International Review of Economics and Finance 65 (2020) 84–93

Contents lists available at ScienceDirect

International Review of Economics and Finance

journal homepage: www.elsevier.com/locate/iref

Can we still blame index funds for the price movements in the agricultural commodities market?

Rafael Baptista Palazzi [a], Antonio Carlos Figueiredo Pinto [a], Marcelo Cabus Klotzle [a,*], Erick Meira De Oliveira [b,c]

[a] IAG Business School, Pontifical Catholic University of Rio de Janeiro (PUC-Rio), Rio de Janeiro, Brazil
[b] Industrial Engineering Department, Pontifical Catholic University of Rio de Janeiro (PUC-Rio), Rio de Janeiro, Brazil
[c] Energy, Information Technology and Services Division, Brazilian Agency for Research and Innovation (Finep), Rio de Janeiro, Brazil

ARTICLE INFO

JEL classification:
G15
Q02

Keywords:
Agricultural commodities
Speculation
Index funds
Nonlinear causality

ABSTRACT

The role of speculation in the commodities market is still controversial. While several studies use linear models of causality to explain the relationship between speculation and price movements, there is a gap regarding the application of these analyses to detect causality. We compare linear and nonlinear methodologies to analyze whether speculation affects commodities' price or if speculators are trend-followers, not only in the bullish market but also in the bearish one. The results suggest that there is no pattern in the cause and effect relationship, so even more sophisticated models are not capable of capturing causal effects.

1. Introduction

From early 2000 onward, the commodities market underwent a profound transformation. Many participants entered the market to diversify their investments. Irwin and Sanders (2011) point out that more than US$ 100 billion of new resources entered this market from 2004 to 2008, which was referred to as the financialization of the commodities market. Coincidentally, commodity prices exploded. Cheng and Xiong (2014) show that the WTI price reached US$ 150 per barrel. Likewise, food prices also increased, which we had not observed since the 1970s (Carter, Rausser, & Smith, 2011; FAO, 2008). Based on these trends, a series of studies by international agencies, academics and even international agencies examined the role of speculation in raising commodity prices (International Monetary Fund, 2008; Irwin & Sanders, 2011; Irwin & Sanders et al., 2009). Index funds were the first source blamed for the price distortion, and international organizations were publicly exposed. For example, Irwin et al. (2011) cite a report from the US Senate subcommittee pointing to the *Commodity Index Traders* (CIT) as responsible for raising prices on wheat futures contracts.

Some researchers found it difficult to establish a causality between the position of speculative funds and the level of commodity prices. Many of these studies use the Granger Causality (GC) test. However, this test has several limitations (de Oliveira, Cunha, Cyrino Oliveira, & Samanez, 2017). Hiemstra and Jones (1994) point out that although the test has the power to show causality in linear

Abbreviations: AIC, Akaike Information Criterion; BIC, Bayesian Information Criterion; CFTC, Commodities Futures Trading Commission; CIT, Commodity Index Traders; DP, Diks and Panchenko; GC, Granger Causality; SCOT, Supplemental Commitments of Traders report; WTI, West Texas Intermediate.

* Corresponding author.
E-mail addresses: rafael_palazzi@phd.iag.puc-rio.br (R.B. Palazzi), figueiredo@iag.puc-rio.br (A.C. Figueiredo Pinto), klotzle@iag.puc-rio.br (M.C. Klotzle), emeira@finep.gov.br (E.M. De Oliveira).

https://doi.org/10.1016/j.iref.2019.10.001
Received 26 March 2019; Received in revised form 19 July 2019; Accepted 2 October 2019
Available online 3 October 2019

relations, it does not offer the same efficiency in nonlinear relations. Grosche (2014) points out limitations in this type of analysis, arguing that a review of these studies demonstrates that the findings are inconclusive. Sanders and Irwin (2017) also identify some criticisms of GC tests, such as a low-power test in volatile commodity futures markets, efficient markets with restricted information, and lack of conditioning variables within models. Given the restrictions in current models, would models that overcome these limitations capture these relationships better?

In this study, we examine the influence of CIT positions and excessive speculation measured by the T index of speculation following Working (1960) on agricultural commodity prices. We use weekly data from the Commodities Futures Trading Commission (CFTC) for the period between 2006 and 2018. We apply linear and nonlinear models of causality to determine whether the speculative performance in the agricultural commodities market actually generated changes in prices using these different econometric approaches. We employ the classical causality model (Granger, 1969) by assuming the first differences of the series. Next, we test the existence of causality using Toda and Yamamoto's (1995) methodology, which deals with the possibility of cointegration between the variables better. Finally, we employ Diks and Panchenko's (2005, 2006) nonlinear model, which tests non-parametric causality. After running the tests, we use filters to control heteroscedasticity with multivariate GARCH models, specifically for nonlinear causality and the Granger GARCH-BEKK tests (Baba, Engle, Kraft, & Kroner, 1990; Bollerslev, Engle, & Wooldridge, 1988; Engle & Kroner, 1995).

The paper proceeds as follows. Section 2 discusses the literature on the relationship between speculation and price changes. One group finds evidence of a relationship between speculation and prices, while another group finds no evidence of causality. Section 3 describes the data and the proxy for speculation. Section 4 presents the econometric methodology to test the causal relationships between the variables. Section 5 presents and discusses the model results. Section 6 concludes and offers suggestions for future research.

2. Literature review

Prior research addresses the causal relationship between index funds and commodity prices. Thus, Irwin and Sanders (2012) call the hypothesis that long-only index investments were the principal causal agents of a hike in future commodity prices the *master hypothesis*. The authors test the hypothesis using the GC method, but find no evidence to support this proposition. A significant part of the literature finds no evidence or a limited relationship (Aulerich, Irwin, & Garcia, 2013; Bohl, Javed, & Stephan, 2012; Capelle-Blancard & Coulibaly, 2011; Gilbert, 2010; Gilbert & Pfuderer, 2014, pp. 122–148; Irwin, 2013; Irwin, Sanders, & Merrin, 2016; Lehecka, 2015; Vercammen & Doroudian, 2014), which is inconsistent with the master hypothesis.

Thus, some studies examine this hypothesis in a similar way and employ the GC test with different approaches. For example, Aulerich et al. (2013) test the GC between the change in the long position of the CIT and the return on the futures contract of the closest screen. The authors test two distinct periods, from 2004 to 2005 and from 2006 to 2008, to allow the rolled positions to appear in the sample. However, they could not prove any relationship between speculation and price variation. Gilbert (2010) also finds no causality between speculation (referred to as *non-commercial*) and returns on commodity prices such as corn, soybeans, and oats. Gilbert and Pfuderer (2014, pp. 122–148) expand the role of agricultural commodities to include markets with lower liquidity such as the live cattle market and lean hogs. They reach a similar conclusion, even for markets with lower liquidity. Capelle-Blancard and Coulibaly (2011) innovated the test using a *seemingly unrelated regression* system, which permits a test of causality that accounts for the correlation between different markets. The result shows that, between 2006 and 2010, *index* funds were not responsible for the increase in agricultural commodity prices. Lehecka (2015) employs the causality test using the Toda and Yamamoto model for different measures of speculation and shows that the results are not very useful in explaining the behavior of prices in the face of the speculative pressure, or pressure by *hedgers*.

