

Kupabado, Moses M.; Kaehler, Juergen

Article — Published Version

Financialization, common stochastic trends, and commodity prices

Journal of Futures Markets

Provided in Cooperation with:

John Wiley & Sons

Suggested Citation: Kupabado, Moses M.; Kaehler, Juergen (2021) : Financialization, common stochastic trends, and commodity prices, Journal of Futures Markets, ISSN 1096-9934, Wiley, Hoboken, NJ, Vol. 41, Iss. 12, pp. 1988-2008, <https://doi.org/10.1002/fut.22269>

This Version is available at:

<https://hdl.handle.net/10419/284742>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



<http://creativecommons.org/licenses/by-nc-nd/4.0/>

RESEARCH ARTICLE

Financialization, common stochastic trends, and commodity prices

Moses M. Kupabado  | Juergen Kaehler

Institute of Economics, University of Erlangen-Nuremberg, Erlangen, Germany

Correspondence

Moses M. Kupabado, Institute of Economics, University of Erlangen-Nuremberg, Alterlangerstr. 24, 91056 Erlangen, Bayern, Germany.
Email: moses.kupabado@fau.de

Funding information

Katholischer Akademischer Ausländer-Dienst, Grant/Award Number: As unconditional PhD Scholarship

Abstract

Commodity financialization has been a subject of discussion since the 2008 financial crisis. It is estimated that between 2003 and 2008, index investors' positions increased from \$13 billion to \$317 billion. Surprisingly, most studies, predominantly based on Granger-causality testing, find no relationship between financialization and commodity prices. We examine the effects of shocks to the common stochastic trends in the index positions, the spot and futures prices of Chicago corn and soybeans, WTI crude oil and Henry Hub natural gas. The results show that financialization has contributed to the price movements of these commodities.

KEYWORDS

commodities, common trends, financialization, futures prices, index investors, spot prices

JEL CLASSIFICATION

C01, C32, G01, G11, G12, G13, Q02, Q13

1 | INTRODUCTION

When in 2007 and 2008 the prices of energy and agricultural commodities increased sharply around the globe it led to protests and riots in several countries (see Headey & Fan, 2010). It was generally held that rising food prices had negative effects on the living standards of low-income households that spend a high proportion of their income on food, according to Engel's law. The verdict, therefore, was that the food price crisis caused an increase in poverty in many low-income developing countries. However, both theoretically and empirically, the sign of this correlation is controversial (Headey & Martin, 2016). Similar commodity-price bubbles emerged in the mid-1970s, the early 1980s, and more recently, in 2011/2012. Since commodity-price bubbles seem to be a re-emerging phenomenon, it is interesting to examine their causal factors.

Michael Masters, a hedge fund manager, blamed the financialization of commodity markets by commodity index traders (CITs) for the price bubble in 2007 and 2008 (Masters, 2008). This became known as the Master's hypothesis. The purpose of this paper is to investigate whether commodity markets are financialized by CITs. CITs are investors who invest in a broad portfolio of commodities. The portfolio is typically constructed as an index, including commodities from sectors such as energy, for example, crude oil and gas, livestock, agriculture, for example, wheat, corn, soybeans and sugar, and metals.

This is an open access article under the terms of the Creative Commons Attribution-NonCommercial-NoDerivs License, which permits use and distribution in any medium, provided the original work is properly cited, the use is non-commercial and no modifications or adaptations are made.

© 2021 The Authors. The *Journal of Futures Markets* published by Wiley Periodicals LLC.

Starting in the 1990s, there was a large influx of commodity index investments into commodity markets, both in the futures and over-the-counter (OTC) markets. It is estimated that between 2003 and 2008, the positions of CITs increased from \$13 billion to \$317 billion (Masters & White, 2008, Chart 5, p. 14). Surprisingly, the great majority of studies, predominantly based on Granger-causality testing, reject the Master's hypothesis (see the reviews by Bohl, 2016; Fattouh et al., 2013; Irwin & Sanders, 2011; Will et al., 2015). In our paper, we use an alternative estimation strategy that can distinguish between short- and long-run effects. Using weekly¹ data from 2006 to 2018, we investigate the impacts of index-based investments on the spot and futures prices of four internationally important commodities, including Chicago Board of Trade (CBOT) corn and soybeans, West Texas Intermediate (WTI) crude oil, and Henry Hub natural gas.

Energy and agricultural commodities have the largest weights in the two most popular commodity indexes, that is, the Standard and Poor's Goldman Sachs Commodity Index (S&P GSCI) and the Bloomberg Commodity Index (BCI) (formerly called Dow Jones UBS commodity index). The price of WTI crude oil (crude oil for short) is the benchmark for crude oil pricing, and Henry Hub natural gas (natural gas for short) has the most traded natural gas futures. The futures contracts on CBOT corn (corn) and CBOT soybeans (soybeans) are the most actively traded agricultural futures contracts. Applying a structural vector error correction model (SVECM) along the lines of King et al. (1991), we examine the effects of shocks to the common stochastic trends (common stochastic long-term components) in the index positions, the spot and futures prices of the commodities. Our results show that financialization has contributed to the movements of the futures and spot prices for corn, soybeans, crude oil, and natural gas.

1.1 | Review of the relevant literature

In several papers, Irwin and his coauthors, (Irwin & Sanders, 2011, 2012a, 2012b; Irwin et al., 2009; Sanders & Irwin, 2011; Sanders et al., 2010; Yan et al., 2018) investigated commodity futures price effects of index funds from various perspectives. These studies concluded that there are no direct empirical linkages between commodity index investments and commodity futures prices. They also contended that commodity index traders provide market liquidity, support for futures price discovery and contribute to the efficient functioning of the commodity futures markets. Some other studies such as (Babalos & Balcilar, 2017; Brunetti et al., 2016; Bruno et al., 2016) derived similar results. Dimpfl et al. (2017) studied price discovery in spot and futures markets of some agricultural commodities. They concluded that futures speculation does not influence commodity futures price movements in the long-run.

However, some studies found evidence in support of Master's hypothesis. The study of Tang and Xiong (2012) on index investments and financialization found that index commodities are strongly correlated with the financial markets than nonindex commodities. Hamilton and Wu (2014) observed that over time, the structure of the risk premia for crude oil futures markets has been influenced more by speculative investing than commercial hedging. Frenk and Turbeville (2011) examined calendar spreads for funds that replicate S&P GSCI. They found strong evidence that the rollover strategies of the funds systematically deviate futures prices from their fundamental values. A study of commodity-linked notes by Henderson et al. (2014) suggested that financial investors in commodity markets significantly influenced commodity futures prices. Similarly, Basak and Pavlova (2016) noted that the entry of index investors into commodity futures markets has not only impacted significantly on futures prices but also spot prices. From the literature review, we conclude that the testing of the Master's hypothesis has produced conflicting results.

1.2 | Motivation for the paper

Although there are several recent and early studies on commodity financialization, policy-oriented contentions on the issue remain. The continuing contentions reflect the importance of this topic and the incomplete understanding of the causative factors of commodity price hikes. Not only that there remains inconclusive evidence on the matter at stake, but the approach and the econometric method we adopt are also different from those used in previous studies in several ways.

¹We would have preferred to examine daily data. However, the US Commodity Futures Trading Commission (CFTC), which is the sole provider of US futures markets' positions data, does not make the daily series public.

First, previous studies relied mostly on correlation analysis, price spread investigations, time series regressions, vector autoregressions (VARs), and Granger-causality (GC) tests (Granger, 1969). Our approach follows the common stochastic trends literature (see King et al., 1991; Stock & Watson, 1988). Stock and Watson (1988) noted that many economic variables contain common stochastic trends and that common factors rather than specific factors can better explain the fluctuations in an economic system. Second, previous studies examined the causal linkages between index investment and commodity futures prices without simultaneously taking the dynamic behavior of the spot prices into consideration. According to Gray (1967), speculative trades in futures markets can have an indirect influence on spot prices, at least theoretically. A recent paper by Sockin and Xiong (2015) showed that price pressure exerted by investors in futures markets can be transferred to the spot markets of the underlying commodities. In a SVECM, we exploit the comovements of the spot and futures prices of the commodities to model how commodity futures prices respond to index investment shocks. Third, most of the studies that reject the Master's hypothesis analyze the time-series data after transformation to stationarity, that is, after first-differencing. This transformation filters out the important long-run properties of the data. Our strategy, instead, is to avoid this over-differencing. Finally, we use data series that are much longer and recent than those used in previous studies.

The rest of the paper is structured as follows. We describe the SVECM and the data in Sections 2 and 3, respectively. The integration and cointegration properties of the data are analyzed in Section 4. We identify the structural model in Section 5 where we also fit the SVECM to the data. We present the results in Section 6. In Sections 7 and 8, we analyze the impacts of net positions on commodity prices. We conclude in Section 9.

2 | ECONOMETRIC MODEL

Since Sims's (1980) seminal paper, reduced-form VAR models have gained popularity in both theoretical and empirical economics. However, in standard VAR analysis, the usefulness of the reduced-form errors (forecast errors) lies in forecasting. They cannot be given structural interpretations and therefore are not appropriate for economic analysis unless they are linked to the structural disturbances. In this regard, structural VARs and structural VARs with cointegrated variables, in the sense of Granger (1981) and Engle and Granger (1987) have become useful for the analysis of economic systems. King et al. (1991) argued that since temporary fluctuations in an economic series die out with time, long-run fluctuations in the series must be due to long-term factors. In this framework, using a structural vector error correction model (SVECM) to study the effects of productivity shocks, King et al. (1991) found that the innovations to the common stochastic trends explain a significant proportion of fluctuations in output. The model has also been used in other areas of economic research, for example, unemployment shocks Brüggemann (2006); Jacobson et al. (1997).

2.1 | Structural vector error correction model

Given a structural VAR(p) model of a K -dimensional system y_t and a corresponding reduced-form model, the link between the reduced-form errors ϵ_t and the structural disturbances u_t is

$$\epsilon_t = Bu_t \quad (1)$$

where B is $K \times K$ matrix of structural parameters, which measure the instantaneous impacts of a change of one variable on the other variables in the system. The forecast errors ϵ_t are specified as a linear combination of the structural disturbances u_t . Through the link in (1), the structural disturbances may be recovered from the forecast errors. The nonsingular covariance matrix Ω_ϵ of the forecast errors is given by

$$\Omega_\epsilon = BB' \quad (2)$$

where use is made of the standard assumption that the covariance matrix of the structural disturbances Ω_u is the identity matrix. Because the matrices Ω_ϵ and BB' are both symmetric, there are only $K(K+1)/2$ independent equations in (2). This means $K(K-1)/2$ additional equations are necessary to identify all the K^2 structural

parameters. The traditional approach to the identification problem uses a Cholesky decomposition of Ω_ϵ . That is an unappealing approach because it leads the model to have a spurious Wold causal chain appearance (see Lütkepohl, 2005, p. 72ff). Our strategy follows King et al. (1991). In this procedure, two sets of restrictions are used to identify the structural innovations. The first set of restrictions is obtained from the system's cointegration structure. The second set of restrictions is obtained by assuming that some disturbances may have only transitory effects on certain variables, usually based on economic theory.

