How Connected Is the Agricultural Commodity market to the News-based Investor Sentiment?

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How connected is the agricultural commodity market to the news-based investor sentiment?

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Abstract

Previous studies indicate a substantial time-variation in the co-movement of commodity futures markets and economic fundamentals. This paper examines the connectedness and directional spillovers for both the agricultural commodity futures markets and the corresponding sentiment indices. We first construct dynamic time-varying connectedness measures both for the agricultural commodity returns and sentiments. Then, we use panel data regressions and time-varying Granger causality tests to evaluate whether the spillovers between these returns and sentiments are influenced by the economic and financial uncertainties, including the global COVID-19 pandemic. In particular, we document that the COVID-19 induced uncertainty influences agricultural commodity returns and sentiments significantly around the first cycle of the pandemic in 2020. Last but not least, economic policy and financial market uncertainty are also found to be significant determinants of the connectedness between agricultural commodity returns and sentiment spillovers.

Keywords: Spillovers; Agricultural commodities; Sentiment; COVID-19; Time-varying robust Granger causality

JEL: C21, C22, G11, G14, G17

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1. Introduction

The financialization of commodity markets is the process of utilization of commodity futures in the portfolio investments in place of more traditional assets. In recent years, it has been a highly debated topic because of the volatile movements of energy and non-energy commodity prices, for example, during the 2007-2008 world food price crisis and the oil price spikes in 2008 and 2020. Specifically, the price peaks in the summer of 2008 have been attributed to a speculative bubble caused by institutional investors. Following these extreme market movements, concerns were raised as to whether speculation was driving commodity prices ([Masters, 2008]). More generally, the behavior of extreme movements in many commodity prices in the 2000s has led some researchers to question the sole importance of the traditional factors in forecasting futures prices.

In the standard economic approach, supply and demand factors have always been the main drivers of commodity price dynamics. The agricultural commodity spot and futures markets are linked with a number of factors, for example, economic and financial factors ([Andreasson et al., 2016]), temperature and climate ([Makkonen et al., 2021]), seasonality ([Nguyen et al., 2015]), investor sentiment (Bahloul and Bouri [2016], Nooijen and Broda [2016], [Andreasson et al., 2016]), and speculation ([Andreasson et al., 2016]). Furthermore, the literature shows that uncertainty matters, and more importantly, the drivers of agricultural commodities' performance vary across market conditions. Tang and Xiong [2012] find that commodities included in investable commodities indices (S&P-GSCI and DJ-AIG) have a higher exposure to shocks, which is driven by investor sentiment rather than macroeconomic fundamentals. Silvennoinen and Thorp [2013] investigate the bi-variate conditional volatility and correlation dynamics for individual commodity futures and financial assets. They use the VIX index to capture investor sentiment and show that expected stock volatility is a transition variable. They conclude that the integration between financial markets and commodities is increasing. The findings of Büyükşahin and Robe [2014] suggest that the inclusion of economic uncertainty and financial stress variables can contribute to the study of commodity market financialization. They consider detailed information on trader categories and demonstrate that the conditional correlation between energy markets and stock markets increases with hedge fund activity in futures trading, suggesting that the composition of traders matters.

Emotion-based sentiment can also influence the price volatility of commodity markets (Bahloul and Bouri [2016], Nooijen and Broda [2016]). Ji et al. [2019] examine trader positions between WTI return and investor sentiment indices by applying the spillover connectedness approach. They find that investor sentiment and speculative activities are the most significant contributors to WTI return variations. Moreover, sentiment plays a leading role in information transmission. Using the quantile cross-spectral dependence approach, Maghyereh and Abdoh [2020] find that the inter-dependence between sentiment and commodity is different across time scales and states. Based on the network spillover connectedness approach, Ji et al. [2020] explore commercial traders' sentiment across agriculture and other commodity markets, including energy, metals, and livestock futures markets. They find that the cross-hedging strategies play an essential role in driving sentiment spillover across futures markets. Ma et al. [2021] examine co-movement dynamics in the international commodity markets using the DCC-GARCH model and show that market sentiment plays an important role in driving the commodity market.