Some other show that speculation did not cause the market bubble in agricultural commodities (Bohl et al., 2012; Irwin et al., 2016, 2009; Lancaster, 1989; Sandersrs & Irwin, 2011; Vercammen & Doroudian, 2014). On the contrary, the performance of the funds can be seen as beneficial to the financial market, as it generates liquidity and can reduce market volatility. Thus, Brunetti, Büyükşahin, and Harris (2016) argue that the increase in speculative positions in the commodities market is benign because investors can help reduce volatility by taking positions contrary to hedgers. Another advantage Irwin et al. (2011) point out is that the expansion of speculative activity in the commodity market may reduce the risk premium and, consequently, the cost of hedging.

However, the literature is not unanimous on the benefits of speculative funds in the commodity market. Some researchers show that such funds may not only trigger an increase in commodity prices, but also increase volatility. Robles, Torero, and Braun (2009) use the spot prices of agricultural commodities (wheat, corn, rice, and soy) supplied by the Food and Agriculture Organization of the United Nations and five variables as proxies for speculation. The GC test shows that speculative activities may influence the prices of these commodities, which may have negative consequences in terms of dealing with hunger in underdeveloped countries. Gutierrez (2013) finds evidence that commodity prices deviated from their equilibrium price from 2007 to 2008. The author uses the bootstrap method to compute the sample probability distribution, whose alternative hypothesis is located in the right part of the distribution. The author then uses the unit root test, which determines the explosive part of the statistical test. The author finds that the first sign of the deviation in the wheat market was in August 2007, followed by corn shortly thereafter in February of 2008.

Although some authors reach different conclusions, some criticize the methods applied in these studies. Grosche (2014) exposes certain limitations: (i) the failure to consider the informational efficiency of the markets, the variation of time, and the response to the effects of the bounded rationality of the different trading strategies; and (ii) limitations in the CFTC's data, which they disclose only weekly, and causality, in the sense that price relative to speculative funds does not necessarily mean that funds follow prices (*trend followers*). The study recommends the use of multivariate models (vector autoregressive, or VAR) as well as nonlinear models of causality. In this sense, Sanders and Irwin (2017) also acknowledge the limitations of GC tests. To address criticisms of GC, the authors apply a time-series correlation between the *Supplemental Commitments of Traders* report (SCOT) and nearby futures returns, as well as a cross-section correlation between the *Index Investment Data* report (IID) and nearby futures returns. The results show a positive correlation between changes in SCOT and nearby futures returns, mainly in years that were not bubble-like. Moreover, shifts in SCOT index position did not coincide with changes in price. The authors also tested the correlation between SCOT index positions and daily market returns. Results show no correlation between index positions and daily market returns. Cross-sectional analysis of IID buy-positions and market returns fails to provide evidence of a relationship, even controlling for other macroeconomic variables.

Baek and Brock (1992) show that linear causality tests have little power to detect nonlinear relationships over time. Thus, some studies improve the analysis from non-parametric econometric tests. Hiemstra and Jones (1994) modify the Baek and Brock version by relaxing the hypothesis that the time series is independent and identically distributed (iid) to test the dynamic relationships. Diks and Panchenko (2006) refine the Hiemstra and Jones test to overcome the possibility of spurious rejection of the null hypothesis. Another limitation is the possibility of cointegration effects in the causality tests in linear and nonlinear series. Bekiros and Diks (2008a,b) investigate the relationship between the *spot* market and the future WTI market empirically, and find that even after applying appropriate models in the BEKK-GARCH family to control conditional heteroscedasticity, the nonlinear relationship persists in some cases, while the linear relationship disappears after filtering.

Therefore, the hypothesis that speculation causes a price increase requires further investigation in the light of the more sophisticated models presented in recent work.

3. Data

3.1. Commodities prices and the CIT position

We collected the futures prices of ten agricultural commodities: corn, cattle (feeder cattle and live cattle), lean hog, soybeans, and wheat from the Chicago Mercantile Exchange (CME), and coffee, cocoa, and sugar from ICE Futures, US, in New York. The prices refer to the contracts of the first active screen of the exchanges.

We use the CIT position for testing the Masters Hypothesis. It is worth noting that depending on the purpose of the speculative hypothesis, a different measure should be applied. That is, Etienne, Irwin, and Garcia (2018) provide sharp distinctions between speculative measures, such as Index Investments, non-commercial activities, Working's T index, and the ESV Index. According to the authors, CIT net position is used to test the Masters Hypothesis whether the net long position can cause a spike in agricultural commodity prices. Working's T index reflects the excess of speculation relative to hedging movements, which could impact the agricultural futures prices.

The CFTC began releasing this report as a supplement to the Commitments of Traders (COT) in 2007 for only twelve agricultural commodities. In this supplement, CFTC removed the positions of the index traders from the non-commercial and commercial positions and separated them by category: CIT long and short. CFTC also removed managed funds, pension funds, and other institutional investors which seek exposure in commodity markets as an asset class, from the position of non-commercials. Over-the-counter (OTC) hedge funds, such as swap dealers, are drawn from the position of the commercials. Sanders, Irwin, and Merrin (2010) show that 85% of the index trader 's position came from the long commercial category of the COT report. The authors argue that most of the long-only index positions initially trade in the OTC markets, then re-enter into futures markets to hedge their exposures through swap dealers (commercial and investments banks).

Even with the improvement in the classification of traders in this new report (SCOT), the CFTC itself warns about possible failures in the classification procedure (CFTC, 2008). Another limitation in the publication is the data horizon, which starts only from 2007. Irwin (2013) points out that the three years prior to 2007, massive fund positions received training. In this case, between 2004 and 2006, there was a rapid increase in the CIT, with index traders' long positions almost tripling in the corn and wheat market. The author also shows that the commodity boom in 2007–2008 may be only a coincidence, since the greatest pressure on CIT positions was in 2004–2006.

Despite its limitations, the SCOT report provides a useful proxy for the position of index traders, as Irwin and Sanders (2012) point out, since the errors associated with the report are small and still reflect the behaviors of index traders in the future agricultural commodities market.

3.2. Speculative proxies

Widely used in the literature, the T index proposed by Working (1960) measures the excess of speculation in the market. The measure captures the excess of speculative positions in relation to hedge positions. The index is calculated as

$$T = \begin{cases} 1 + \dfrac{SS}{HL + HS};\ if \quad HS > HL, or \\ 1 + \dfrac{SL}{HL + HS};\ if \quad HS < HL \end{cases}, \tag{1}$$

where *SL* and *SS* are the *Long Position* and *Short Position*, respectively, while *HL* and *HS* are the positions *hedgers* bought and sold. The minimum value is 1, so the excess beyond 1 reflects the level of speculation that *hedgers* did not absorb.