In this set up, the starting point is usually the reduced-form VECM ($p - 1$) with r cointegration relations,

$$\Delta y_t = \mu + \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \epsilon_t \quad (3)$$

where Δ is first difference operator, y_t is a $K \times 1$ vector of $I(1)$ variables, $\Pi = \alpha\beta'$, where α is $K \times r$ matrix of adjustment coefficients, β' is $r \times K$ matrix of cointegration vectors, r is the number of stationary linear combinations in y_t , Γ_i , $i = 1, 2, \dots, p - 1$ are $K \times K$ matrices containing short-run coefficients, and μ is $K \times 1$ vector of fixed intercepts. According to the Granger Representation Theorem (Johansen, 1991, 1995), the process (3) has a Beveridge-Nelson decomposition:

$$y_t = \Xi \sum_{i=1}^t \epsilon_i + \sum_{j=0}^{\infty} \Xi_j^* \epsilon_{t-j} + y_0^*, t = 1, 2, \dots \quad (4)$$

The term $\Xi \sum_{i=1}^t \epsilon_i$, which represents the common trends, is the K -dimensional random walk component of the system y_t . The matrix $\Xi = \beta_\perp \left[\alpha'_\perp \left(I_K - \sum_{i=1}^{p-1} \Gamma_i \right) \beta_\perp \right]^{-1} \alpha'_\perp$, where \perp denotes orthogonal complement, depends on the reduced-form VECM parameters and has reduced rank, that is, $\text{rank}(\Xi) = K - r < K$. Hence, there are $K - r$ independent common trends in the system² (see Lütkepohl, 2005, p. 369). Substituting (1) into the common trends term in (4) and noting that the second term vanishes in the long-run, the long-run impacts of the structural shocks u_i on y_t are given by $\frac{\partial y_t}{\partial u_i} = \Xi B$.

The structural innovations u_t have a nonsingular covariance matrix Ω_u . Therefore, matrix B must be nonsingular. Since ΞB is a nonsingular transformation of Ξ , then $\text{rank}(\Xi B) = K - r$. This means $K - r$ of the structural shocks u_t have permanent effects and the remaining r of them have temporary effects so that r columns of the long-run impact matrix ΞB can be restricted to zero (see Lütkepohl, 2005, Chapter 9.2, p. 370). However, since ΞB has reduced rank, each column of zeros represents $K - r$ independent restrictions only, so that the r columns of zeros represent $r(K - r)$ independent restrictions only. Thus, $K(K - 1)/2 - r(K - r)$ restrictions remain to be specified for identification. Of the remaining number of restrictions, $r(K - r)/2$ of them are necessary to identify the r temporary shocks and $(K - r)[(K - r) - 1]/2$ of them are necessary to identify the $K - r$ permanent shocks.

Formally, the restrictions needed for the identification of the temporary and the permanent shocks may, respectively, be written as follows:

$$R_s \text{vec}(B) = r_s \quad (5)$$

$$R_{\Xi B} \text{vec}(\Xi B) = r_l \quad (6)$$

where $R_{\Xi B}$ and R_s are matrices that select the long- and short-run parameters, respectively. r_s and r_l are, usually, vectors of zeros with suitable dimensions and the operator vec stacks the columns of a $m \times n$ matrix into a $mn \times 1$ column vector. These two restrictions together with (2) solve the SVECM.

²The infinite sum $\sum_{j=0}^{\infty} \Xi_j^* \epsilon_{t-j}$ in (4) is the stationary component of the system because $\Xi_j^* \rightarrow 0$ as $j \rightarrow \infty$. The term y_0^* is a vector of initial values. Thus, (4) says that the multivariate process y_t may be decomposed into a multivariate random walk term $\Xi \sum_{i=1}^t \epsilon_i$, a stationary term $\sum_{j=0}^{\infty} \Xi_j^* \epsilon_{t-j}$ and the initial values y_0^* . The K random walks $\sum_{i=1}^t \epsilon_i$ are multiplied by a reduced rank matrix. That is, the rank of Ξ is $K - r$. In effect, there are $K - r$ random walks driving the K components of the system y_t . In cointegration terminology, the process y_t is said to have $K - r$ common stochastic trends and r stationary (short-run) terms.

2.2 | Estimation of structural vector error correction model

The estimation of the SVECM model is performed in two steps. The first step involves the estimation of the reduced-form model (3) using Gaussian maximum-likelihood (ML) to obtain the cointegration matrices α and β as well as the short-run coefficients Γ_i , $i = 1, 2, \dots, p - 1$. Using the estimated cointegration parameters, Ξ can be computed. In the second step, the structural parameters B are estimated by maximizing the concentrated log-likelihood l_c :

$$\log l_c(B) = \text{constant} - \frac{T}{2} \log |B|^2 - \frac{T}{2} \text{tr}(B'^{-1} B^{-1} \tilde{\Omega}_\epsilon)$$

where T is the sample size and $\tilde{\Omega}_\epsilon$ is the estimated reduced-form VECM error covariance matrix, subject to the long-run restrictions (5) and (6). The ML estimator of matrix B is consistent and asymptotically normal under the usual assumptions and therefore, the significance of the estimated parameters can be assessed using their t -ratios.

3 | DATA

We use two sets of data for the analysis. The first set consist of Chicago Mercantile Exchange Group commodity prices on corn, soybeans, crude oil, and natural gas. These are drawn from Quandl: www.quandl.com/. The second set consist of long futures positions on the above mentioned commodities. These are drawn from the database of US Commodity Futures Trading Commission (CFTC): www.cftc.gov/. We describe these sets of data in the following.

Since 2006, the CFTC has been publishing weekly³ commitment of traders (COT) reports on futures and options contracts traded on the US exchanges. The legacy COT report classifies traders into commercial and noncommercial categories. The commercial futures market participants are the dealers of physical commodities. They include consumers, processors, producers, and merchants, as well as swap dealers. They buy or sell futures contracts to insure themselves against the commodity price risk they face in the cash market. Swap dealers use the futures markets to hedge their OTC transactions. The CFTC (2021) describes the noncommercial futures market participants as speculators, including money managers, for example, hedge funds, institutional investors, for example, pension funds, and many other reportable traders.

Since September 4, 2009, the CFTC also provides disaggregated commitment of traders (DCOT) reports for agriculture, natural gas, electricity, metals, petroleum, and other physical contracts.⁴ The DCOT report has four key trader groups. The legacy COT commercial traders' category is further disaggregated into two subcategories. These include (1) producers/merchants/processors/users and (2) swap dealers. Also, the legacy COT noncommercial traders' category is further disaggregated into two subcategories namely, (1) money managers and (2) other reportables. The main objective of the disaggregation is to isolate swap dealers from the handlers of physical commodities in the commercial category and isolate the money managers from other reportables in the noncommercial category.

In addition to the legacy COT and DCOT reports, the traders in some 12 agricultural markets are classified into COT commodity index trader supplement. The supplement provides a breakdown of the reportable positions in the agricultural markets into commercial and noncommercial categories and an additional category called commodity index traders (CITs). Thus, the CITs are drawn from both the broad COT commercial and noncommercial categories so that, for example, the swap dealers who are classified as commercial traders in the COT are included as CITs in the supplement. Also, institutional investors such as pension funds that put their funds with money managers are included in the CIT supplement. The CITs and money managers mostly follow a strategy of buying futures contracts listed in commodity indexes and holding them for extended periods, replacing each front-month contract, on expiration, with the next-month contract (CFTC, 2021). Thus, they take mostly long positions so that their net position in the futures markets is mostly positive.

The corn and soybeans data for the analysis consist of spot and futures prices, and long positions in the CFTC CIT supplement. The data for crude oil and natural gas consist of spot and futures prices, and long positions for money

³The CFTC has daily positions data, but choose to publish it on weekly basis.

⁴CFTC started providing DCOT data from 2009. But they backcasted (i.e., backward forecasted) the series to 2006.

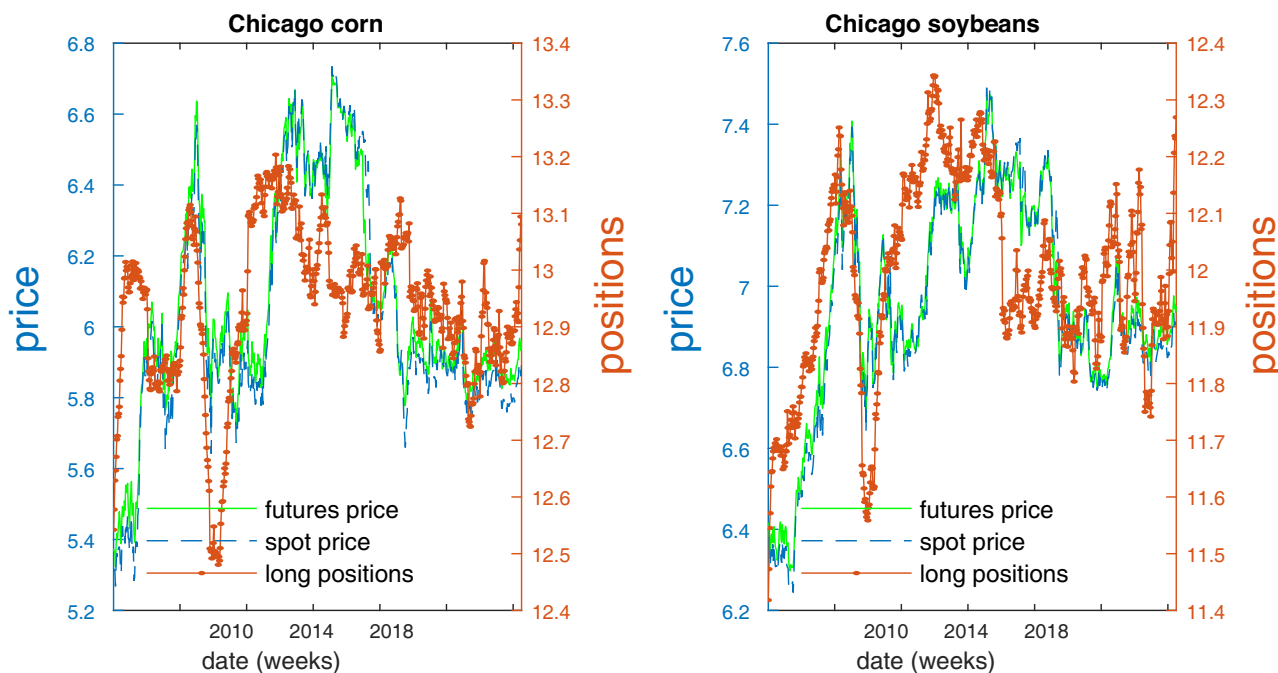


FIGURE 1 Log of long futures positions of commodity index traders, spot and nearby futures prices of corn and soybeans

managers in the DCOT. Thus, for each commodity that we study, that is, corn (c), soybeans (b), crude oil (o), and natural gas (g), the variables under investigation include futures price (f_t), spot price (s_t) and long position series (i_t).⁵ Thus, each commodity system may be represented by the vector (f_t, s_t, i_t) . We performed all analyses with data expressed in natural logs.

