffee	1.04 (0.97, 1.13)	**1.14 (1.05, 1.24)**	1.14 (1.05, 1.24)
Milk	1.01 (0.95, 1.07)	**1.26 (1.16, 1.38)**	1.26 (1.16, 1.38)
Orange	0.99 (0.94, 1-05)	**0.91 (0.85, 0.97)**	0.91 (0.85, 0.97)
Sugar	1.03 (0.97, 1.10)	**1.02 (0.97, 1.09)**	1.02 (0.97, 1.09)
Wheat	1.00 (0.95, 1.06)	**0.93 (0.88, 0.99)**	0.93 (0.88, 0.99)

The values in bold are those referring to the selected specification. The values in parenthesis are the 95 % confidence bands.

Table 7
Summary of estimated coefficients for the fractional integration factor in the log-transform selected models estimated in Table 5.

Series	No terms	A constant	A constant + trend	—
			0.0019 (6.49)	—
			—	—
			—	—
			—	—
Bacon	1.22 (1.12, 1.34)	1.1964 (47.73)	—	0.188
Cocoa	1.10 (1.01, 1.20)	5.441 (97.03)	—	-0.010
Coffee	1.14 (1.05, 1.24)	4.311 (59.28)	—	-0.003
Milk	1.26 (1.16, 1.38)	3.438 (101.28)	—	-0.211
Orange	0.91 (0.85, 0.97)	3.285 (35.14)	—	0.003
Sugar	1.02 (0.97, 1.09)	1.064 (8.50)	—	0.070
Wheat	0.93 (0.88, 0.99)	5.357 (68.96)	—	0.029

The values in parenthesis in the third and fourth columns are their corresponding t-values. The last column report the seasonal AR coefficients.

consumption has caused that major crises and disruptions were often associated with trade shocks, as the expiration of the Laurel-Langley agreement in 1974 or the Caribbean sugar crisis in 1983 [92,93]. These market tensions may result in the highest d-values of all crops under analysis.

Finally, we have wheat that is the crop with smaller maturity time (140 days for spring wheat and 170 days for winter wheat [94]). This crop is especially sensible for temperature variations and rainfall. For instance, lower wheat yields in North America by 1.0–10.0 % per degree warming with associated weather extremes is reducing yield stability [95], making variety adaptation to future climate an important issue. In addition, it is the largest harvested cereal crop, cultivated on 126 countries [96] but still with a trade dependence of traditional

Table 8
Structural breaks [79] and possible associated reasons.

	Data starting	Structural breaks	Possible reason
Beef	1980	1999M10	EU ban all US beef imports
Coccoa	1990	none	
Coffee	1990	1997M06	Record peak and heavy drop. Essentially depressed coffee prices have been caused by five consecutive years (1998/99 to 2002/03) in which total coffee production has exceeded demand [80]*
Milk	1967	2003M07	Deregulation of the EU milk market started
Orange	1967	1990M06	Mix between Gulf war fears and damage to the Florida orange crop due to winter freeze
Sugar	1961	1974M12; 1983M11	1974: World sugar production drop and Laurel-Langley Agreement expired. This meant that the Philippines lost its quota for sugar exports 1983: Caribbean sugar crisis ([81]; Goddard, R. (2001).
Wheat	1959	2010M4	Severe drought in Russia and wildfires that destroyed one-fifth of its wheat production.

wheat-importing countries (especially in the Middle East and North Africa) and large consumer countries (India and China) where there is needed large volumes of wheat to feed their own populations [97].

In order to understand the interactions and the relationship of these time series in the long run and the temperature impact, we follow Johansen and Nielsen [63,64] using a Fractional Cointegrating VAR (FCVAR) model. The results are summarized across Tables 9–12. According to these results, we focus on two terms. First, we focus on the integrating and cointegrating components (d ≠ b); and second, on the beta or slope term to analyze the direct relationship between the temperatures and prices.