Also, we use long and short CIT positions and analyze each separately. The master hypothesis is that the pressure of purchased funds created a bubble in the commodity market and had its apex in 2006–2008 (the price of sugar had its bubble afterwards, in 2010–2011). However, some commodities fell over time, as Fig. 1 shows. Thus, we include the CIT short position to analyze whether there was pressure on the movement of commodities separately. Our sample period runs from the beginning of the data provided in the SCOT

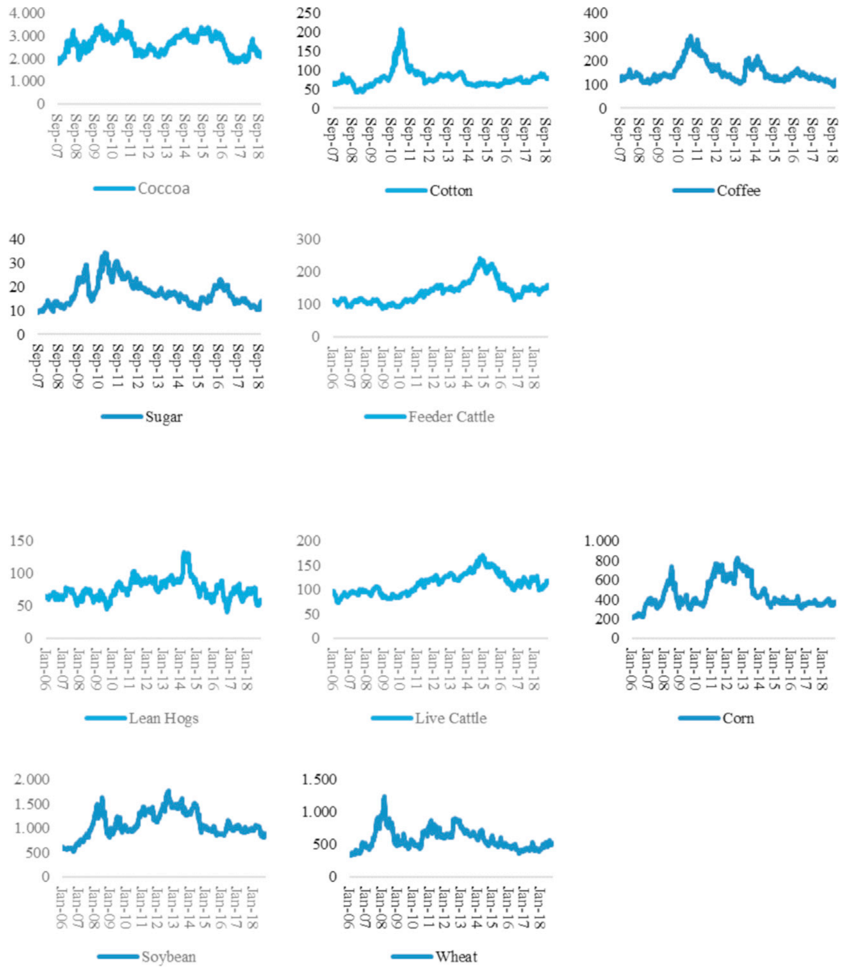

Fig. 1. Commodity prices. The graphs show future commodity prices for the period between 2006 and 2007 and 2018. For each commodity, the contracts are measured on different scales: Cocoa – 10 metric tons; Cotton – 50,000 pounds; Coffee – 37,500 pounds; Sugar – 112,000 pounds; Feeder Cattle – 50,000 pounds; Lean Hogs – 40,000 pounds; Live Cattle – 40,000 pounds; Corn - 5000 bushels; soybean – 5000 bushels; wheat – 5000 bushels. *Source: Bloomberg.*

report (2006 and 2007) until 2018.

Table 1 (panels A, B, C, and D) presents the descriptive statistics. The series are all non-stationary according to the Augmented Dickey–Fuller tests (measured by constant and constant plus intercept) for all data. In panel A of Table 1, the prices are transformed into log-return $r_i = \ln P_t - \ln P_{t-1}$. We see excess of kurtosis for the price series exhibiting heavy (leptokurtic) tails. We find negative asymmetry in more than half of the series. In Panel B, we analyze the T index, which shows no negative asymmetry for any commodity, though we find excess kurtosis in all series. To detect the null hypothesis of normality, we apply the Jarque–Bera test, and thus reject the null hypothesis of normality for all commodities, both prices and positions, using the speculation index. Panels C and D show the log of the return of the positions of funds bought and sold.

With current data and a broader window, we may observe that prices returned to the prevailing levels prior to the 2008 bubble. Therefore, an up-to-date analysis of the relationship between speculation and commodity prices is important in terms of the other studies of the topic.

4. Methodology

4.1. Granger Causality (GC)

GC, much used in the empirical literature, analyzes the dependency relationship between variables over time (Granger, 1980). Irwin (2013), who published several studies on this subject using this model, argues that it is already established that the results of GC tests should be interpreted with caution. For example, he cites studies that state that rejecting the null hypothesis of Granger's causation may not reflect a true causal relationship between x and y, but rather, the omission of variable z, which is the cause of both x and y.

Table 1
Descriptive statistics and unit root (price series).