The series for the agricultural commodities, that is, corn (c) and soybeans (s) are presented in Figure 1. Each series consist of weekly observations ranging from January 3, 2006 to April 3, 2018. The series can be visualized as having gone through several phases. It appears that the stochastic processes underlying each series is not stationary. Also, the futures and spot prices move closely together as suggested by the cash-and-carry arbitrage theory. The series for the energy commodities, that is, crude oil (o) and natural gas (g) are presented in Figure 2. Each series consist of weekly observations ranging from June 13, 2006 to April 3, 2018. Like the agricultural commodities, it appears that the stochastic process underlying each series is not stationary. Also, the futures and spot prices move closely together. The long positions in the crude oil and the natural gas markets have slight upward trends.

4 | INTEGRATION AND COINTEGRATION PROPERTIES OF THE DATA

For the analysis of the SVECM model, the cointegration properties of the series will provide useful information for the identification of the structural innovations (Lütkepohl, 2005, p. 366). In the next section, we examine the integration and cointegration properties of the data.

4.1 | Tests for unit root

To investigate the underlying data generating processes for each series, we apply the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1979) for the presence of a stochastic trend (null hypothesis of a unit root). We include both an

⁵We use long positions for the analysis because Masters (2008) asserts that long positions of CITs exert upward pressure on commodity futures prices.

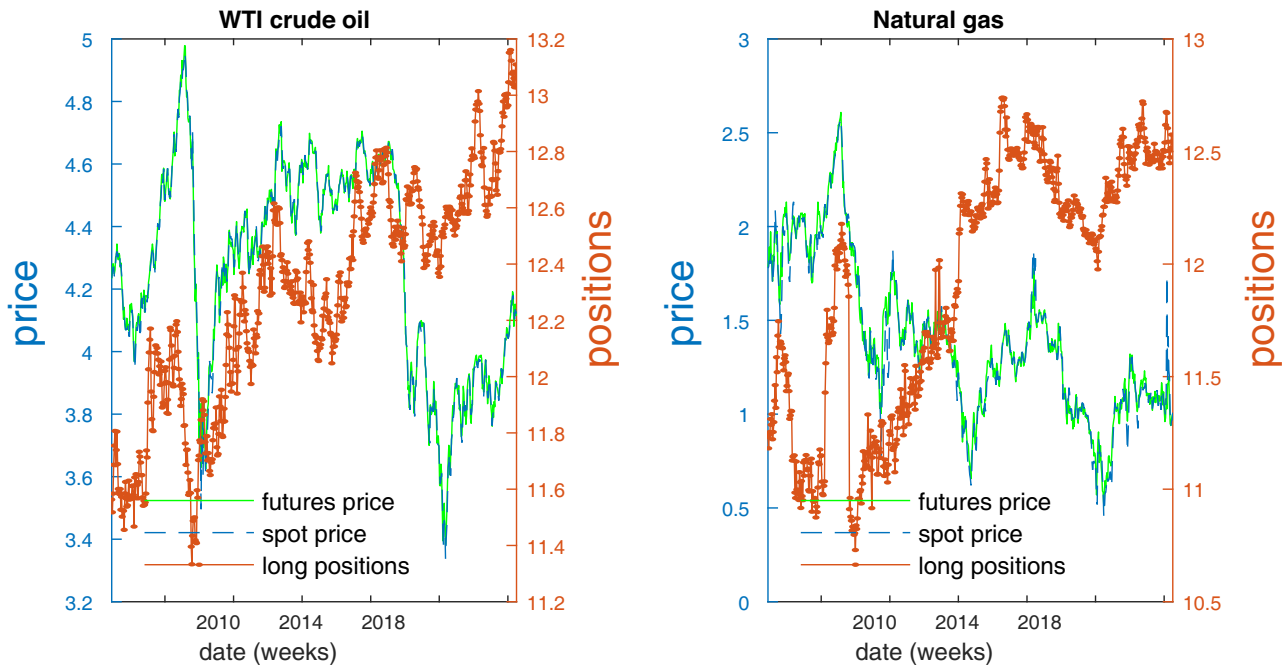


FIGURE 2 Log of long futures positions of money managers, spot and nearby futures prices of crude oil and natural gas

intercept and a linear trend term in each ADF regression for the series in levels. In the regressions for the first differences, we include only intercepts. These specifications are plausible given the time series plots in Figures 1 and 2. Initially, we set the maximum number of lags to $p_{max} = 19$ based on Schwert's criterion (Schwert, 2002) and allowed the optimal number of lagged differences to be chosen by the standard information criteria, that is, the BIC and the AIC (see Lütkepohl, 2005, Chapter 4). However, the different criteria preferred a different number of lagged differences, and sometimes residual autocorrelation remains. To obtain the number of lags that remove residual autocorrelation, we estimate a sequence of ADF regressions with an increasing number of lagged differences for $p = 1, 2, \dots$ in an iterative loop. The optimal p is chosen when the null hypothesis of no remaining residual autocorrelation cannot be rejected. We performed all the tests by specifying a significance level of 0.05.

Table 1 shows the tests results. The left panel shows the test results for the series in levels. For each commodity system, we cannot reject the null hypothesis of unit root in the levels of the series f_t , s_t and i_t since the ADF test statistics are larger than the 5% critical values of this left-tailed test. For the first differences Δf_t , Δs_t , and Δi_t in the right panel, we reject the unit root null hypothesis in each series because the ADF test statistics are smaller than the ADF critical values. We can therefore treat all the series as $I(1)$ variables.

4.2 | Johansen rank tests for cointegration

In this analysis, we have $K = 3$ variables for each commodity system. They include the long positions (i_t), the spot price (s_t) and the futures price (f_t). Thus, there can be at most two cointegration relations for each commodity system where one cointegration relation implies two common trends among the variables and two cointegration relations imply one common trend. To identify the number of common trends for each commodity system, we performed the two variants of the Johansen cointegration (rank) tests: the trace and the maximum eigenvalue tests. The two tests differ in the alternative hypothesis. Both tests first assess the null hypothesis of $r = 0$ cointegration relations among the three-dimensional time series. The alternative null hypothesis is three cointegration relations (trace test) or $r + 1$ cointegration relations (maximum eigenvalue test). Both tests proceed with testing for the rank of matrix $\Pi = \alpha\beta$ in (3), and each consist of a sequence of testing with increasing r . The test sequence is terminated when the null hypothesis cannot be rejected for the first time. There is cointegration among the time series if $0 < r < 3$. If $r = 3$, the time series

TABLE 1 ADF tests for unit root in the spot prices, the futures prices, and the long positions of commodity index traders in corn and soybeans markets, and money managers in crude oil and natural gas markets

Series in levels						Series in first differences					
Series	h	Stat	cValue	BIC	Lags	Series	h	Stat	cValue	BIC	Lags
Corn						Corn					
f_t^c	0	-2.453	-3.418	-2176.086	1	Δf_t^c	1	-17.213	-2.867	-2171.213	1
s_t^c	0	-2.297	-3.418	-2116.721	1	Δs_t^c	1	-17.014	-2.867	-2112.957	1
i_t^c	0	-3.416	-3.418	-2823.603	9	Δi_t^c	1	-6.5282	-2.867	-2824.731	8
Soybeans						Soybeans					
f_t^b	0	-2.181	-3.418	-2452.823	1	Δf_t^b	1	-16.843	-2.867	-2452.932	1
s_t^b	0	-2.095	-3.418	-2374.105	5	Δs_t^b	1	-12.710	-2.867	-2380.974	4
i_t^b	0	-2.842	-3.418	-2742.414	2	Δi_t^b	1	-15.589	-2.867	-2747.170	1
Crude oil						Crude oil					
f_t^o	0	-2.903	-3.418	-1943.722	8	Δf_t^o	1	-6.543	-2.867	-1948.053	7
s_t^o	0	-2.554	-3.418	-2095.019	7	Δs_t^o	1	-8.884	-2.867	-2109.131	5
i_t^o	0	-3.274	-3.418	-1678.371	15	Δi_t^o	1	-16.688	-2.867	-1772.515	1
Natural gas						Natural gas					
f_t^g	0	-3.097	-3.418	-1599.431	1	Δf_t^g	1	-18.102	-2.867	-1594.463	1
s_t^g	0	-3.403	-3.418	-1438.622	1	Δs_t^g	1	-16.502	-2.867	-1432.421	1
i_t^g	0	-2.939	-3.418	-1384.005	1	Δi_t^g	1	-18.409	-2.867	-1380.016	1

Note: s_t is the spot price, f_t is the futures price and i_t is the long positions. Δ is first difference operator. Stat is the test statistic, and cValue is the critical value. h is the test decision where 0 indicates a failure to reject the null hypothesis of unit root and 1 indicates rejection of the null hypothesis. The number of lags for each series was chosen such that no residual autocorrelation remains.

are not cointegrated and if $r = 0$, the time series are all stationary. To illustrate the Johansen model specification, it is useful to restate the VECM ($p - 1$) in (3) as follows:

$$\Delta y_t = \alpha(\beta' y_{t-1} + c_0 + d_0 t) + \sum_{i=1}^{p-1} \Gamma \Delta y_{t-i} + c_1 + d_1 t + \epsilon_t.$$

where y_t , α , β , ϵ_t , and Δ remain as defined previously. c_0 is an $r \times 1$ vector of intercepts in the cointegrating relations, d_0 is an $r \times 1$ vector of coefficients for linear time trends in the cointegrating relations, c_1 is an $K \times 1$ vector of linear trend terms in the levels of the data and d_1 is a $K \times 1$ vector of coefficients for quadratic trend terms in the levels of the data. Considering the plots in Figures 1 and 2, we allowed for intercepts c_0 in the cointegration relations and linear trends c_1 in the levels of the data. To obtain the VAR orders for each system, we estimate a sequence of VARs, that is, $VAR(p)$, $p = 1, 2, \dots$ in an iterative loop. For each $VAR(p)$, we use the test of Ljung and Box (Box et al., 1994) to check for remaining residual autocorrelation for each series in the system. The optimal p for the VAR is chosen when the null hypothesis of no remaining autocorrelation cannot be rejected simultaneously for all the system residuals.