Our work contributes to the literature by computing the time-varying connectedness network between agricultural commodity returns and sentiments, focusing on the COVID-19 pandemic period. The network approach allows us to capture not only the spillovers between each commodity's returns and their sentiments but also the cross-market spillovers between returns and sentiment. To measure investor sentiment, we consider the daily commodity-specific Thomson Reuters Market Psych Indices (TRMI). This unique data set derives investor sentiment by performing textual analysis from various sources, including news, social media, press releases, and regulatory filings.[1] Thus, it represents an extensive measure of investor sentiment, compared to the popular Google search-based sentiment measures in the literature. Furthermore, we use time-varying Granger causality tests and panel data regressions to identify the potential determinants of the returns-sentiments spillovers in

[1] The TRMI incorporates textual analysis from the top 2,000 global news outlets and 800 global financial/social media sites.

agricultural commodity markets, including economic and financial uncertainty and the uncertainty from the COVID-19 pandemic. Our final data set consists of twelve agricultural commodity future returns and sentiments: Cattle, Cocoa, Coffee, Corn, Cotton, Lean Hogs, Orange Juice, Palm oil, Soybean, Soybean oil, Sugar, and Wheat, and several macroeconomic indicators, such as the daily Infectious Disease Equity Market Volatility Tracker (EMVID), the U.S. economic policy uncertainty index (EPU), the Aruoba-Diebold-Scotti Business Conditions Index (ADS), the Bloomberg World agriculture index, and the U.S. Dollar Index (DXY) returns.

Our results show that the total spillover index among agricultural commodity returns and sentiments peaks in 2015, 2019, and 2020. The absolute value of the net connectedness tends to increase at the beginning of 2020, which suggests the increasing spillover effects in agricultural markets during the COVID-19 pandemic. We find that the connectedness among agricultural returns and sentiments is time-varying. However, on average, there have been increasing spillovers between returns and sentiments since the financialization of the commodity market. This implies that investor sentiment can be used to forecast agricultural commodity market movements, providing useful information for investors and policymakers. Furthermore, our results show that financial and economic uncertainty indexes, mainly the COVID-19 induced uncertainty, lead to an increase in the connectedness between agricultural commodity returns and sentiments.

The remainder of the paper is structured as follows. Section 2 provides a brief literature review. Section 3 introduces data and summary statistics, followed by time-varying connectedness and time-varying causality methodology in Section 4. Our empirical results are reported in Section 5. Finally, Section 6 concludes the paper.

2. Literature review

2.1. Agricultural commodity markets, other asset classes, and other macroeconomic factors

Sharp increases in agricultural prices in recent years have sparked interests among scholars to study the determinants of agricultural commodity prices.

First, a large literature documents the interaction among agricultural commodity futures, other asset classes, and macroeconomic factors. Malliaris et al. [1996], He and Chen [2011], Ke et al. [2019] study the correlations among agricultural commodity prices and find evidence of a long-term correlations across commodity markets. With respect to the relationship between agricultural commodity markets and other asset classes, previous work has provided evidence on the linkage between agricultural commodities and equity [Hernandez et al., 2021, Baldi et al., 2016], energy [Han et al., 2020, Diebold et al., 2017], precious metals [Naeem et al., 2022, Kang et al., 2017], cryptocurrency [Ji et al., 2019], and macroeconomic factors [Nam, 2021, Caporale et al., 2017, Joëts et al., 2017]. This strand of literature is dominated by studies on the relationship between agricultural commodities and future prices. For example, Han et al. [2020] find a bidirectional linkage between energy and agricultural futures, which has been strengthened in recent years. Using wavelet approaches, Tiwari et al. [2020] find that the agricultural sector is the main shock receiver from other markets, while industrial inputs are the main volatility transmitters across all frequencies. Umar et al. [2021] study the spillovers across energy, agricultural and metal markets using more 200 years of data from 1780 to 2020. They find an increase in connectedness during volatile periods such as economic crises, political uncertainty and commodity driven supply shocks. Kang et al. [2019] explores the connectedness between oil and agricultural commodity prices using the frequency connectedness models. They show that vegetable oil is the most influential source of volatilities. Moreover, there are bi-directional and asymmetric spillovers between oil and agricultural commodity markets. Yahya et al. [2019] study the temporal and frequency connectedness between oil and agricultural prices and find an increase in connectedness after 2006, which is explained by stronger connection among return movements in the long run. Ji et al. [2018] study the tail dependence between energy and agricultural commodity markets and show a stronger dependence at the lower tail during bearish regimes than during bullish regimes. Tiwari et al. [2018] analyze the lead-lag relationship between oil prices and 21 agricultural commodities. They document a high co-movements among the markets at the long-run horizon, and an increase in the connection between commodity markets and oil markets after 2000. Luo and Ji [2018], Zhang and Qu [2015] study the cross-country spillovers from