For choosing the temperature proxy, it has been selected the region of the producer leader to analyze the direct temperature impact. Therefore, it has been chosen South America for the sugar, orange and coffee as Brazil is the largest producer of these three commodities; Asia

Table 9
Results of the FCVAR model for South America temperature deviations (Sugar, Orange and Coffee).

South America	$d \neq b$	Cointegrating equation beta	
		Temperature deviation	Commodities
Temperature deviation vs Sugar	$d =$ 0.642 (0.108) $b =$ 0.642 (0.217) $\Delta^d\left(\begin{bmatrix} \textit{Temp. Dev.} \\ \textit{Sugar} \end{bmatrix} - \begin{bmatrix} 0.289 \\ 20.061 \end{bmatrix}\right) = L_d\begin{bmatrix} -0.022 \\ -0.424 \end{bmatrix}\nu_t + \sum_{i=1}^{2}\widehat{\Gamma}_i\Delta^d L_d^i(X_t - \mu) + \varepsilon_t$	1.000	0.069
Temperature deviation vs Orange	$d =$ 0.687 (0.108) $b =$ 0.687 (0.159) $\Delta^d\left(\begin{bmatrix} \textit{Temp. Dev.} \\ \textit{Orange} \end{bmatrix} - \begin{bmatrix} 0.365 \\ 183.480 \end{bmatrix}\right) = L_d\begin{bmatrix} -0.102 \\ -5.267 \end{bmatrix}\nu_t + \sum_{i=1}^{2}\widehat{\Gamma}_i\Delta^d L_d^i(X_t - \mu) + \varepsilon_t$	1.000	0.007
Panel III: Temperature deviation vs Coffee	$d =$ 0.628 (0.042) $b =$ 0.628 (0.000) $\Delta^d\left(\begin{bmatrix} \textit{Temp. Dev.} \\ \textit{Coffee} \end{bmatrix} - \begin{bmatrix} 0.514 \\ 104.278 \end{bmatrix}\right) = L_d\begin{bmatrix} -0.013 \\ 1.067 \end{bmatrix}\nu_t + \sum_{i=1}^{2}\widehat{\Gamma}_i\Delta^d L_d^i(X_t - \mu) + \varepsilon_t$	1.000	-0.047

Table 10
Results of the FCVAR model for Asia temperature deviations (Wheat).

Asia	$d \neq b$	Cointegrating equation beta	
		Temperature deviation	Commodities
Temperature deviation vs Wheat	$d =$ 0.918 (0.071) $b =$ 0.219 (0.073)	1.000	0.001
	$\Delta^d\left(\begin{bmatrix} Temp.\ Dev. \\ Wheat \end{bmatrix} - \begin{bmatrix} 0.271 \\ 1242.558 \end{bmatrix}\right) = L_d\begin{bmatrix} -14.335 \\ 156.977 \end{bmatrix}\nu_t + \sum_{i=1}^{2} \widehat{\Gamma}_i \Delta^d L_d^i (X_t - \mu) + \varepsilon_t$		

Table 11
Results of the FCVAR model for Africa temperature deviations (Cocoa).

Africa	$d \neq b$	Cointegrating equation beta	
		Temperature deviation	Commodities
Temperature deviation vs Cocoa	$d =$ 0.975 (0.063) $b =$ 0.082 (0.000)	1.000	0.001
	$\Delta^d\left(\begin{bmatrix} Temp.\ Dev. \\ Cocoa \end{bmatrix} - \begin{bmatrix} 0.648 \\ 1377.560 \end{bmatrix}\right) = L_d\begin{bmatrix} -246.732 \\ -3211.703 \end{bmatrix}\nu_t + \sum_{i=1}^{2} \widehat{\Gamma}_i \Delta^d L_d^i (X_t - \mu) + \varepsilon_t$		

for the wheat case as China is its largest producer; and Africa for the cocoa as it is mostly produced in Côte the Ivoire, Ghana and Nigeria. Fig. 4 shows a map with the main geographic productions of these crops. Finally, for the case of bacon and milk we have chosen the US for proxy index as these are fresh commodities.