Table 2 reports the results of the cointegration tests for each commodity system (f_t, s_t, i_t). We performed each test at the 0.05 significance level. In the sequence of null hypothesis for different values of r , the decision $h = 0$, that is, the cointegration rank, is determined when the p -value exceeds 0.05. For the corn system, the trace test suggests that there exist two cointegration relations, that is, one common trend in (f_t, s_t, i_t). On the other hand, the maximum eigenvalue test suggests the existence of one cointegration relation, that is, two common trends in (f_t, s_t, i_t). Since the trace test has smaller BIC and AIC values, the corn system is best characterized by one common trend. Both tests provide evidence of two common trends for soybeans and natural gas systems and one common trend for the crude oil system.

TABLE 2 Johansen cointegration tests among the long positions, the spot and futures prices of corn, soybeans, crude oil and natural gas

Trace test							Eigenvalue test						
r	h	Stat	p value	BIC	AIC	Lags	r	h	Stat	p value	BIC	AIC	Lags
Corn							Corn						
0	1	63.208	0.001				0	1	37.153	0.001			
1	1	26.054	0.048	-8153.744	-8589.424	9	1	0	17.848	0.083	-8096.302	-8571.824	9
2	0	8.207	0.257				2	0	8.207	0.258			
Soybeans							Soybeans						
0	1	58.170	0.001				0	1	37.845	0.001			
1	0	20.325	0.215	-8726.176	-9002.203	5	1	0	12.177	0.444	-8655.882	-8971.866	5
2	0	8.148	0.264				2	0	8.148	0.264			
Crude oil							Crude oil						
0	1	131.432	0.001				0	1	97.018	0.001			
1	1	34.414	0.004	-6988.489	-7222.576	4	1	1	28.300	0.003	-6936.024	-7209.76	4
2	0	6.114	0.504				2	0	6.114	0.504			
Natural gas							Natural gas						
0	1	304.834	0.001				0	1	282.063	0.001			
1	0	22.772	0.117	-4761.483	-4836.678	0	1	0	14.462	0.238	-4733.634	-4848.597	0
2	0	8.310	0.245				2	0	8.310	0.245			

Note: Cointegration tests for the system (f_t, s_t, i_t) : f_t is the futures price, s_t is the spot price, i_t is the long positions. r is the null hypothesis and h is the test decision where 1 denotes rejection of the null hypothesis and 0 denotes a failure to reject the null hypothesis. The number of lags for each VAR was chosen such that no system residual autocorrelation remains.

5 | IDENTIFICATION OF THE STRUCTURAL MODEL

For each commodity system, the number of structural parameters in matrix B , to be estimated, is $K^2 = 9$. Of these, only $K(K + 1)/2 = 6$ are identified, so we require a total of three additional restrictions for the identification of all the structural parameters. The cointegration structure of each system provides a number of the required restrictions (see Lütkepohl, 2005, Chapter 9.2) for the discussion of the structural model identification. In the cointegration tests, we find $r = 1$ cointegration relation (i.e., two common trends) for soybeans and natural gas systems and $r = 2$ cointegration relations (i.e., one common trend) for corn and crude oil systems. We will therefore discuss the structural model identification for both cases of one and two cointegration relations.

Suppose $r = 1$, that is, one stationary relation, we can impose one column of zeros on the long-run impact matrix ΞB (see Lütkepohl, 2005, Chapter 9.2). This means that a shock to one of the variables has zero long-run impact on the system. But one column of zeros in ΞB represents one independent restriction only. Thus, of the three required restrictions, only one is provided by the cointegration structure. Therefore, we need two additional restrictions for the identification of all the structural shocks. Specifically, to identify all the permanent shocks, we need one additional restriction and to identify all the temporary shocks, we also need one additional restriction. Now, suppose $r = 2$, that is, two stationary relations, there are two short-run shocks so matrix ΞB can have at most two columns of zeros. This means that the shocks to some two variables in the system do not have long-run impacts. The two columns of zeros in ΞB , implied by the cointegration structure, represent two independent restrictions only. Since there is only one permanent shock, it is identified without further restrictions. However, one additional restriction is needed to disentangle the effects of the two temporary shocks.

For both cases of $r = 1$ and $r = 2$, the restrictions provided by the cointegration structure are not enough. Therefore, we need to make some assumptions to obtain additional restrictions. Economic theory sometimes suggests that some variables in an economic system can have only short-run effects on certain variables while some other variables can

have long-run effects. For example, a typical assumption in classical macroeconomics is that nominal variables have only short-run impacts on real variables, for example, the impact of money supply on unemployment or real GDP. Similarly, we make assumptions based on the well-known comovement behavior between spot and futures prices of commodities to impose the remaining restrictions on the structural model.

Financial theory, based on the cash-and-carry arbitrage model, predicts a relative 1:1 correspondence between spot and futures price of assets (Hull, 2016, Chapter 5). This means that the dynamics of spot and futures markets are determined simultaneously. Therefore, we can say that the spot price has no impact on the futures price or vice versa. For $r = 1$, we have two common trends in (f_t, s_t, i_t) . Ordering the structural shocks to the futures price ϵ_t^f , the spot price ϵ_t^s and the long positions ϵ_t^i in the vector $(\epsilon_t^f, \epsilon_t^s, \epsilon_t^i)$, the short- and long-run impact matrices maybe specified respectively as follows⁶

$$B = \begin{pmatrix} * & 0 & * \\ * & * & * \\ * & * & * \end{pmatrix}, \Xi B = \begin{pmatrix} 0 & 0 & * \\ 0 & * & * \\ 0 & * & * \end{pmatrix},$$

where the asterisks represent the unrestricted impact estimates. The principal diagonal elements represent own impact estimates. The structure of matrix B means that the spot price shock ϵ_t^s has zero short-run impact on the futures price. The structure of matrix ΞB means that the futures price shock ϵ_t^f has zero long-run impact on all the system variables. This is based on the cointegration structure. In addition, the spot price shock ϵ_t^s has zero long-run impact on the futures price. Of course, we could have instead imposed the long-run restrictions implied by the cointegration structure on the spot price shock, that is, zeros in the second column of ΞB .⁷ The long positions shock ϵ_t^i is allowed to have nonzero short- and long-run impacts on all the variables. Together, all the 0s represent three independent restrictions, as explained above.

For $r = 2$, we have one common trend in (f_t, s_t, i_t) . The structures of the short- and long-run impacts matrices are

$$B = \begin{pmatrix} * & * & * \\ 0 & * & * \\ * & * & * \end{pmatrix}, \Xi B = \begin{pmatrix} 0 & 0 & * \\ 0 & 0 & * \\ 0 & 0 & * \end{pmatrix},$$

where the asterisks represent the unrestricted impact estimates, with the principal diagonal elements representing own impact estimates. Together, the 0s represent three independent restrictions. The cointegration structure entirely defines matrix ΞB , and where we allowed the long positions shock ϵ_t^i to have nonzero impacts on all the variables. Matrix B is based on the assumption that the futures price shock ϵ_t^f has zero short-run effect on the spot price.⁸

6 | RESULTS

Since the results will depend on the identification restrictions, we will estimate the structural model based on both possible cases of the model identification to check the robustness of the impacts of long positions on the commodity prices.

⁶In each matrix, the first row contains the impacts on the futures price, the second row contains the impacts on the spot price and the third row contains the impacts on long positions.

⁷If instead, we impose the long-run restrictions implied by the cointegration structure on the spot price shock and allow the futures price shock to have zero impacts on the spot price, then using the same ordering $(\epsilon_t^f, \epsilon_t^s, \epsilon_t^i)$, the structures of the short- and long-run matrices are

$$B = \begin{pmatrix} * & * & * \\ 0 & * & * \\ * & * & * \end{pmatrix}, \Xi B = \begin{pmatrix} * & 0 & * \\ 0 & 0 & * \\ * & 0 & * \end{pmatrix}.$$

⁸If we assume instead that the spot price shock ϵ_t^s has zero short-run impact on the futures price, then matrix B is defined as follows:

$$B = \begin{pmatrix} * & 0 & * \\ * & * & * \\ * & * & * \end{pmatrix}.$$

6.1 | The point estimates

Using the identification scheme that we described above, we estimated the short- and long-run impacts of the shocks to the spot price, the futures price, and the long positions in each commodity market. Bootstrap t -values, based on 4000 replications, are in parenthesis.⁹

- Corn system ($\epsilon_t^f, \epsilon_t^s, \epsilon_t^i$) characterized by one common trend

$$B^1 = \begin{pmatrix} 0.017 & 0.020 & \mathbf{0.036} \\ (3.573) & (1.889) & (4.227) \\ 0 & 0.022 & \mathbf{0.041} \\ & (2.658) & (5.110) \\ 0.002 & -0.017 & 0.015 \\ (0.203) & (-2.423) & (3.398) \end{pmatrix}, \Xi B^1 = \begin{pmatrix} 0 & 0 & \mathbf{0.055} \\ & & (3.772) \\ 0 & 0 & \mathbf{0.060} \\ & & (3.772) \\ 0 & 0 & 0.014 \\ & & (3.772) \end{pmatrix} \quad (7)$$

$$B^2 = \begin{pmatrix} 0.027 & 0 & \mathbf{0.036} \\ (3.271) & & (4.169) \\ 0.017 & 0.014 & \mathbf{0.041} \\ (1.706) & (3.331) & (5.048) \\ -0.012 & -0.013 & 0.015 \\ (-2.078) & (-1.652) & (3.481) \end{pmatrix}, \Xi B^2 = \begin{pmatrix} 0 & 0 & \mathbf{0.055} \\ & & (3.854) \\ 0 & 0 & \mathbf{0.060} \\ & & (3.854) \\ 0 & 0 & 0.014 \\ & & (3.854) \end{pmatrix}. \quad (8)$$

In B^1 of (7), the futures price shock is restricted to have zero short-run impact on the spot price. Conversely, in B^2 of (8), the spot price shock is restricted to have zero short-run impact on the futures price. Note first that, whereas shocks to long positions induce positive signs on the coefficients for the spot and futures prices, the shocks to the spot and futures prices induce mostly negative signs on the coefficients of long positions. In both (7) and (8), the principal diagonal coefficients of the short-run impact matrix B , which give the impacts of own shocks, are statistically significant. More interesting or important are the last columns of matrices B and ΞB , where we have the short- and long-run impacts of the long positions' shocks. In these columns, the coefficients in (7) and (8), highlighted in bold, indicate that the way the identifying restrictions are imposed does not matter for the impact of the long positions' shock. At the 5% level, the coefficients are significantly positive as they are more than two standard errors from 0. These suggest that the long positions of commodity index traders in corn futures markets impact positively on corn prices, both in the short and long runs.