	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis	J-B	Obs	DF (c.)	DF (ct)
Panel A: Return on prices (P_t)											
Cocoa	0.000	0.002	0.154	−0.124	0.041	0.488	4.236	124.590***	1206	−9.201***	−9.200***
Cotton	0.000	0.002	0.162	−0.145	0.040	−0.192	4.153	35.777***	581	−23.653***	−23.637***
Feeder Cattle	0.000	0.002	0.096	−0.120	0.024	−0.374	4.469	75.589***	668	−25.756***	−25.737***
Lean Hogs	–	−0.001	0.205	−0.224	0.047	0.231	6.975	445.795***	668	−25.708***	−25.706***
Live Cattle	0.000	0.001	0.093	−0.110	0.024	−0.192	4.542	70.296***	668	−27.769***	−27.751***
Coffee	0.000	−0.000	0.177	−0.145	0.044	0.082	3.663	11.294***	581	−24.279***	−24.278***
Corn	0.001	0.002	0.233	−0.256	0.044	−0.179	6.869	420.143***	668	−27.243***	−27.292***
Soybean	0.000	0.002	0.120	−0.200	0.035	−0.528	5.300	178.291***	668	−26.867***	−26.941***
Sugar	0.001	−0.001	0.171	−0.230	0.050	−0.101	4.370	46.431***	581	−25.850***	−25.889***
Wheat	0.001	- 0.002	0.169	−0.176	0.047	0.214	3.720	19.508***	668	−26.529***	−26.542***
Panel B: Speculation index (T)											
Cocoa	1.197	1.161	2.048	1.017	0.139	2.222	9.793	3311.146***	1206	−5.778***	−6.375***
Cotton	1.111	1.070	1.569	1.011	0.097	1.762	6.786	648.722 ***	581	−4.660***	−4.715***
Feeder Cattle	1.421	1.396	2.729	1.052	0.215	1.484	7.711	864.163***	668	−6.159***	−6.314***
Lean Hogs	1.269	1.223	1.927	1.028	0.166	1.079	3.990	157.130***	668	−4.638***	−4.634***
Live Cattle	1.178	1.165	1.407	1.036	0.095	0.418	2.061	44.107***	669	−4.420***	−4.561***
Coffee	1.183	1.157	1.553	1.028	0.128	1.128	3.642	133.473***	581	−4.008***	−4.227***
Corn	1.167	1.138	1.453	1.032	0.110	0.816	2.562	79.624***	668	−3.972***	−5.293***
Soybean	1.131	1.105	1.472	1.034	0.080	1.308	4.736	274.903***	668	−4.718***	−4.761***
Sugar	1.135	1.082	1.430	1.005	0.117	0.733	2.129	70.467***	581	−3.047**	−3.857**
Wheat	1.419	1.379	1.993	1.091	0.202	0.602	2.389	50.803***	668	−3.866***	−4.191***
Panel C: Long position of the *index traders*											
Cocoa	0.001	0.004	2.155	−2.078	0.137	−1.597	157.966	1,206,244.168***	1205	−34.643***	−34.632***
Cotton	0.000	0.000	0.110	−0.122	0.028	−0.426	5.544	174.172***	581	−21.597***	−21.645***
Feeder Cattle	0.002	0.003	0.161	−0.157	0.043	−0.178	4.508	66.783***	668	−24.856***	−24.84877***
Lean Hogs	0.001	0.002	0.127	−0.265	0.028	−1.060	16.908	5508.944***	668	−22.947***	−22.932***
Live Cattle	0.001	0.002	0.078	−0.116	0.021	−0.350	6.555	365.488***	668	−9.904***	−9.880***
Coffee	0.001	0.001	0.166	−0.260	0.033	−0.503	12.849	2372.528***	581	−20.448***	−20.448***
Corn	0.001	0.002	0.154	−0.129	0.026	−0.167	8.000	699.013***	668	−23.659***	−23.657***
Soybean	0.001	0.003	0.139	−0.140	0.029	−0.582	7.116	509.242***	668	−22.523***	−22.514***
Sugar	0.000	0.001	0.101	−0.094	0.025	−0.138	5.248	124.230***	581	−20.017***	−19.999***
Wheat	−0.001	0.002	0.181	−0.843	0.057	−8.419	121.310	397,480.074***	668	−25.531***	−25.51953***
Painel D: Short position of the *index traders*											
Cocoa	0.004	0.014	18.975	−18.534	1.103	0.235	241.980	2,867,485.111***	1205	−21.582***	−21.575***
Cotton	0.003	0.020	1.773	−1.206	0.270	−0.718	9.841	1182.794***	581	−19.868***	−19.855***
Feeder Cattle	0.002	0.000	18.980	−19.787	2.755	−0.386	37.240	32,647.828***	668	−6.304***	−6.323***
Lean Hogs	0.006	0.001	18.159	−16.524	1.529	0.872	94.043	230,790.975***	668	−13.045***	−13.120***
Live Cattle	0.003	0.014	16.013	−20.699	1.112	−5.113	245.346	1,637,601.370***	668	−20.928***	−20.912***
Coffee	0.007	0.018	1.438	−1.919	0.245	−0.795	16.572	4520.386***	581	−20.787***	−20.770***
Corn	0.003	0.021	0.927	−1.630	0.182	−2.058	18.938	7541.748***	668	−26.693***	−20.315***
Soybean	0.004	0.013	1.436	−0.952	0.189	−0.330	12.627	2591.544***	668	−26.074***	−26.055***
Sugar	0.001	0.015	0.438	−0.708	0.136	−1.295	7.353	621.138***	581	−18.350***	−18.335***
Wheat	0.003	0.008	1.241	−1.687	0.199	−0.605	16.348	5000.014***	668	−19.160***	−19.193***

Notes: Descriptive statistics on the weekly observations of 10 commodities presented between 2006 and 2007 and 2018. The log-returns of the series prices ($r_i = \ln P_t - \ln P_{t-1}$) of commodities in the Chicago (CME) or New York (ICE Futures US) exchanges are source from the Bloomberg platform. *, **, and *** show significance at the 10%, 5%, and 1% level, respectively. Augmented Dickey–Fuller (DF) tests were applied, as measured by the constant (DF c.) and the (DF ct) intercept.

Notes: Descriptive statistics on the weekly observations of 10 commodities presented between 2006 and 2007 and 2018 in terms of the index of speculation (T). *, **, and *** show significance at the 10%, 5%, and 1% level, respectively. Augmented DF tests were applied, as measured by the constant (DF c.) and the (DF ct) intercept.

Notes: Descriptive statistics on the weekly observations of 10 commodities presented between 2006 and 2007 and 2018, in terms of the returns of the long positions of the *index traders* (CIT). *, **, and *** show significance at the 10%, 5%, and 1% level, respectively. Augmented DF tests were applied, as measured by the constant (DF c.) and the (DF ct) intercept.

Notes: Descriptive statistics on the weekly observations of 10 commodities presented between 2006 and 2007 and 2018. The returns on the sell positions of the *index traders*' (CIT) are presented. *, **, and *** show significance at the 10%, 5%, and 1% level, respectively. Augmented DF tests were applied, as measured by the constant (DF c.) and the (DF ct) intercept.

4.2. Augmented Granger-causality test

The GC test was modified over time to capture the dynamics of the cointegration relationship in time series using the VAR model. Thus, Granger (1980) shows that in some cases, the test does not detect causal relationship when the series are cointegrated. Engle and Granger (1987) point out that if variables x and y are non-stationary and cointegrated, then this could invalidate the test. To address the problems of cointegration and unit roots, Sims, Stock, and W Watson (1990) show that a system that includes a unit root and using a VAR model to test constraints on coefficients does not apply to different orders of integration. Thus, Toda and Yamamoto (1995) propose a solution that deals with the problem of stationarity and cointegration. Their model guarantees that the chi-square (X) distribution is asymptotic (modified Wald statistical test). The procedure is to determine the optimal *lag* (k) based on some criterion, such as (Akaike, 1974) Akaike (1974) (b) and (Schwarz, 1978) Schwarz (1978) (Bayesian information criteria); the order ($k + d_{max}$) is estimated, where d is the maximum order of integration of the model

$$Y_t = \alpha + \sum_{i=1}^{h+d} \beta_i Y_{t-i} + \sum_{i=1}^{k+d} \gamma_j X_{t-j} + u_{yt} \tag{2}$$

$$X_t = \alpha + \sum_{i=1}^{h+d} \theta_i Y_{t-i} + \sum_{i=1}^{k+d} \delta_j X_{t-j} + u_{xt} \quad , \tag{3}$$

where h and k are the *lag lengths* of Y_t and X_t; u_t's are the assumed error terms as white noise. The estimation of VAR ($k + d$) makes it possible for the X^2 distribution of the Wald test with k degrees of freedom to be admitted. Thus, the *lag length* of the model should be smaller than the integration order.