The case of the long-term relationship between temperatures and sugar, orange and coffee prices in South America is analyzed in Table 9. We observe that the order of integration of the individual series (d) is getting the same magnitude in the reduction in the degree of integration in the cointegrating regression (b). These results imply I(0) cointegrating errors, since (d −b) = 0 in all these three cases. These results support the hypothesis of cointegration in its classical way as the orders of integration are 1 for the parent series and 0 for the equilibrium relationship, respectively. Therefore, we can determine that the error correction term would follow a stationary process, and the shock related to the temperature into the prices will be short-lived. In addition, regarding bacon and milk, we find similar results using the United States as temperature proxy, where also d - b = 0 and thus we also have a I(0) cointegrating error for these cases.

However, we observe different results in the case of wheat and cocoa, that are based in the regions of Asia and Africa respectively. In the case of wheat, we find an order of integration of the individual series (d) about 0.918, with a degree of integration in the cointegrating regression (b) of 0.219. Therefore, we find an order of integration (d-b) of about 0.699. Similar results are observed for the cocoa, with an order of integration of the individual series (d) of 0.975 and a degree of integration in the cointegrating regression of 0.082. Thus, in this case the order of integration (d - b) is 0.893 for the cointegrating relationship. Consequently, for these two commodities we may conclude that the resulting long run equilibrium time series follows a long memory process, which suggests potential forecasting at longer horizons [99]. Also, as (d - b) < 1 these values would imply that the duration of the shock is long-lived (although it is mean reverting) and the error correction term follows a nonstationary process.

Therefore, we believe that policy intervention should be driven to restore equilibrium in the supply side, and specifically to protect the future supply capacity during the shock length. With regards to temperature shocks, if we focus in the (d - b) parameters for evaluating the shock length, we find that it is long-lived only in the case of wheat and cocoa, although it is still mean reverting. Therefore, temperature shocks should be valuated more in depth for these specific crops.

Regarding the protection of crop supply capacity, it is also important to evaluate the maturity cycle of the crop and their ability to stock. For instance, for cocoa or orange new plantations will take 5-9 years [84, 82], while coffee and sugar takes only 18-24 months [86,90]. Therefore, investment should be taken in the first case with longer perspective and consequently, governments should provide security conditions to afford these long-term investments. Some policies might favor access to credit as funding programs, R&D incentives or agricultural insurances to favor these long-term investments. In addition, incentives for climate-resilient infrastructure (e.g., irrigation systems) may help to stabilize yields in the long-term, reducing price volatility. One example can be the extension of irrigation fields in the Brazilian coffee [100]

In the short term, we believe that price stabilisation policies should be used only to control price shocks and protect farmers' production capacity. At this juncture, extended market intervention has the potential to engender dependency, resulting in farmers placing considerable reliance on farm subsidies. For instance, the Philippine sugar industry, following the termination of the Laurel-Langley US Agreement [93], offers a pertinent case study. Should prices be artificially elevated, farmers may be encouraged to cultivate crops in excess of demand, resulting in a subsequent oversupply and a decline in commodity prices over time.

Finally, we look at the beta cointegrating equation for all the cases analyzed. We may conclude here that an increase in the temperature would imply a positive reaction in the prices between 0.001 and 0.189, depending on the commodity. Only in the case of coffee we see a negative value of beta negative, implying a negative slope. Such results would also be in line with the reduction of the negative slopes experienced the commodities between 1960's and 1990 (see Table 1). Due to these values, we believe that the specific impact generated by the global warming might be reversed in the future.

Therefore, current tensions in food commodities should be primarily generated by some other factors, as COVID-19 bottlenecks or

Table 12
Results of the FCVAR model for United States temperature and precipitation deviations (Bacon and Milk).