- Soybeans system ($\epsilon_t^f, \epsilon_t^s, \epsilon_t^i$) characterized by two common trends

$$B^1 = \begin{pmatrix} 0.009 & 0 & \mathbf{0.037} \\ (2.189) & & (14.606) \\ -0.038 & 0.037 & \mathbf{0.034} \\ (-0.070) & (0.068) & (14.073) \\ 0.032 & -0.051 & 0.011 \\ (0.071) & (-0.113) & (4.790) \end{pmatrix}, \Xi B^1 = \begin{pmatrix} 0 & 0 & \mathbf{0.036} \\ & & (9.880) \\ 0 & 0.000 & \mathbf{0.037} \\ & (0.906) & (9.878) \\ 0 & -0.027 & 0.014 \\ & (-0.906) & (3.161) \end{pmatrix} \quad (9)$$

$$B^2 = \begin{pmatrix} 0.009 & -0.003 & \mathbf{0.037} \\ (0.202) & (-0.068) & (15.461) \\ 0 & 0.012 & \mathbf{0.034} \\ & (2.697) & (13.892) \\ -0.020 & -0.010 & 0.010 \\ (-0.499) & (-0.268) & (4.617) \end{pmatrix}, \Xi B^2 = \begin{pmatrix} -0.000 & 0 & \mathbf{0.036} \\ (-2.397) & & (10.084) \\ 0 & 0 & \mathbf{0.037} \\ & & (10.087) \\ -0.027 & 0 & 0.013 \\ (-2.397) & & (3.044) \end{pmatrix} \quad (10)$$

In (9), the spot price shock is restricted to have zero short- and long-run impacts on the futures prices. The futures price shock has zero long-run impact on the system. Conversely, in (10), the futures price shock is restricted to have zero short- and long-run impacts on the spot price. The spot price shock has zero long-run impact on the system. The results indicate that the way the restrictions are imposed does not matter for the role of the variable of interest. The estimates in the last columns, highlighted in bold, mean that at the 5% level, the long positions of commodity index traders in soybeans futures market impact significantly on soybeans prices, both in the short and long runs.

⁹We varied the number of bootstrap replications to above and below 4000, but the qualitative results do not change.

- Crude oil system ($\epsilon_t^f, \epsilon_t^s, \epsilon_t^i$) characterized by one common trend

$$B^1 = \begin{pmatrix} 0.021 & 0.030 & \mathbf{0.021} \\ (12.343) & (7.277) & (3.317) \\ 0 & 0.027 & \mathbf{0.014} \\ & (11.690) & (3.917) \\ -0.014 & -0.022 & 0.048 \\ (-1.447) & (-4.100) & (9.042) \end{pmatrix}, \Xi B^1 = \begin{pmatrix} 0 & 0 & \mathbf{0.058} \\ & & (6.438) \\ 0 & 0 & \mathbf{0.059} \\ & & (6.438) \\ 0 & 0 & 0.019 \\ & & (6.438) \end{pmatrix} \quad (11)$$

$$B^2 = \begin{pmatrix} 0.037 & 0 & \mathbf{0.021} \\ (9.162) & & (3.333) \\ 0.022 & 0.015 & \mathbf{0.014} \\ (9.210) & (12.810) & (3.893) \\ -0.026 & -0.001 & 0.048 \\ (-3.400) & (-0.180) & (8.909) \end{pmatrix}, \Xi B^2 = \begin{pmatrix} 0 & 0 & \mathbf{0.058} \\ & & (6.322) \\ 0 & 0 & \mathbf{0.059} \\ & & (6.322) \\ 0 & 0 & 0.019 \\ & & (6.322) \end{pmatrix} \quad (12)$$

The results for the crude oil system are given in (11) and (12). The identification scheme is the same as that in the corn system. Whether we impose the restrictions on the futures price shock in B^1 or spot price shock in B^2 , the coefficients in the last columns mean that at the 5% level, the long positions of money managers in the crude oil futures market have short- and long-run impacts on crude oil prices.

- Natural gas system ($\epsilon_t^f, \epsilon_t^s, \epsilon_t^i$) characterized by two common trends

$$B^1 = \begin{pmatrix} 0.004 & 0 & \mathbf{-0.065} \\ (1.287) & & (-0.881) \\ -0.053 & 0.001 & \mathbf{-0.033} \\ (-1.345) & (8.044) & (-0.881) \\ -0.000 & 0.078 & 0.001 \\ (-0.098) & (8.044) & (0.609) \end{pmatrix}, \Xi B^1 = \begin{pmatrix} 0 & 0 & \mathbf{-0.063} \\ & & (-0.879) \\ 0 & 0.001 & \mathbf{-0.067} \\ & (8.044) & (-0.879) \\ 0 & 0.078 & 0.001 \\ & (8.044) & (0.301) \end{pmatrix} \quad (13)$$

$$B^2 = \begin{pmatrix} 0.001 & -0.004 & \mathbf{-0.065} \\ (7.837) & (-1.109) & (-0.748) \\ 0 & 0.053 & \mathbf{-0.033} \\ & (7.732) & (-0.748) \\ -0.078 & 0.000 & 0.000 \\ (-7.837) & (0.101) & (0.178) \end{pmatrix}, \Xi B^2 = \begin{pmatrix} 0.001 & 0 & \mathbf{-0.063} \\ (7.837) & & (-0.746) \\ 0 & 0 & \mathbf{-0.067} \\ & & (-0.746) \\ -0.078 & 0 & 0.000 \\ (-7.837) & & (0.048) \end{pmatrix} \quad (14)$$

In (13) and (14), we have the results for natural gas system. The identification scheme is the same as that in the soybeans system. Unlike in the systems for corn, soybeans, and crude oil, the coefficients in the last columns mean that at the 5% level, the long positions of money managers in the natural gas futures market do not have a significant impact on natural gas prices both in the short and long runs. In addition, the coefficients are negative.

6.2 | Forecast error variance (FEV) decompositions

FEV decomposition of a variable is the proportion of h -step ahead forecast error variance accounted for by the innovations of each variable in the system. Table 3 gives the FEV for corn system (top panel) and crude oil system (bottom panel), up to 20 periods.¹⁰ Both systems are characterized by one common trend. The top panel shows that the long positions of index traders account for a high proportion of the forecast error variance in the futures and spot prices for corn. The innovations to the long positions of index traders account for 64%–74% of the forecast error variance in the futures price and about 78% of the forecast error variance in the spot price at any forecast horizon.

The lower panel of Table 3 gives the variance decomposition in the crude oil system. The contribution of the long positions of money managers to the forecast error variances of the spot and futures prices increase with increasing horizon. The variance decompositions for soybeans and natural gas systems are shown Table 4 where we see even

¹⁰Like the point estimates we discussed in the last section, the FEVs depend on the identifying restrictions. The FEVs in Table 3 are based on the assumption that the spot price shock has zero impact on the futures price. We also used the restriction that the futures price shock has zero impact on the spot price. For the variable of interest, that is, the long positions, the identification scheme has little effects on the qualitative values of the FEVs.

TABLE 3 Forecast error variance decomposition: corn and crude oil systems

Period	Futures price (f_t^c)			Spot price (s_t^c)			Positions (i_t^c)		
	f_t^c	s_t^c	i_t^c	f_t^c	s_t^c	i_t^c	f_t^c	s_t^c	i_t^c
1	0.36	0.00	0.64	0.13	0.09	0.78	0.28	0.30	0.42
2	0.37	0.00	0.63	0.15	0.08	0.77	0.27	0.29	0.44
3	0.36	0.00	0.64	0.15	0.07	0.77	0.25	0.29	0.45
4	0.36	0.00	0.64	0.16	0.07	0.77	0.25	0.29	0.46
5	0.35	0.00	0.64	0.17	0.07	0.77	0.24	0.28	0.48
⋮	⋮	⋮		⋮	⋮	⋮	⋮	⋮	⋮
15	0.30	0.00	0.70	0.20	0.03	0.77	0.19	0.19	0.62
16	0.29	0.00	0.71	0.20	0.03	0.77	0.19	0.18	0.63
17	0.28	0.00	0.71	0.19	0.03	0.78	0.19	0.17	0.64
18	0.28	0.00	0.72	0.19	0.03	0.78	0.19	0.17	0.65
19	0.27	0.00	0.73	0.19	0.03	0.79	0.19	0.16	0.65
20	0.26	0.00	0.74	0.18	0.03	0.79	0.19	0.15	0.66
Period	Futures price (f_t^o)			Spot price (s_t^o)			Positions (i_t^o)		
	f_t^o	s_t^o	i_t^o	f_t^o	s_t^o	i_t^o	f_t^o	s_t^o	i_t^o
1	0.75	0.00	0.25	0.53	0.26	0.21	0.22	0.00	0.78
2	0.76	0.01	0.23	0.69	0.09	0.22	0.26	0.00	0.74
3	0.73	0.01	0.26	0.70	0.06	0.24	0.27	0.00	0.73
4	0.64	0.01	0.35	0.66	0.04	0.30	0.29	0.00	0.71
5	0.53	0.01	0.46	0.55	0.04	0.42	0.28	0.00	0.71
⋮	⋮	⋮		⋮	⋮	⋮	⋮	⋮	⋮
15	0.19	0.02	0.79	0.19	0.03	0.78	0.25	0.02	0.73
16	0.18	0.02	0.80	0.18	0.02	0.79	0.24	0.02	0.73
17	0.17	0.02	0.81	0.17	0.02	0.81	0.24	0.02	0.74
18	0.16	0.02	0.82	0.16	0.02	0.82	0.24	0.02	0.74
19	0.15	0.02	0.83	0.15	0.02	0.83	0.23	0.02	0.74
20	0.14	0.02	0.84	0.14	0.02	0.84	0.23	0.02	0.75

Note: This table presents the forecast error variance decomposition of spot prices s_t , futures prices f_t and long positions i_t in corn c system (f_t^c, s_t^c, i_t^c) (top panel) and crude oil o system (f_t^o, s_t^o, i_t^o) (bottom panel). At each period, the estimates show the proportion of the forecast error variance in the dependent variable attributable to each variable.

stronger impacts of investment positions on the futures prices. Thus, in all the systems, the long positions are important in explaining the forecast error variances of the commodity prices.

7 | THE IMPACTS OF NET POSITIONS

The CFTC reports both short and long positions data on the commodities in our analysis. We used long positions for the previous analysis. We find that the positions of commodity index traders and money managers impact on commodity prices except the market prices for natural gas. Figure 3 might explain the lack of evidence that long positions of money managers impact on natural gas prices. The plots show the net positions (long positions minus short positions) on the commodities in our analysis. Except for natural gas, the positions on the remaining commodities are net long. That is, money managers in the natural gas futures market take mostly short positions.