4.3. Nonlinear causality - Diks and Panchenko (Diks & Panchenko, 2006)

Nonlinear models of causality are more common in the literature. The traditional GC model has little power to detect the nonlinear behavior of variables (persistence or structural breaks, for example). Hiemstra and Jones (1994) modified Baek and Brock's (1992) model, which relaxes the hypothesis that the series are iid, allowing the series to show weak temporal dependence. Diks and Panchenko (2005) present a non-parametric test for Granger non-causality that avoids spurious rejection of the null hypothesis.

In the design of a bivariate test, the null hypothesis that past observations of $\{X_t\}$ do not contain additional information on Y_{t+1} is reformulated by Diks and Panchenko (2006) in terms of marginal distributions, as follows:

$$H_0 : \frac{f_{X,Y,Z}(x,y,z)}{f_Y(y)} = \frac{f_{X,Y}(x,y)}{f_Y(y)} \cdot \frac{f_{Y,Z}(y,z)}{f_Y(y)}$$

For simplicity, the authors consider $Z_t = Y_{t+1}$ and remove the time indices t. Thus, for each fixed value of y, X and Z are conditionally independent in $Y = y$. Thus, they show that another way of writing the null hypothesis is:

$$q \equiv E\left[f_{X,Y,Z}(X,Y,Z) f_Y(Y) - f_{X,Y}(X,Y) f_{Y,Z}(Y,Z)\right] = 0$$

Next, taking $\widehat{f}_W(W_i)$ as a local density estimate of a random vector d_W - variate $\boldsymbol{W}$ in $\boldsymbol{W}_i$, defined by $\widehat{f}_W(W_i) = \frac{(2\varepsilon_n)^{-d_W}}{n-1} \sum_{jj \neq i} I_{ij}^W$, where $I_{ij}^W = I(W_i - W_j < \varepsilon_n)$, $I(\cdot)$ is the indicator function (that takes a value of 1 when true and null when false) and ε_n is the bandwidth parameter dependent on n (number of observations in the series); the Diks and Panchenko (2006) statistic test is:

$$T_n(\varepsilon_n) = \frac{n-1}{n(n-2)} \sum_i \left(\widehat{f}_{X,Z,Y}(X_i, Z_i, Y_i) \widehat{f}_Y(Y_i) - \widehat{f}_{X,Y}(X_i, Y_i) \widehat{f}_{Y,Z}(Y_i, Z_i)\right)$$

In the case of a bivariate test, the test is consistent; its power of rejection of a null hypothesis that is actually false tends to 1 (100%) as the amount of available data increases when $\varepsilon_n = Cn^{-\beta}$, where C is a positive constant and $\beta \in (1/4, 1/3)$. The asymptotic distribution to the normal pattern, in turn, is guaranteed in the absence of dependence between the $\boldsymbol{W}_i$ **vectors.** However, in a time series context, the authors demonstrate that asymptotic normality is guaranteed for weakly dependent data as long as the covariance between local density estimators is taken into account. The proof for this asymptotic property is developed under the "mixing" conditions of Denker and Keller (1983). In practice, we assume that taking $\varepsilon_n = Cn^{-\beta}$, with C being a positive constant and $\beta \in (1/4, 1/3)$, we have:

$$\sqrt{n} \, \frac{(T_n(\varepsilon_n) - q)}{S_n} \xrightarrow{D} N(0,1) \quad ,$$

where $\xrightarrow{D}$ denotes convergence in the distribution and S_n is the estimator of the asymptotic variance of T_n.

Regarding the choice of ε_n, the *bandwidth* is optimal, in the sense of providing an estimator T_n with the smallest (*Mean Squared Error*, or MSE).

$$\varepsilon_n = Cn^{-2/7}$$

For practical applications, however, Diks and Panchenko (2006) recommend a truncation, as follows:

$$\varepsilon_n = min\left(Cn^{-2/7};\ 1.5\right)$$

that is, the value of ε_n is truncated to hold the maximum at 1.5 to avoid obtaining very large bandwidth values in the case of a small number of available observations (n) for the series. In our study, we choose a conservative value and use $\varepsilon_n = 1$, in line with other studies (Andreasson, Bekiros, Nguyen, & Uddin, 2016; S. D.; Bekiros & Diks, 2008b).

5. Results

Considering the approaches described, we present the results of the linear and nonlinear tests for each of the variables, the T index of speculation, and the long and short positions of the CITs below. The following tables show the relationships investigated.

Table 2 presents the results of the Toda and Yamamoto (Toda & Yamamoto, 1995) method before and after the filtering to control conditional heteroscedasticity.

Even with the versatility of the models, heteroscedasticity can affect the series. Thus, we use the equations using ARCH family filters. We find a characteristic behavior in the financial market when periods of high volatility are preceded by low volatility, and vice versa. Thus, the ARCH family models can better capture this stylized fact; the variance of the present error term is related to the size of the error of the previous period. We can test the conditional distribution of the error term using the normal distribution (Gaussian), Student's *t*, and the generalized error distribution. The choice of the best model is given by the statistical significance of the parameters and the values of information criteria, such as AIC and Bayesian Information Criterion.

The results in Table 2 indicate that there is no causal relationship between the funds and speculation towards the price in most commodities. However, the CIT sell position for sugar and wheat point to causality, in the direction of price; that is, the sell position may have influenced prices.

Note: Toda-Yamamoto procedure (Modified Wald statistics). Commodity (X) → Price (Y) denotes the position of CITs, and Granger speculation (T) does not cause price, or vice versa. *, **, and *** show significance at the 10%, 5%, and 1% level, respectively. The "*GARCH filtered residuals*" column shows the results of the TY procedure using the residuals filtered by appropriate GARCH models. The size of lags was determined by the BIC and AIC criteria, with a maximum of 6 lags.

The choice of the *lead-lag* plays an important role in the application of causality tests. In Tables 2 and 3 (Standard Granger), to determine the optimal number of lags of the bivariate VAR, the number of lags is set to 6 by means of some AIC or BIC (in this case, we choose it by the smallest number of lags for parsimony).

Note: Granger causality test. Commodity (X) → Price (Y) denotes position of CITs, and Granger speculation (T) does not cause price, or vice versa. *, **, and *** show significance at the 10%, 5%, and 1% level, respectively. The column BEKK Filter shows the residuals of VAR filtered using the BEKK method. Size of lag was determined by the BIC and AIC levels, with a maximum of 6 lags.