United States	$d \neq b$	Cointegrating equation beta		
		Temperature deviation	Precipitation deviation	Commodities
Temperature, precipitation deviations and Milk	$d =$ 0.597 (0.122) $b =$ 0.597 (0.122)	1.000	22.412	0.026
		$\Delta^d\left(\begin{bmatrix} Temp. \\ Prec. \\ Milk \end{bmatrix} - \begin{bmatrix} -0.109 \\ 0.082 \\ 189.817 \end{bmatrix}\right) = L_d\begin{bmatrix} 0.020 \\ -0.029 \\ 0.072 \end{bmatrix}\nu_t + \sum_{i=1}^{2} \widehat{\Gamma}_i \Delta^d L_d^i (X_t - \mu) + \varepsilon_t$		
Temperature, precipitation deviations and Bacon	$d =$ 0.441 (0.240) $b =$ 0.441 (0.231)	1.000	-0.368	0.189
		$\Delta^d\left(\begin{bmatrix} Temp. \\ Prec. \\ Beef \end{bmatrix} - \begin{bmatrix} 0.642 \\ 0.043 \\ 3.319 \end{bmatrix}\right) = L_d\begin{bmatrix} -0.242 \\ -0.075 \\ 0.038 \end{bmatrix}\nu_t + \sum_{i=1}^{2} \widehat{\Gamma}_i \Delta^d L_d^i (X_t - \mu) + \varepsilon_t$		