U.S./global oil prices to Chinese agricultural commodity markets. Overall, the literature documents a significant spillovers across agricultural commodities and other asset classes.

As the COVID-19 pandemic has caused disruptions to global financial markets, several researchers have documented the evolution of the agricultural commodity markets during this period. Umar et al. [2022] explore the connectedness among softs, grains and livestock commodity indexes during the COVID-19 period and find that the dynamic spillovers among these markets peaked during the first and third waves of the COVID-19 pandemic. Adekoya and Oliyide [2021] show strong volatility spillovers among commodity and financial markets and find significant Granger causality from the COVID-19 case growth rate and the infectious disease equity market volatility indexes to the connectedness across the markets, particularly at the low and middle quantiles. Using wavelet methods, Umar et al. [2021] study the impact of the COVID-19 pandemic on the volatility of commodity prices. They find that energy, agricultural and precious metals can be diversifying hedges during the pandemic while non-precious metals offer the best diversification during the recovery phase of the pandemic. Bakas and Triantafyllou [2020] find a strong negative influence of the COVID-19 pandemic on commodity volatility, especially the crude oil market. Salisu et al. [2020] explore the impact of the COVID-19 fear index on commofity price returns. They find that commodity returns increase as COVID-19 fear rises. Wang et al. [2020] revisits the correlations between crude oil and agricultural futures markets during the COVID-19 period. They find stronger connection between crude oil and agricultural markets after the pandemic, especially between crude oil and sugar. Moreover, the cross-correlations among all agricultural futures increase, except for the orange juice market.

2.2. Investor sentiment and agricultural commodity markets: Backgrounds and testable hypotheses

In addition to movements in the financial markets and macroeconomics factors, emotion-based sentiment can also influence the price volatility of commodity markets (Bahloul and Bouri [2016], Nooijen and Broda [2016], Maghyereh and Abdoh [2019]). In the context of the agricultural commodity market, Ji et al. [2020] analyze the connectedness between commercial traders' sentiment in agriculture, energy, metals and livestock future markets, where sentiment indexes are constructed based on Bahloul [2018]. They show that producer/ merchant/ processor/user in agricultural and energy markets mainly engage in cross-hedging in the futures market, and most of them would choose metals as a safe investment option. In contrast, swap dealers operate more in two markets, for example, between agricultural and metal markets, or between agricultural and energy markets. Borgards and Czudaj [2022] test whether long-short speculators are able to generate short-term returns based on their sentiment for 12 agricultural commodity markets. They find that sentiment period returns are positive and differ significantly from neutral sentiment periods for all commodities. This highlights the relevance of sentiment in determining agricultural commodity movements. Cao and Robe [2022] study agricultural market uncertainty and sentiment around USDA announcements. They find a significant decline in implied volatility for corn and soybean after the report releases.

In the above literature, the cross-market spillovers between investor sentiment and agricultural commodity performance have not been fully explored.[2] In addition, previous research has not documented the evolution of agricultural investor sentiment and how it influence agricultural market returns during the COVID-19 period. As this period is characterized by highly extreme investor sentiment, the sentiment-return relationship during this period may be substantially different from that during the pre-pandemic period. Our work contributes to the literature by analyzing the time-varying connectedness network between agricultural commodity returns and sentiments, with a focus on the COVID-19 pandemic period. This approach allows us to capture not only the spillovers between each commodity's returns and their own sentiments, but also the cross-market spillovers between returns and sentiments. In addition, by considering all variables in a network, we are able to identify which sentiment or returns are the main drivers of shocks in the agricultural commodity market. This provides useful information for investors to design their diversification and hedging strategies. Moreover, different from previous studies, we utilize Thom-

[2]For example, how do a change in investor sentiment in the corn market influence investor sentiment and the performance of the soybean market?

son Reuters Market Psych Indices (TRMI), a unique data set that measures investor sentiment based on textual analysis from various sources such as news, social medial, press releases and regulatory findings.[3] These indices are constructed for each individual commodity and represent an extensive, real-time measure of investor sentiment. Since the previous literature document significant spillovers between investor sentiment and commodity returns, we derive the following hypothesis:

Hypothesis 1: There are significant own-market spillovers between investor sentiment and agricultural commodity returns.