Table 3 shows the results of the GC test using bivariate VAR. Next, we filter the residuals using the BEKK-CARCH multivariate model. A formulation that can be viewed as a restricted version of the VECH model is a specific parameterization of the multivariate GARCH model defined in Engle and Kroner (1995). This formulation is called BEKK, an acronym that stands for Baba, Engle, Kraft and Kroner (Baba et al., 1990), in line with recent studies on nonlinear causality (Andreasson et al., 2016; S. D.; Bekiros & Diks, 2008a), and has the following form:

Table 2
TY causality.

Toda Yamamoto Causality				GARCH filtered residuals		
Commodities	CIT_L	CIT_S	T	CIT_L	CIT_S	T
Coccoa→ Price	–	–	–	–	–	–
Price→ Coccoa	–	*	–	***	–	–
Cotton→Price	–	–	–	–	–	–
Price→Cotton	–	–	–	**	*	–
Feeder Cattle→ Price	–	–	–	–	***	–
Price→ Feeder Cattle	–	–	***	–	***	***
Lean Hogs→Price	**	–	–	–	–	–
Price→ Lean Hogs	–	–	***	–	–	–
Live Cattle→Price	–	–	–	–	**	–
Price→ Live Cattle	***	–	***	***	–	–
Coffee→ Price	–	–	–	–	–	–
Price→ Coffee	–	–	***	–	***	–
Corn→ Price	–	–	–	*	–	–
Price→Corn	*	*	***	*	–	–
Soybean→ Price	–	–	–	–	–	–
Price→ Soybean	***	–	*	***	***	–
Sugar→Price	*	**	–	–	**	–
Price→ Sugar	–	–	***	–	–	–
Wheat→ Price	–	***	–	–	***	–
Price→ Wheat	–	–	***	–	–	–

Table 3
Granger standard causality (Wald-Granger).

Granger-Wald (VAR)				BEKK-GARCH Filtered Residuals		
Commodities	CIT_L	CIT_S	T	CIT_L	CIT_S	T
Cocoa→ Price	–	–	–	–	–	–
Price→ Cocoa	–	*	–	**	*	***
Cotton→Price	–	–	–	–	–	–
Price→Cotton	**	–	–	**	–	–
Feeder Cattle→ Price	–	–	–	*	*	–
Price→ Feeder Cattle	–	–	***	–	–	***
Lean Hogs→Price	**	–	–	***	–	**
Price→ Lean Hogs	–	–	***	*	**	***
Live Cattle→Price	–	–	–	–	***	*
Price→ Live Cattle	**	–	***	***	–	***
Coffee→ Price	–	–	–	–	–	–
Price→ Coffee	–	–	***	–	–	***
Corn→ Price	–	–	–	*	–	–
Price→Corn	–	*	***	–	–	–
Soybean→ Price	–	–	–	–	–	**
Price→ Soybean	***	–	*	**	–	**
Sugar→Price	–	*	–	–	**	**
Price→ Sugar	–	–	***	–	–	–
Wheat→ Price	–	***	–	–	***	–
Price→ Wheat	–	–	***	–	–	***

$$H_t = C'C + \sum_{i=1}^{q} A_i' \varepsilon_{t-i} \varepsilon_{t-i}' A_i + \sum_{j=1}^{p} B_j' H_{t-j} B_j, \tag{4}$$

where now C, A_i and B_j are N x N matrices, being C lower triangular. In this model the conditional covariance matrices are positive definite by construction, which is an attractive property.

Before and after filtering using BEKK-GARCH, Table 3 indicates that there is no relationship between speculation and the commodity prices. That is, speculation did not cause price variation for most commodities. However, there is one relationship, in the Granger sense, from speculation to price. Thus, our findings suggest that prices guide speculators (*trend followers*). This is in line some prior studies (Guilleminot, Ohana, & Ohana, 2014; Lehecka, 2015). Furthermore, as Table 2 shows, the sold positions of the CITs seem to have caused price variation for sugar; with filtering, the significance level increases.

With the data filtered using the multivariate BEKK-GARCH model, the use of the Diks and Panchenko (2006)nonlinear test makes it possible to determine whether the model can describe the relationship among the analyzed commodities. Filtering is applied when there is a failure to accept the null hypotheses of non-causality of the nonlinear model (S. Bekiros, 2014).

Table 4
Diks and Panchenko nonlinear causality (2006).

DP (2006)				BEKK-GARCH Filtered Residuals		
Commodities	CIT_L	CIT_S	T	CIT_L	CIT_S	T
Coccoa→ Price	–	–	–	–	–	–
Price→ Coccoa	–	–	–	–	–	–
Cotton→Price	–	–	–	–	–	–
Price→Cotton	–	–	*	–	–	–
Feeder Cattle→ Price	***	–	**	***	–	*
Price→ Feeder Cattle	–	–	***	–	–	**
Lean Hogs→Price	–	–	*	–	–	–
Price→ Lean Hogs	–	–	**	–	–	–
Live Cattle→Price	**	–	–	**	–	–
Price→ Live Cattle	*	–	**	–	–	–
Coffee→ Price	–	–	–	–	–	–
Price→ Coffee	–	–	**	–	–	–
Corn→ Price	–	–	–	–	–	–
Price→Corn	–	–	***	–	–	–
Soybean→ Price	–	–	–	–	–	–
Price→ Soybean	–	–	–	–	–	–
Sugar→Price	**	–	–	**	–	–
Price→ Sugar	–	–	–	–	–	–
Wheat→ Price	–	*	–	–	–	–
Price→ Wheat	–	–	**	–	–	–

Note: Nonlinear causality DP (2006) T_n statistic. Commodity (X) → Price (Y) denotes position of CITs, and Granger speculation (T) does not cause price, or vice versa. *, **, and *** show significance at the 10%, 5%, and 1% level, respectively. Bandwidth set at $\varepsilon_n = 1$ and lag $\ell = 1$. VAR residuals filtered using a BEKK-GARCH multivariate specification.

The test consists of applying the DP model to the stationary series to detect whether there is some nonlinear relationship. Following this step, the filtered residuals of the VAR-BEKK model are generated to verify whether the nonlinear relationship persists. We set both bandwidth and lag at 1. According to Bekiros and Diks (2008a), if the bandwidth is defined as having a value greater than (or less than) 1, it will result in a smaller (or larger) p-value.

As Table 4. Diks and Panchenko nonlinear causality (2006) shows, most of the results were inconclusive, and after filtering, the significance of the relationships diminished. In contrast to these findings, we note that a buy position on the part of the CITs generated pressure on the price of sugar, feeder cattle, and live cattle, both before and after the filtering. This confirms that statistical significance is weaker after filtering for all commodities.