TABLE 4 Forecast error variance decomposition: soybeans and natural gas systems

Period	Futures price (f_t^b)			Spot price (s_t^b)			Positions (i_t^b)		
	f_t^b	s_t^b	i_t^b	f_t^b	s_t^b	i_t^b	f_t^b	s_t^b	i_t^b
1	0.06	0.00	0.94	0.37	0.34	0.30	0.28	0.69	0.03
2	0.04	0.03	0.93	0.36	0.32	0.32	0.28	0.69	0.03
3	0.03	0.02	0.95	0.32	0.29	0.39	0.27	0.69	0.03
4	0.02	0.01	0.97	0.29	0.26	0.45	0.26	0.70	0.04
5	0.03	0.02	0.95	0.26	0.23	0.52	0.25	0.71	0.04
⋮	⋮	⋮		⋮	⋮	⋮	⋮	⋮	⋮
15	0.06	0.04	0.89	0.14	0.12	0.74	0.17	0.74	0.09
16	0.06	0.04	0.90	0.13	0.11	0.76	0.16	0.74	0.09
17	0.06	0.04	0.90	0.12	0.11	0.77	0.16	0.74	0.10
18	0.06	0.04	0.91	0.12	0.10	0.78	0.16	0.75	0.10
19	0.05	0.04	0.91	0.11	0.10	0.79	0.15	0.75	0.10
20	0.05	0.03	0.92	0.11	0.10	0.79	0.15	0.75	0.10
Period	Futures price (f_t^g)			Spot price (s_t^g)			Positions (i_t^g)		
	f_t^g	s_t^g	i_t^g	f_t^g	s_t^g	i_t^g	f_t^g	s_t^g	i_t^g
1	0.15	0.00	0.85	0.86	0.09	0.05	0.00	0.98	0.02
2	0.18	0.00	0.82	0.70	0.07	0.24	0.00	0.99	0.01
3	0.18	0.00	0.82	0.58	0.05	0.37	0.00	0.99	0.01
4	0.15	0.00	0.85	0.49	0.04	0.47	0.00	0.99	0.01
5	0.13	0.00	0.87	0.44	0.03	0.53	0.00	0.99	0.01
⋮	⋮	⋮		⋮	⋮	⋮	⋮	⋮	⋮
15	0.05	0.00	0.95	0.17	0.02	0.81	0.00	0.99	0.01
16	0.04	0.00	0.95	0.16	0.02	0.82	0.00	0.99	0.01
17	0.04	0.00	0.96	0.15	0.01	0.83	0.00	0.99	0.01
18	0.04	0.00	0.96	0.14	0.01	0.84	0.00	0.99	0.01
19	0.04	0.00	0.96	0.14	0.01	0.85	0.00	0.99	0.01
20	0.03	0.00	0.96	0.13	0.01	0.86	0.00	0.99	0.01

Note: This table presents the forecast error variance decomposition of spot prices s_t , futures prices f_t and long positions i_t in soybeans b system (f_t^b, s_t^b, i_t^b) (top panel) and natural gas g system (f_t^g, s_t^g, i_t^g) (bottom panel). At each period, the estimates show the proportion of the forecast error variance in the dependent variable attributable to each variable.

Most studies on commodity financialization use net positions or similar measures to analyze the impact of financialization on commodity futures markets. The argument is that some traders that hold long positions may also hold offsetting short positions. We follow the same procedures outlined in the previous analysis to examine the impacts of net positions on commodity prices. Since we already performed ADF unit root tests for the spot and futures prices, we only perform unit root tests for net positions in this section. Except the natural gas series, the net positions exhibit trending behavior. We, therefore, allowed for linear trends in the ADF regressions for corn, soybeans and crude oil series, and an intercept in the series for natural gas. Table 5 reports the test results. There is evidence of unit root in the levels of the net positions, but there is no such evidence in the first differences of the series. Hence, the net positions can be treated as I(1) variables.

We also investigate whether the net positions share common trends with the spot and futures prices. In the systems for corn, soybeans and crude oil, we allowed for linear trends in the levels of the data and intercepts in

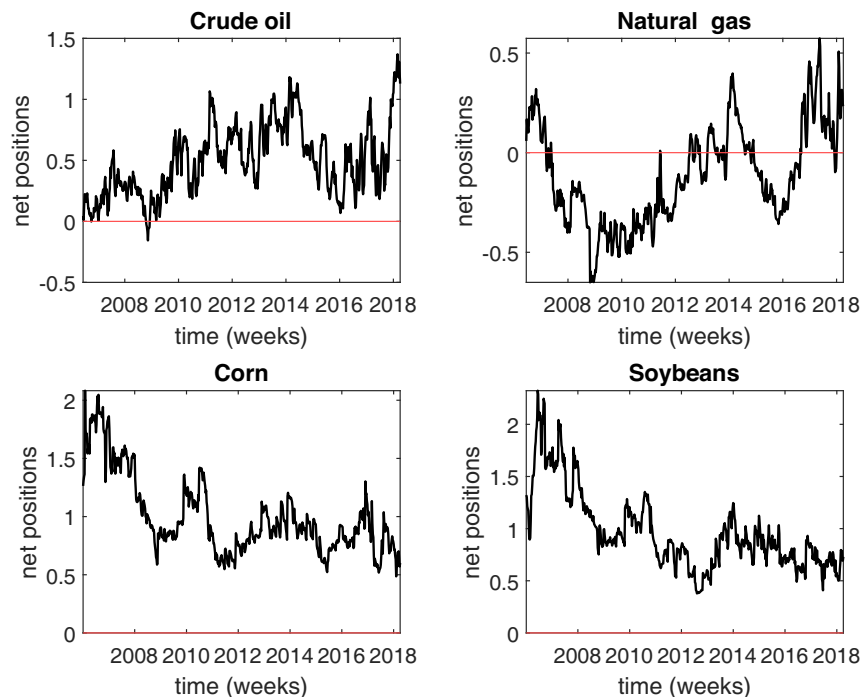


FIGURE 3 Net positions (long-short) for money managers in crude oil and natural gas futures markets, and for commodity index traders in corn and soybeans futures markets

TABLE 5 ADF tests for unit root in net positions ($neti_t$) of commodity index traders for corn (c) and soybeans (b), and money managers for crude oil (o) and natural gas (g)

Net positions in levels					Net positions in 1st diffs.				
Series	Stat	cValue	BIC	Lags	Series	Stat	cValue	BIC	Lags
$neti_t^c$	-2.405	-2.867	-1553.711	13	$\Delta neti_t^c$	-6.352	-1.941	-1560.177	12
$neti_t^b$	-2.332	-2.867	-1385.35	9	$\Delta neti_t^b$	-8.035	-1.941	-1392.742	8
$neti_t^o$	-3.453	-2.867	-1300.89	3	$\Delta neti_t^o$	-15.088	-1.941	-1304.861	3
$neti_t^g$	-2.818	-2.867	-1973.752	1	$\Delta neti_t^g$	-16.551	-1.941	-1969.953	1

Note: Δ is first difference operator. Stat is the test statistic and cValue is the critical value. The number of lags for each series was chosen such that no residual autocorrelation remains.

the cointegration relations. For the natural gas system, we allowed for only intercepts in both the cointegration relations and the levels of the data. The cointegration test results are presented in Table 6. For all the commodity systems, the trace and maximum value tests provide the same evidence of the number of common trends. That is, one cointegration relation for corn system and two cointegration relations for soybeans, crude oil, and natural gas systems.

8 | RESULTS: THE IMPACTS OF NET POSITIONS

Following a similar identification scheme in Section 5, we estimated the short- and long-run impacts of shocks to the spot price, the futures price, and the net positions in corn, soybeans, crude oil, and natural futures markets.¹¹

¹¹In the previous analysis involving gross long positions, we placed the short- and long-run restrictions on the futures price shock and then on the spot price shock. We conduct a similar analysis with net positions, but we present only the results for the case in which the futures price shock is restricted to have zero impact on the spot price. Placing the restrictions on the spot price shock does not affect our conclusions.

TABLE 6 Johansen cointegration tests among the net positions, the spot and futures prices of corn, soybeans, crude oil, and natural gas

Trace test							Eigenvalue test						
<i>r</i>	<i>h</i>	Stat	pValue	BIC	AIC	Lags	<i>r</i>	<i>h</i>	Stat	pValue	BIC	AIC	Lags
Corn							Corn						
0	1	35.015	0.003				0	1	53.455	0.004			
1	0	11.610	0.495	-6692.512	-7327.11	13	1	0	18.440	0.350	-6735.463	-7330.336	13
2	0	6.830	0.419				2	0	6.830	0.419			
Soybeans							Soybeans						
0	1	71.850	0.001				0	1	38.032	0.001			
1	1	33.818	0.005	-7225.941	-7621.752	8	1	1	27.117	0.004	-7173.439	-7609.119	8
2	0	6.700	0.435				2	0	6.700	0.435			
Crude oil							Crude oil						
0	1	118.474	0.001				0	1	88.799	0.001			
1	1	29.675	0.016	-6532.991	-6806.727	5	1	1	22.903	0.015	-6474.018	-6787.374	5
2	0	6.773	0.426				2	0	6.773	0.426			
Natural gas							Natural gas						
0	1	141.519	0.001				0	1	126.168	0.001			
1	1	15.351	0.015	-5348.942	-5441.796	1	1	1	13.923	0.017	-5317.108	-5449.708	0
2	0	1.428	0.353				2	0	1.428	0.353			

Note: Cointegration tests for the system (f_t, s_t, net_t) : f_t is the futures price, s_t is the spot price, net_t is the net positions. r is the null hypothesis and h is the test decision where 1 denotes rejection of the null hypothesis and 0 denotes a failure to reject the null hypothesis. The number of lags for each VAR was chosen such that no system residual autocorrelation remains.