Note that as subsets of the overall agricultural commodity market, a shock in one agricultural commodity sentiment or returns can spill over to other markets. An advantage of our network approach is that we are able to investigate the cross-market spillovers among investor sentiment and agricultural commodity returns and identify the main drivers of shocks across the variables. Thus, our second hypothesis involves our predictions about the connectedness between returns and sentiment from different markets.

Hypothesis 2: There are positive cross-market spillovers between investor sentiment and agricultural commodity returns, however, the magnitudes of these spillovers depend on the underlying relationship between the commodities.

We also contribute to the literature by identifying the relationship between investor sentiment and agricultural commodity returns during the COVID-19 pandemic, a period of high volatility and extreme investor sentiment. Specifically, we use time-varying Granger causality tests and panel data regressions to identify the potential determinants of the returns-sentiments spillovers in agricultural commodity markets, including economic and financial uncertainty and the uncertainty from the COVID-19 pandemic. Our results show significant cross-market spillovers among agricultural

[3] Maghyereh and Abdoh [2019] use the TRMI index to study the role of investor sentiment on a wide range of metal and energy prices.

commodity returns and sentiments, thereby unraveling the complex roles of sentiment in the agricultural commodity markets. Based on the conclusions from previous research on the heightened market sentiment and volatilities during the COVID-19 period,[4] we derive the following hypothesis:

Hypothesis 3: Market uncertainty, such as COVID-19 induced uncertainty and economic policy uncertainty, has a positive and significant impact on the spillovers among agricultural market sentiments and returns.

3. Data

Our data set consists of twelve agricultural commodity future (log) returns spanning the period from January 1, 2013 to November 5, 2020 for the following commodities: Cattle, Cocoa, Coffee, Corn, Cotton, Lean Hogs, Orange Juice, Palm oil, Soybean, Soybean oil, Sugar, and Wheat. We also use daily commodity-specific Thomson Reuters Market Psych Indices (TRMI) derived from news, social media, press releases, and regulatory filings. The sentiment indices are based on the text analysis of over 2,000 top global news outlets and 800 global financial/social media sites. The indices are derived through an innovative patent-pending system for extracting complex meaning from text using natural language processing applications. TRMI indices have values ranging from -1 to 1 where negative values indicate negative (bearish) sentiment and values bigger than zero represent a positive (bullish) sentiment.

To measure uncertainty related to infectious disease outbreaks, we use the daily Infectious Disease Equity Market Volatility Tracker (EMVID) constructed byBaker et al. [2020]. The EMVID index counts the number of articles including infectious disease-related keywords such as a pandemic, virus, flu, disease, coronavirus, etc.[5] by searching approximately 3,000 US Newspapers. Then, the EMVID index is normalized by the total number of articles for a given day. To control the global macroe-

[4]For example, Baker et al. [2020], Altig et al. [2020]

[5]The complete list of keywords can be accessible from `https://www.policyuncertainty.com/infectious_EMV.html`

conomic and financial conditions, we also collect a set of control variables, including the U.S. economic policy uncertainty index (EPU) of Baker et al. [2016], and Aruoba-Diebold-Scotti Business Conditions Index (ADS) of Aruoba et al. [2009]. To construct the EPU index, Baker et al. [2016] counts a string of words related to economic and policy uncertainty by searching news in 10 prominent U.S. newspapers. The ADS index is a high-frequency measure of economic activity based on macroeconomic indicators driving economic growth. For each agricultural commodity, we calculate 30-day realized volatility, a well-known measurement for fluctuations of underlying commodities. Moreover, we include the Bloomberg World agriculture index and U.S. Dollar Index (DXY) returns. The data of the agricultural returns and control variables are obtained from Bloomberg.