Considering our results, the hypothesis that speculators and the *index* funds caused price hikes may not be accepted in light of our tests. However, one must exercise caution in admitting the hypotheses that the agents are *trend followers* given that the nonlinear model is more precise in capturing relationships over time, and the results show no such relationship after filtering.

6. Conclusion

Using different approaches, we illustrate whether there is any relationship between speculation and the position of the funds in the prices of ten commodities extracted from the CFTC report. We tested the hypothesis that speculators and *index* funds were responsible for the pressure on agricultural commodity prices, both by models that capture the linear relationship and by those seeking to indicate possible nonlinear relationships.

The results suggest that speculation did not cause changes in agricultural commodity prices. Linear models point precisely in the opposite direction, that Granger prices cause speculation; that is, speculators seem to be guided by price changes. They buy when the price increases and sell when the price falls (*trend followers*). In fact, the nonlinear test was inconclusive, with no consistent relationship in either direction.

In general, the results indicate that causal relations in both directions are weak. However, caution should be exercised in testing since the data disclosed may distort relationships. Among these distortions is the fact that the position is disclosed only weekly; that is, within weeks, there may be important movements that the analysis does not include. In addition, large investment funds may use different strategies in different markets, and may also operate *intraday* or take some position without apparent cause and effect, which masks the pattern of causation. Large traders who operate as *hedgers* may take a speculative position. Irwin, Garcia, Good, and Kunda (2009) point out that *hedgers* act as speculators with exclusive information in some cases. Another factor to consider is that the period prior to 2006 not disclosed in the SCOT report—which may limit the test.

Therefore, with the data available at this time, it is not possible to prove the effect of speculation on commodity prices, even with robust methodologies. Although the findings point to no causality, one may not conclude that speculation did not play a role in price pressure, or vice versa. There is still a gap in the dissemination of data in these markets.

This study highlights findings that are relevant to financial market regulators, *traders*, and commodity producers. We suggest that future studies should aim to address the question of whether there was a herd or cascade behavior that caused prices to escalate, and whether the trigger was any reason besides speculation.

Declaration of competing interest

None.

Acknowledgments

This work was carried out with the support of Conselho Nacional de Desenvolvimento Científico e Tecnológico (Brazilian National Council for Scientific and Technological Development - CNPq), grant numbers 306532/2016-6 and 408470/2016-0 and Fundação Carlos Chagas Filho de Amparo à Pesquisa do Estado do Rio de Janeiro (Carlos Chagas Filho Foundation for Research Support in the State of Rio de Janeiro - FAPERJ), grant number E-26/202.824/2018. We thank Sophie Van Huellen for her comments and suggestions.

References

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control, 19*(6), 716–723. https://doi.org/10.1109/TAC.1974.1100705.

Andreasson, P., Bekiros, S., Nguyen, D. K., & Uddin, G. S. (2016). Impact of speculation and economic uncertainty on commodity markets. *International Review of Financial Analysis, 43*, 115–127. https://doi.org/10.1016/j.irfa.2015.11.005.

2006 Aulerich, N. M., Irwin, S. H., & Garcia, P. (2013). Bubbles, food prices, and speculation: Evidence from the CFTC's daily large trader data files. In J. B. DeLong, & K. Magin (Eds.), *A short note on the size of the dot-com bubble* (pp. 1–14). National Bureau of Economic Research. https://doi.org/10.3386/w19065. January, *J. H. and K. K. (2004*). Lost Decade in Translation: Did the US Learn from Japan's (Vol. w19065)..

Baba, Y., Engle, R., Kraft, D., & Kroner, K. (1990). *Multivariate simultaneous generalized arch*. department of economics, university of california at san diego. Retrieved from https://scholar.google.com.pk/scholar?hl=en&q=Baba%2C+Engle%2C+Kraft+and+Kroner+%281990%29+&btnG=&as_sdt=1%2C5&as_sdtp=.

Baek, E. G., & Brock, W. A. (1992). *A general test for nonlinear Granger causality: Bivariate model* (Madison, WI).

Bekiros, S. (2014). Nonlinear causality testing with stepwise multivariate filtering: Evidence from stock and currency markets. *The North American Journal of Economics and Finance, 29*, 336–348. https://doi.org/10.1016/j.najef.2014.06.005.

Bekiros, S. D., & Diks, C. G. H. (2008a). The nonlinear dynamic relationship of exchange rates: Parametric and nonparametric causality testing. *Journal of Macroeconomics, 30*(4), 1641–1650. https://doi.org/10.1016/j.jmacro.2008.04.001.

Bekiros, S. D., & Diks, C. G. H. (2008b). The relationship between crude oil spot and futures prices: Cointegration, linear and nonlinear causality. *Energy Economics, 30*(5), 2673–2685. https://doi.org/10.1016/J.ENECO.2008.03.006.

Bohl, M. T., Javed, F., & Stephan, P. M. (2012). Do commodity index traders destabilize agricultural futures prices? *SSRN, 59*(2), 125–148. https://doi.org/10.2139/ssrn.2088426.

Bollerslev, T., Engle, R. F., & Wooldridge, J. M. (1988). A capital asset pricing model with time-varying covariances. *Journal of Political Economy, 96*(1), 116–131. https://doi.org/10.1086/261527.

Brunetti, C., Büyükşahin, B., & Harris, J. H. (2016). Speculators, prices, and market volatility. *Journal of Financial and Quantitative Analysis, 51*(5), 1545–1574. https://doi.org/10.1017/S0022109016000569.

Capelle-Blancard, G., & Coulibaly, D. (2011). Index trading and agricultural commodity prices: A panel Granger causality Analysis1 1The authors thank Agnès Bénassy-Quéré, Valérie Mignon and Sophie Piton for helpful comments. The usual disclaimer applies. *International Economics, 126–127*, 51–71. https://doi.org/10.1016/S2110-7017(13)60036-0.

Carter, C. A., Rausser, G. C., & Smith, A. (2011). Commodity booms and busts. *Annual Review of Resource Economics, 3*(1), 87–118. https://doi.org/10.1146/annurev.resource.012809.104220.

CFTC, C. F. T. C. (2008). Commodity swap dealers & index traders with commission recommendations. Retrieved from http://online.wsj.com/public/resources/documents/cftcstaffreportonswapdealers09.pdf.

Cheng, I.-H., & Xiong, W. (2014). Financialization of commodity markets. *Annual Review of Financial Economics, 6*(1), 419–441. https://doi.org/10.1146/annurev-financial-110613-034432.

Denker, M., & Keller, G. (1983). On U-statistics and v. mise' statistics for weakly dependent processes. *Zeitschrift für Wahrscheinlichkeitstheorie und Verwandte Gebiete, 64*(4), 505–522. https://doi.org/10.1007/BF00534953.

Diks, C., & Panchenko, V. (2005). A note on the Hiemstra-Jones test for Granger non-causality. Studies in nonlinear dynamics and econometrics. .