- Corn system $(\epsilon_t^f, \epsilon_t^s, \epsilon_t^i)$

$$B = \begin{pmatrix} 0.010 & -0.004 & -0.043 \\ (1.552) & (-0.459) & (-1.193) \\ 0 & 0.008 & -0.045 \\ & (1.495) & (-1.190) \\ 0.039 & 0.045 & 0.008 \\ (1.439) & (1.229) & (1.256) \end{pmatrix}, \Xi B = \begin{pmatrix} 0 & 0 & -0.051 \\ & & (-1.161) \\ 0 & 0.003 & -0.055 \\ & (1.252) & (-1.157) \\ 0 & 0.043 & 0.030 \\ & (1.252) & (1.180) \end{pmatrix} \quad (15)$$

- Soybeans system $(\epsilon_t^f, \epsilon_t^s, \epsilon_t^i)$

$$B = \begin{pmatrix} 0.009 & 0.003 & -0.037 \\ (2.163) & (0.345) & (-1.593) \\ 0 & 0.016 & -0.032 \\ & (2.910) & (-1.553) \\ 0.061 & 0.037 & 0.018 \\ (1.510) & (1.567) & (1.576) \end{pmatrix}, \Xi B = \begin{pmatrix} 0 & 0 & -0.038 \\ & & (-1.535) \\ 0 & 0 & -0.040 \\ & & (-1.535) \\ 0 & 0 & 0.034 \\ & & (1.535) \end{pmatrix} \quad (16)$$

- Crude oil system $(\epsilon_t^f, \epsilon_t^s, \epsilon_t^i)$

$$B = \begin{pmatrix} 0.020 & 0.027 & 0.023 \\ (9.090) & (5.955) & (3.591) \\ 0 & 0.026 & 0.013 \\ & (10.859) & (3.355) \\ -0.030 & -0.030 & 0.067 \\ (-2.221) & (-3.492) & (7.292) \end{pmatrix}, \Xi B = \begin{pmatrix} 0 & 0 & 0.062 \\ & & (6.590) \\ 0 & 0 & 0.063 \\ & & (6.590) \\ 0 & 0 & 0.034 \\ & & (6.590) \end{pmatrix} \quad (17)$$

TABLE 7 Forecast error variance decomposition: corn and crude oil systems with net positions

Period	Futures price (f_t^c)			Spot price (f_t^c)			Net positions ($neti_t^c$)		
	f_t^c	s_t^c	$neti_t^c$	s_t^c	f_t^c	$neti_t^c$	s_t^c	f_t^c	$neti_t^c$
1	0.06	0.00	0.94	0.00	0.02	0.97	0.31	0.68	0.01
2	0.06	0.00	0.94	0.00	0.02	0.98	0.30	0.70	0.01
3	0.05	0.00	0.95	0.00	0.01	0.98	0.28	0.71	0.01
4	0.05	0.00	0.95	0.00	0.01	0.99	0.27	0.72	0.01
5	0.04	0.00	0.96	0.00	0.01	0.99	0.25	0.73	0.02
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
15	0.03	0.00	0.97	0.01	0.01	0.98	0.16	0.74	0.10
16	0.03	0.00	0.97	0.01	0.01	0.98	0.15	0.74	0.11
17	0.02	0.00	0.97	0.01	0.01	0.98	0.14	0.74	0.12
18	0.02	0.00	0.98	0.01	0.01	0.99	0.13	0.74	0.12
19	0.02	0.00	0.98	0.01	0.01	0.99	0.13	0.74	0.13
20	0.02	0.00	0.98	0.01	0.01	0.99	0.12	0.74	0.14
Period	Futures price (f_t^o)			Spot price (s_t^o)			Net positions ($neti_t^o$)		
	f_t^o	s_t^o	$neti_t^o$	f_t^o	s_t^o	$neti_t^o$	f_t^o	s_t^o	$neti_t^o$
1	0.68	0.00	0.32	0.52	0.29	0.19	0.28	0.01	0.72
2	0.66	0.01	0.33	0.62	0.11	0.27	0.30	0.01	0.70
3	0.62	0.01	0.37	0.60	0.07	0.32	0.31	0.01	0.69
4	0.46	0.01	0.54	0.50	0.05	0.45	0.30	0.01	0.69
5	0.33	0.01	0.66	0.36	0.03	0.61	0.29	0.01	0.70
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
15	0.09	0.00	0.90	0.09	0.01	0.90	0.22	0.01	0.76
16	0.09	0.00	0.91	0.09	0.01	0.90	0.22	0.01	0.77
17	0.08	0.00	0.91	0.08	0.01	0.91	0.21	0.01	0.77
18	0.08	0.00	0.92	0.08	0.01	0.92	0.21	0.01	0.78
19	0.07	0.00	0.92	0.07	0.01	0.92	0.20	0.01	0.78
20	0.07	0.00	0.93	0.07	0.01	0.93	0.20	0.01	0.79

Note: This table presents the forecast error variance decomposition of spot prices s_t , futures prices f_t and net positions $neti_t$ in corn c system ($f_t^c, s_t^c, neti_t^c$) (top panel) and crude oil o system ($f_t^o, s_t^o, neti_t^o$) (bottom panel). At each period, the estimates show the proportion of the forecast error variance in the dependent variable attributable to each variable.

- Natural gas system ($\epsilon_t^f, \epsilon_t^s, \epsilon_t^i$)

$$B = \begin{pmatrix} 0.031 & 0.022 & \mathbf{0.053} \\ (2.600) & (2.941) & (1.890) \\ 0 & 0.052 & \mathbf{0.016} \\ & (14.107) & (1.460) \\ -0.037 & -0.012 & \mathbf{0.024} \\ (-2.220) & (-2.906) & (2.342) \end{pmatrix}, \Xi B = \begin{pmatrix} 0 & 0 & \mathbf{0.092} \\ & & (2.084) \\ 0 & 0 & \mathbf{0.092} \\ & & (2.084) \\ 0 & 0 & \mathbf{-0.016} \\ & & (-2.084) \end{pmatrix} \quad (18)$$

Bootstrap t -values, based on 4000 replications, are in parenthesis. The short- and long-run impacts of the shocks to net positions of each commodity are in the third columns of each matrix. For the agricultural systems in (15) and (16), that is, corn and soybeans, all the coefficient estimates are less than two standard errors from 0. Thus, unlike the model involving gross long positions, there is no evidence that the net positions of commodity index traders impact on the

TABLE 8 Forecast error variance decomposition: soybeans and natural gas systems with net positions

Period	Futures price			Spot price			Net positions		
	f_t^b	s_t^b	$neti_t^b$	f_t^b	s_t^b	$neti_t^b$	f_t^b	s_t^b	$neti_t^b$
1	0.06	0.00	0.94	0.01	0.19	0.80	0.87	0.07	0.06
2	0.06	0.01	0.92	0.02	0.19	0.78	0.87	0.08	0.05
3	0.06	0.01	0.92	0.03	0.15	0.82	0.86	0.08	0.05
4	0.05	0.01	0.93	0.03	0.13	0.84	0.86	0.08	0.07
5	0.05	0.01	0.94	0.03	0.11	0.86	0.85	0.07	0.08
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
15	0.03	0.01	0.96	0.02	0.04	0.94	0.66	0.09	0.24
16	0.03	0.01	0.96	0.02	0.04	0.94	0.64	0.09	0.26
17	0.03	0.01	0.97	0.02	0.04	0.94	0.63	0.09	0.28
18	0.03	0.01	0.97	0.02	0.04	0.94	0.61	0.10	0.30
19	0.03	0.01	0.97	0.02	0.03	0.95	0.59	0.10	0.31
20	0.02	0.01	0.97	0.02	0.03	0.95	0.58	0.10	0.33
Period	Futures price			Spot price			Net positions		
	f_t^g	s_t^g	$neti_t^g$	f_t^g	s_t^g	$neti_t^g$	f_t^g	s_t^g	$neti_t^g$
1	0.46	0.00	0.54	0.32	0.63	0.05	0.56	0.06	0.38
2	0.46	0.00	0.54	0.42	0.39	0.19	0.59	0.05	0.35
3	0.44	0.00	0.56	0.44	0.27	0.29	0.60	0.05	0.35
4	0.42	0.00	0.58	0.43	0.20	0.36	0.61	0.05	0.34
5	0.40	0.00	0.60	0.42	0.16	0.42	0.61	0.05	0.34
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
15	0.29	0.01	0.70	0.29	0.05	0.66	0.63	0.04	0.32
16	0.28	0.01	0.71	0.28	0.05	0.67	0.64	0.04	0.32
17	0.27	0.01	0.72	0.27	0.05	0.68	0.64	0.04	0.32
18	0.27	0.01	0.73	0.26	0.04	0.69	0.64	0.04	0.32
19	0.26	0.01	0.73	0.25	0.04	0.70	0.64	0.04	0.32
20	0.25	0.01	0.74	0.25	0.04	0.71	0.64	0.04	0.32

Note: This Table presents the forecast error variance decomposition of spot prices s_t , futures prices f_t and net positions $neti_t$ in soybeans b system ($f_t^b, s_t^b, neti_t^b$) (top panel) and natural gas g system ($f_t^g, s_t^g, neti_t^g$) (bottom panel). At each period, the estimates show the proportion of the forecast error variance in the dependent variable attributable to each variable.

spot and futures prices of corn and soybeans. These findings for the agricultural commodities, based on the net positions, is consistent with the findings of some studies, for example (Ederer et al., 2016; Irwin & Sanders, 2012b) that also use net positions. In the case of the crude oil system in (17), the evidence remains similar to the case involving gross long positions. Our findings on crude oil agree with studies such as Tang and Xiong (2012), Singleton (2013), Mou (2011), Ederer et al. (2016), and Mayer (2012). Whereas the gross long positions of money managers do not impact on natural gas prices, the results in (18) show that the net positions of these traders have significantly positive long-run impact on natural gas prices. Finally, we observe in (17) and (18) that shocks to net positions of money managers have significantly positive impacts on crude oil and natural gas prices, but the shocks to spot and futures prices, on the other hand, have significant negative effects on the net positions of money managers in these markets. Overall, our findings are consistent with (Gray, 1967; Sockin & Xiong, 2015) who noted that price pressure exerted in futures markets by investors can be transferred to the cash markets of the underlying commodities.

Table 7 gives the FEVs for corn and crude oil systems involving net positions.¹² It is notable that although the net index positions in the corn system do not have a significant impact on the spot and futures prices, the innovations to the variable account for a large proportion of the forecast error variance in these prices. At any forecast horizon, the innovations to the net positions of index traders account for 94%–98% and 97%–99% of the forecast error variances in the futures and spot prices, respectively. Thus, although the point estimates are not statistically significant relative to own shocks, the shocks to the net positions of index traders are important for the determination of the spot and futures prices of corn. The importance of own shocks is negligible at any horizon. In the lower panel, we have the FEVs for crude oil system. The net positions of money managers account for high proportions of the forecast error variances in the spot and futures prices. The FEVs for the soybeans and the natural gas systems are presented in Table 8. They compare similarly with the FEVs for corn and crude oil systems.