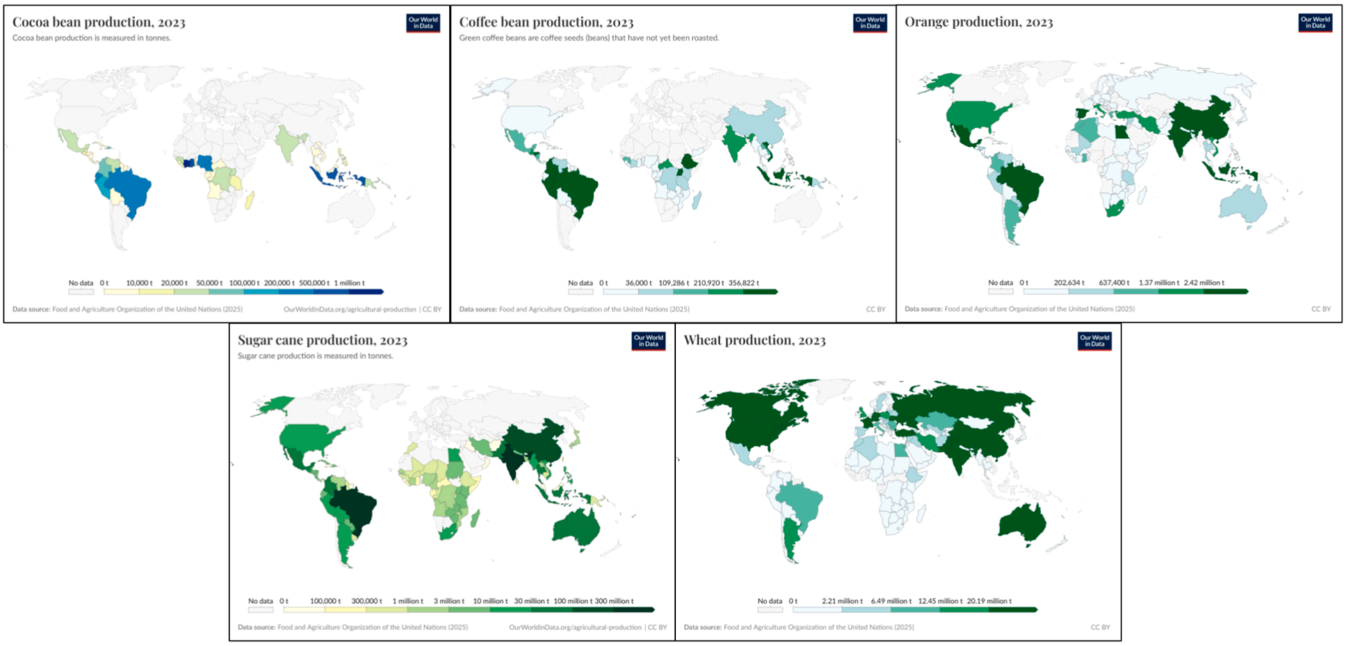

Fig. 4. Selected commodity crop production. Taken from World in Data [98].
Note: Figures taken from World in Data [98]. Dataset from Food and Agriculture Organization of the United Nations (2025) – with major processing by Our World in Data. Food and Agriculture Organization of the United Nations, “Production: Crops and livestock products”. All data, visualizations, and code produced by Our World in Data are completely open access under the Creative Commons BY license. You have the permission to use, distribute, and reproduce these in any medium, provided the source and authors are credited.

geopolitical conflicts. For instance, the rise of wheat prices due to the Ukranian war, could imply a major impact in the global economy as this shock would be expected to be permanent since d (0.93, 1.09) lies in the interval d = 1. In any case, we have seen that the price reduction trend of breakfast commodities has been slowed down especially after 1990s (see Table 1). Thus, if the persistence of the global warming shock continues, it would continue to affect the prices in the upcoming years with a positive reaction in prices.

6. Conclusions

Throughout this article the degree of persistence and mean reversion properties of certain food commodities have been investigated, along with the impact that global warming effects in terms of the temperature deviations are having on their price. In particular, those food commodities included in the breakfast index (sugar, cocoa, coffee, milk, bacon, orange and wheat), have been analyzed by studying the degree of integration of their individual pricing monthly time series; and their temperature relationships for the regions in terms of the regression slopes and FCVAR cointegration rank.

Firstly, descriptive empirical results indicate that in terms of the measurement of global warming effect impacts, changes in prices are noticeable with regards to temperature. Moreover, when using a polynomial trend for longer time series (before the 1970s), the pricing-temperature relationship shows a general negative slope in real terms, after discounting the general inflation effects. This result might indicate that until now and in the long term, productivity gains were still compensating for the worsening effect of climate change. However, as the slopes for the same commodities tend to have a clear decrease in the mid-term series (after the onset of the 1990s), this empirical evidence might indicate that the increase of temperature deviations in recent times might be impacting more negatively over the productivity gains than before. Thus, it can be said that after 1990s there is smaller price variation for temperature deviations and therefore, the decrease of the prices of breakfast commodities has been slowed down.

Regarding the persistence analysis with fractional integration, our empirical results indicate that temperature deviations are individually mean reverting and display long memory behavior. For the commodity prices, however, the orders of integration are close to 1 and mean reversion is only observed in the case of orange and wheat with the log prices. This evidence uggests that food commodities are more vulnerable to shocks and their effects are expected to be permanent, and therefore, such results would point a higher exposure to the poorer population segments due to their high demand elasticity.

As a robustness approach, we also estimate the integration order for each series, using other parametric [101] and semiparametric [102,103] methods. The results, though quantitative slightly different, qualitatively were very similar, supporting the hypothesis of long memory and mean reversion for the climatological data, and the unit root hypothesis for the commodity prices.

Finally, the results of the cointegration analysis confirm the evidence of positive impact in prices of temperature deviations, especially for wheat and cocoa where the resulting time series follow long memory processes (0.9 < d < 1), and temperature shocks are expected long lived duration in the prices although they were mean reverting. For the rest of the cases, we find smaller values of d (0.44 < d < 0.69), and as $(d - b) = 0$, it would mean that the shock duration will be short-lived with a smaller risk for the global economy.

CRediT authorship contribution statement

Miguel A. Martin-Valmayor: Validation, Writing – original draft, Data curation, Writing – review & editing, Investigation, Visualization, Conceptualization. **Luis A. Gil-Alana:** Validation, Project administration, Formal analysis, Writing – original draft, Software, Investigation, Writing – review & editing, Supervision, Methodology, Visualization, Resources, Funding acquisition. **Manuel Monge:** Validation, Formal analysis, Writing – review & editing, Methodology, Software, Writing – original draft, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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