Diks, C., & Panchenko, V. (2006). A new statistic and practical guidelines for nonparametric Granger causality testing. *Journal of Economic Dynamics and Control, 30*(9–10), 1647–1669. https://doi.org/10.1016/j.jedc.2005.08.008.

Engle, R. F., & Kroner, K. F. (1995). Multivariate simultaneous generalized arch. *Econometric Theory, 11*(1), 122–150. Retrieved from http://www.jstor.org/stable/3532933.

Engle, R., & Granger, C. (1987). Co-integration and error correction: representation, estimation, and testing. *Econometrica, 55*(2), 251–276. https://doi.org/10.2307/1913236.

Etienne, X. L., Irwin, S. H., & Garcia, P. (2018). Speculation and corn prices. *Applied Economics, 50*(44), 4724–4744. https://doi.org/10.1080/00036846.2018.1466992.

FAO, F., & A.O of the U.N.. (2008). *The state of food insecurity in the world* (Rome).

Gilbert, C. L. (2010). How to understand high food prices. *Journal of Agricultural Economics, 61*(2), 398–425. https://doi.org/10.1111/j.1477-9552.2010.00248.x.

Gilbert, C. L., & Pfuderer, S. (2014). *The financialization of food commodity markets*. BT-Handbook on Food). Edward Elgar Publishing. Retrieved from https://econpapers.repec.org/RePEc:elg:eechap:14879_6.

Granger, C. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica, 37*(3), 424–438. Retrieved from https://econpapers.repec.org/RePEc:ecm:emetrp:v:37:y:1969:i:3:p:424-38.

Granger, C. W. J. (1980). Testing for causality. A personal viewpoint. *Journal of Economic Dynamics and Control, 2*(C), 329–352. https://doi.org/10.1016/0165-1889(80)90069-X.

Grosche, S.-C. (2014). What does Granger causality prove? A critical examination of the interpretation of Granger causality results on price effects of index trading in agricultural commodity markets. *Journal of Agricultural Economics, 65*(2), 279–302. https://doi.org/10.1111/1477-9552.12058.

Guilleminot, B., Ohana, J. J., & Ohana, S. (2014). The interaction of speculators and index investors in agricultural derivatives markets. *Agricultural Economics, 45*. https://doi.org/10.1111/agec.12122.

Gutierrez, L. (2013). Speculative bubbles in agricultural commodity markets. *European Review of Agricultural Economics, 40*(2), 217–238. https://doi.org/10.1093/erae/jbs017.

Hiemstra, C., & Jones, J. D. (1994). Testing for linear and nonlinear Granger causality in the stock price- volume relation. *The Journal of Finance, 49*(5), 1639–1664. https://doi.org/10.2307/2329266.

International Monetary Fund. (2008). *World economic outlook: Financial stress, downturns, and recoveries*. Washingto DC. Retrieved from https://www.imf.org/external/pubs/ft/weo/2008/02/.

Irwin, S. H. (2013). Commodity index investment and food prices: Does the "masters hypothesis" explain recent price spikes? *Agricultural Economics, 44*(SUPPL1), 29–41. https://doi.org/10.1111/agec.12048.

Irwin, S. H., Garcia, P., Good, D. L., & Kunda, E. L. (2009). Spreads and non-convergence in CBOT corn, soybean, and wheat futures: Are index funds to blame? *Applied Economic Perspectives and Policy, 33*(58), 116–142. Retrieved from http://www.jstor.org/stable/41237211.

Irwin, S. H., & Sanders, D. R. (2011). Index funds, financialization, and commodity futures markets. *Applied Economic Perspectives and Policy, 33*(1), 1–31. Retrieved from http://www.jstor.org/stable/41237206.

Irwin, S. H., & Sanders, D. R. (2012). Testing the Masters Hypothesis in commodity futures markets. *Energy Economics, 34*(1), 256–269. https://doi.org/10.1016/j.eneco.2011.10.008.

Irwin, S. H., Sanders, D. R., & Merrin, R. P. (2016). Devil or angel? The role of speculation in the recent commodity price boom (and bust). *Journal of Agricultural & Applied Economics, 41*(02), 377–391. https://doi.org/10.1017/s1074070800002856.

Lancaster, M. (1989). Summary for policymakers. *Climate Change 2013 - The Physical Science Basis, 53*. https://doi.org/10.1017/CBO9781107415324.004.

Lehecka, G. V. (2015). Do hedging and speculative pressures drive commodity prices, or the other way round? *Empirical Economics, 49*(2), 575–603. https://doi.org/10.1007/s00181-014-0886-7.

de Oliveira, E. M., Cunha, F. A. F. S., Cyrino Oliveira, F. L., & Samanez, C. P. (2017). Dynamic relationships between crude oil prices and socially responsible investing in Brazil: Evidence for linear and non-linear causality. *Applied Economics, 49*(22), 2125–2140. https://doi.org/10.1080/00036846.2016.1234695.

Robles, M., Torero, M., & Braun, J. von (2009). *When speculation matters: International food policy research institute, issue brief 57. IFPRI - issue brief*. International Food Policy Research Institute. Retrieved from https://www.cabdirect.org/cabdirect/abstract/20093129784.

Sanders, D. R., & Irwin, S. H. (2017). Bubbles, froth and facts: Another look at the masters hypothesis in commodity futures markets. *Journal of Agricultural Economics, 68*(2), 345–365. https://doi.org/10.1111/1477-9552.12191.

Sanders, D. R., Irwin, S. H., & Merrin, R. P. (2010). The adequacy of speculation in agricultural futures markets: Too much of a Good thing? *Applied Economic Perspectives and Policy, 32*(1), 77–94. https://doi.org/10.1093/aepp/ppp006. Retrieved from.

Sandersrs, D. R., & Irwin, S. H. (2011). The impact of index funds in commodity futures markets: A systems approach. *Journal of Alternative Investments, 14*(1), 40–49. https://doi.org/10.3905/jai.2011.14.1.040.

Schwarz, G. (1978). Estimating the dimension of a model. *Annals of Statistics, 6*(2), 461–464. Retrieved from http://www.jstor.org/stable/2958889.

Sims, C., Stock, J., & W Watson, M. (1990). Inference in linear time series models with some unit roots. *Econometrica, 58*. https://doi.org/10.2307/2938337.

Toda, H. Y., & Yamamoto, T. (1995). Statistical inference in vector autoregressions with possibly integrated processes. *Journal of Econometrics, 66*(1–2), 225–250. https://doi.org/10.1016/0304-4076(94)01616-8.

Vercammen, J., & Doroudian, A. (2014). Portfolio speculation and commodity price volatility in a stochastic storage model. *American Journal of Agricultural Economics, 96*(2), 517–532. https://doi.org/10.1093/ajae/aat098.

Working, H. (1960). Speculation on hedging markets. *Food Research Institute Studies, 01*(2), 136578. Retrieved from https://econpapers.repec.org/article/agsfrisst/136578.htm.