9 | CONCLUSIONS

Using a structural error correction model, we analyzed the impact of financialization on the futures and spot prices of Chicago corn, Chicago soybeans, WTI crude oil, and Henry Hub natural gas. We exploited the observed comovements between the spot and futures prices of the commodities to examine how these prices respond to index investment shocks. We found that the commodity prices share common trends with the futures positions of index traders and money managers. By imposing the long-run restrictions implied by the cointegration structure on the structural model of each commodity system, we estimated the short- and long-run effects. First, we used, as the measure of financialization, the long positions of commodity index traders in corn and soybeans futures markets and the long positions of money managers in natural gas and crude oil futures markets. The results show that shocks to long positions have significant short- and long-run impacts on both the spot and futures prices of all the commodities except natural gas. We also used net positions, consistent with the practice in similar studies. The results show that the net positions of index traders in the agricultural markets, that is, the futures markets for corn and soybeans, have no significant impacts on futures and spot prices. In the market for crude oil, both long and net positions impact on the spot and futures prices. However, in the natural gas market, the long positions of money managers do not impact on natural gas prices, but the net positions of these traders have an impact on the prices. Forecast error variance decompositions show that shocks to index traders and money manager's positions contribute more to the forecast error variance of the spot and futures prices than the contributions of own price shocks. We conclude that financialization has impact on commodity prices for corn, soybeans, crude oil, and natural gas, both in the short and long runs.

ACKNOWLEDGMENTS

We thank Dr. Johannes Agbahey for reading the paper and making useful comments. Open Access funding enabled and organized by Projekt DEAL.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in Mendeley Data at <https://doi.org/10.17632/hh79js6nxt.1> and <https://doi.org/10.17632/byjv249xcw.1>.

ORCID

Moses M. Kupabado  <https://orcid.org/0000-0001-5598-9029>

REFERENCES

- Babalos, V., & Balcilar, M. (2017). Does institutional trading drive commodities prices away from their fundamentals: Evidence from a nonparametric causality-in-quantiles test. *Finance Research Letters*, 21, 126–131. <https://doi.org/10.1016/j.frl.2016.11.017>
- Basak, S., & Pavlova, A. (2016). A model of financialization of commodities. *Journal of Finance*, 71(4), 1511–1556. <https://doi.org/10.1111/jofi.12408>
- Bohl, M. T. (2016). Treiben indexfonds agrarrohstoffpreise? Nein! *Perspektiven der Wirtschaftspolitik*, 17(2), 155–171. Retrieved October 10, 2020, from https://www.wiwi.uni-muenster.de/me/sites/me/files/Veroeffentlichungen/indexfonds_text_18_11_2015-2.pdf
- Box, G. E. P., Jenkins, G. M., & Reinsel, G. C. (1994). *Time series analysis: Forecasting and control* (3rd ed.). Prentice-Hall.

¹²Similar to the long positions model, the FEVs values with respect to net positions are robust to changes in the model's identification restrictions.

- Brüggemann, R. (2006). Sources of German unemployment: A structural vector error correction analysis. *Empirical Economics*, 31(2), 409–431. <https://link.springer.com/article/10.1007/s00181-005-0021-x>
- Brunetti, C., Büyükkahin, 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>
- Bruno, V. G., Büyükkahin, B., & Robe, M. A. (2016). The financialization of food? *American Journal of Agricultural Economics*, 99(1), 243–264. <https://doi.org/10.1093/ajae/aaw059>
- Commodity Futures Trading Commission (2021). *Market data & economic analysis: Explanatory notes*. www.cftc.gov/MarketReports/CommitmentsofTraders/ExplanatoryNotes/index.htm
- Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, 74(366a), 427–431. <https://doi.org/10.1080/01621459.1979.10482531>
- Dimpfl, T., Flad, M., & Jung, R. C. (2017). Price discovery in agricultural commodity markets in the presence of futures speculation. *Journal of Commodity Markets*, 5, 50–62. <https://doi.org/10.1016/j.jcomm.2017.01.002>
- Engle, R. F., & Granger, C. W. (1987). Cointegration and error correction: Representation, estimation, and testing. *Econometrica*, 55, 251–276. <https://www.jstor.org/stable/1913236>
- Ederer, S., Heumesser, C., & Staritz, C. (2016). Financialization and commodity prices—An empirical analysis for coffee, cotton, wheat and oil. *International Review of Applied Economics*, 30(4), 462–487. <https://doi.org/10.1080/02692171.2015.1122745>
- Fattouh, B., Kilian, L., & Mahadeva, L. (2013). The role of speculation in oil markets: What have we learned so far? *Energy Journal*, 7–33. <https://www.jstor.org/stable/41970495>
- Frenk, D., & Turbeville, W. (2011). Commodity index traders and the boom/bust cycle in commodities prices. In *Bust Cycle in Commodities Prices*. <https://doi.org/10.2139/ssrn.1945570>
- Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica*, 37, 424–438. <https://www.jstor.org/stable/1913236>
- Granger, C. W. (1981). Some properties of time series data and their use in econometric model specification. *Journal of Econometrics*, 16(1), 121–130. [https://doi.org/10.1016/0304-4076\(81\)90079-8](https://doi.org/10.1016/0304-4076(81)90079-8)
- Gray, R. W. (1967). Price effects of a lack of speculation. *Food Research Institute Studies*, 7, 177–194. <http://purl.umn.edu/134947>
- Hamilton, J. D., & Wu, J. C. (2014). Risk premia in crude oil futures prices. *Journal of International Money and Finance*, 42, 9–37. <https://doi.org/10.1016/j.jimonfin.2013.08.003>
- Headey, D. D., & Fan, S. (2010). Reflections on the global food crisis: How did it happen? How has it hurt? And how can we prevent the next one? IFPRI Research Monograph, International Food Policy Research Institute (IFPRI). <https://doi.org/10.2499/9780896291782RM165>
- Headey, D. D., & Martin, W. J. (2016). The impact of food prices on poverty and food security. *Annual Review of Resource Economics*, 8, 329–351. <https://doi.org/10.1146/annurev-resource-100815-095303>
- Henderson, B. J., Pearson, N. D., & Wang, L. (2014). New evidence on the financialization of commodity markets. *Review of Financial Studies*, 28(5), 1285–1311. <https://doi.org/10.1093/rfs/hhu091>
- Hull, J. (2016). *Futures, options and other derivatives* (10th ed.). Pearson Education, Inc.
- Irwin, S. H., & Sanders, D. R. (2011). Index funds, financialization, and commodity futures markets. *Applied Economic Perspectives and Policy*, 33(1), 1–31. <https://doi.org/10.1093/aep/ppq032>
- Irwin, S. H., & Sanders, D. R. (2012a). Financialization and structural change in commodity futures markets. *Journal of Agricultural and Applied Economics*, 44(3), 2371–396. <https://doi.org/10.1017/S1074070800000481>
- Irwin, S. H., & Sanders, D. R. (2012b). 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. (2009). The devil or angel? The role of speculation in the recent commodity price boom (and bust). *Journal of Agricultural and Applied Economics*, 44(2), 377–391. <https://doi.org/10.1017/S1074070800002856>
- Jacobson, T., Vredin, A., & Warne, A. (1997). Common trends and hysteresis in Scandinavian unemployment. *European Economic Review*, 41(9), 1781–1816. [https://doi.org/10.1016/S0014-2921\(96\)00027-X](https://doi.org/10.1016/S0014-2921(96)00027-X)
- Johansen, S. (1991). Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. *Econometrica*, 59, 1551–1580.
- Johansen, S. (1995). *Likelihood-based inference in cointegrated vector autoregressive models*. Oxford University Press.
- King, R., Plosser, C. I., Stock, J. H., & Watson, M. W. (1991). Stochastic trends and economic fluctuations. *American Economic Review*, 81(4), 819–840. <https://doi.org/10.3386/w2229>
- Lütkepohl, H. (2005). *New introduction to multiple time series analysis*. Springer Science & Business Media.
- Masters, M. W. (2008). Testimony of Michael W. Masters, Managing Member/Portfolio Manager, Masters Capital Management, LLC, before the Permanent Committee on Homeland Security and Governmental Affairs, United States Senate. 110th Cong., 2nd session, May 20 and June 24.
- Masters, M. W., & White, A. K. (2008). *The accidental Hunt brothers: How institutional investors are driving up food and energy prices*. The Accidental Hunt Brothers Blog, Special Report posted July, 31, 2009.
- Mayer, J. (2012). The growing financialisation of commodity markets: Divergences between index investors and money managers. *Journal of Development Studies*, 48(6), 751–767. <https://doi.org/10.1080/00220388.2011.649261>
- Mou, Y. (2011). *Limits to arbitrage and commodity index investment: Front-running the Goldman roll* (Doctoral dissertation). Columbia University. <https://doi.org/10.7916/D8H41ZDD>

- Quandl; 2018; Commodity Prices: Corn, soybeans, WTI crude oil and Henry Hub natural gas, Chicago Mercantile Exchange Group; Quandl [dataset]. <https://www.quandl.com/>
- Sanders, 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. <https://doi.org/10.3905/jai.2011.14.1.040>
- 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/aep/p006>
- Schwert, G. W. (2002). Tests for unit roots: A Monte Carlo investigation. *Journal of Business and Economic Statistics*, 20(1), 5–17. <https://doi.org/10.1198/073500102753410354>
- Sims, C. A. (1980). Macroeconomics and reality. *Econometrica*, 48, 1–48. <https://doi.org/10.2307/1912017>
- Singleton, K. J. (2013). Investor flows and the 2008 boom/bust in oil prices. *Management Science*, 60(2), 300–318. <https://doi.org/10.1287/mnsc.2013.1756>
- Sockin, M., & Xiong, W. (2015). Informational frictions and commodity markets. *Journal of Finance*, 70(5), 2063–2098. <https://doi.org/10.1111/jofi.12261>
- Stock, J. H., & Watson, M. W. (1988). Testing for common trends. *Journal of the American Statistical Association*, 83(404), 1097–1107. <https://doi.org/10.1080/01621459.1988.10478707>
- Tang, K., & Xiong, W. (2012). Index investment and the financialization of commodities. *Financial Analysts Journal*, 68(6), 54–74. <https://doi.org/10.2469/faj.v68.n6.5>
- US commodity Futures Trading Commission; 2006–2018; Commission Commitments of Traders; Data at CFTC [dataset]. <https://www.cftc.gov/MarketReports/CommitmentsofTraders/HistoricalCompressed/index.htm>
- Will, M. G., Prehn, S., Pies, I., & Glauben, T. (2015). Is financial speculation with agricultural commodities harmful or helpful? A literature review of empirical research. *Journal of Alternative Investments*, 18(3), 84–102. <https://doi.org/10.3905/jai.2016.18.3.084>
- Yan, L., Irwin, S. H., & Sanders, D. R. (2018). Mapping algorithms, agricultural futures, and the relationship between commodity investment flows and crude oil futures prices. *Energy Economics*, 72, 486–504. <https://doi.org/10.1016/j.eneco.2018.04.005>

How to cite this article: Kupabado, M. M., Kaehler, J. (2021). Financialization, common stochastic trends, and commodity prices. *Journal of Futures Markets*, 41, 1988–2008. <https://doi.org/10.1002/fut.22269>