Table 1 provides descriptive statistics for the variables used in this study. The average daily returns over the sample period are close to zero for all agricultural commodities, whereas the averages of the sentiment values are negative for all commodities except for Cocoa and Coffee. The kurtosis statistic is above three for limited cases, implying that these series do not have fatter tails than the normal distribution. The Jarque–Bera statistic rejects the null hypothesis of normality for all series except for the sentiment of Coffee.

Table 1: Descriptive statistics

	Mean	Std dev.	Kurtosis	Skewness	Range	Min	Max	Jarque-Bera	Transformation
Cattle	-0.0001	0.013	17.45	-1.690	0.224	-0.156	0.068	0.00	log difference
Cocoa	0.0000	0.016	1.131	-0.076	0.133	-0.069	0.064	0.00	log difference
Coffee	-0.0001	0.020	1.862	0.272	0.194	-0.076	0.118	0.00	log difference
Corn	-0.0003	0.015	46.99	-2.752	0.346	-0.269	0.077	0.00	log difference
Cotton	0.0000	0.014	3.507	-0.352	0.160	-0.106	0.054	0.00	log difference
Lean Hogs	-0.0001	0.026	20.53	-0.957	0.471	-0.235	0.236	0.00	log difference
Orange Juice	0.0000	0.019	1.429	0.145	0.163	-0.074	0.089	0.00	log difference
Palm Oil	0.0002	0.014	3.412	-0.065	0.170	-0.103	0.068	0.00	log difference
Soybean Oil	-0.0002	0.012	1.038	0.210	0.110	-0.044	0.066	0.00	log difference
Soybean	-0.0001	0.013	8.877	-1.158	0.160	-0.105	0.055	0.00	log difference
Sugar	-0.0001	0.014	1.553	0.063	0.120	-0.058	0.062	0.00	log difference
Wheat	-0.0001	0.016	1.022	0.253	0.135	-0.069	0.066	0.00	log difference
Cattle-S	-0.1202	0.066	0.629	0.378	0.456	-0.310	0.147	0.00	level
Cocoa-S	0.0123	0.103	0.426	0.016	0.993	-0.570	0.423	0.00	level
Coffee-S	0.0227	0.078	0.193	-0.032	0.543	-0.244	0.298	0.18	level
Corn-S	-0.0535	0.062	0.807	0.259	0.509	-0.243	0.266	0.00	level
Cotton-S	-0.0405	0.081	0.356	0.129	0.570	-0.322	0.249	0.00	level
Lean Hogs-S	-0.1248	0.135	3.230	0.651	1.667	-0.667	1.000	0.00	level
Orange Juice-S	-0.0776	0.335	1.629	0.215	2.000	-1.000	1.000	0.00	level
Palm Oil-S	-0.0817	0.129	0.054	0.191	0.840	-0.477	0.363	0.00	level
Soybean Oil-S	-0.1155	0.377	0.028	0.248	2.000	-1.000	1.000	0.00	level
Soybean-S	-0.0558	0.075	0.499	0.004	0.646	-0.397	0.248	0.00	level
Sugar-S	-0.0680	0.064	0.728	0.128	0.545	-0.355	0.190	0.00	level
Wheat-S	-0.0584	0.067	0.667	0.442	0.508	-0.297	0.211	0.00	level
VOL	0.0116	0.006	3.877	1.711	0.032	0.004	0.036	0.00	level
EPU	1.9337	0.283	0.897	0.479	2.386	0.521	2.907	0.00	log level
ADS	-0.3787	3.490	37.10	-5.376	36.44	-28.00	8.441	0.00	level
DXY	0.0030	0.182	2.466	0.045	2.090	-1.043	1.048	0.00	log difference
EMVID	0.2297	0.394	4.273	2.255	1.841	0.000	1.841	0.00	log level
EQUITY	-0.0011	0.650	337.4	-3.590	31.20	-16.87	14.33	0.00	log difference

4. Methodology

4.1. TVP-VAR-Based Dynamic Connectedness Approach

Using the approach of Antonakakis et al. [2020], we estimate the dynamic connectedness measures based on time-varying parameter vector auto-regression (TVP-VAR). In particular, we employ the following TVP-VAR model:

$$z_t = B_t z_{t-1} + u_t \qquad u_t, \sim N(0, S_t) \tag{1}$$

$$vec(B_t) = vec(B_{t-1}) + v_t, \qquad v_t \sim N(0, R_t) \tag{2}$$

where B_t and S_t are $k \times k$ dimensional matrices and z_t, z_{t-1} and u_t are $k \times 1$ dimensional vector. $vec(B_t)$ and v_t are $k^2 \times 1$ dimensional vectors whereas R_t is a $k^2 \times k^2$ dimensional matrix.[6]

Furthermore, we compute the H-step ahead (scaled) generalized forecast error variance decomposition (GFEVD) suggested by Koop et al. [1996], which is independent of the variable ordering. Subsequently, we rewrite the TVP-VAR as a vector moving average (VMA) process utilizing the following equation: $z_t = \sum_{i=1}^{p} B_{it} z_{t-i} + u_t = \sum_{j=0}^{\infty} A_{jt} u_{t-j}$. Considering that cross-variable and own variance shares do not necessarily add up to one, the (unscaled) GFEVD, $\phi^g_{ij,t}(H)$, is normalized so that, the (scaled) GFEVD, $\tilde{\phi}^g_{ij,t}(H)$, shows the effect of variable j has on variable i with regard to its share of forecast error variance. This measure is represented by,

$$\phi^g_{ij,t}(H) = \frac{S^{-1}_{ii,t} \sum_{t=1}^{H-1} (\iota_i' A_t S_t \iota_j)^2}{\sum_{j=1}^{k} \sum_{t=1}^{H-1} (\iota_i A_t S_t A_t' \iota_i)} \qquad \tilde{\phi}^g_{ij,t}(H) = \frac{\phi^g_{ij,t}(H)}{\sum_{j=1}^{k} \phi^g_{ij,t}(H)}$$

where $\sum_{j=1}^{k} \tilde{\phi}^g_{ij,t}(H) = 1$, $\sum_{i,j=1}^{k} \tilde{\phi}^g_{ij,t}(H) = k$, and ι_i corresponds to a selection vector with unity on the ith position and zero otherwise. Then, the total connectedness

[6] Using the Bayesian information criterion (BIC), we select one lag length for the TVP-VAR model.

index (TCI) is computed using the following equations based on the GFEVD:

$$TO_{jt} = \sum_{i=1, i\neq j}^{k} \tilde{\phi}^g_{ij,t}(H) \tag{3}$$

$$FROM_{jt} = \sum_{i=1, i\neq j}^{k} \tilde{\phi}^g_{ji,t}(H) \tag{4}$$

$$NET_{jt} = TO_{jt} - FROM_{jt} \tag{5}$$

$$TCI_t = k^{-1} \sum_{j=1}^{k} TO_{jt} \equiv k^{-1} \sum_{j=1}^{k} FROM_{jt}. \tag{6}$$

$$NPDC_{ij,t} = \tilde{\phi}_{ij,t}(H) - \tilde{\phi}_{ji,t}(H) \tag{7}$$

where $\tilde{\phi}^g_{ij,t}(H)$ represents the effect of a shock in commodity j has on commodity i. Eq.(3) illustrates the overall impact of a shock in commodity j has on all *other* commodities which is defined as *total directional connectedness to others* whereas Eq.(4) indicates the aggregated influence all *other* commodities have on commodity j (*total directional connectedness from others*). Eq.(5) subtracts the influence of commodity j has on others by the influence *others* have on commodity j, giving us the *net total directional connectedness* which provides information to identify whether a commodity is a net receiver or a net transmitter of the shocks in the network. Commodity j is a net receiver (*transmitter*) of shocks - and hence driven (*driving*) by the network - when the effect of commodity j has on others is larger (*smaller*) than the influence all others have on commodity j, $NET_{jt} > 0$ ($NET_{jt} < 0$). Eq.(6) represent the TCI_t that is the average effect of one commodity has on all *others*. Higher values of this measure implies that the network becomes more connected, implying that a shock in one commodity will have more impact on others. Finally, Eq.(7) defines *net pairwise directional connectedness* ($NPDC_{ij,t}$) which indicates whether variable j is driving variable i or vice versa.

4.2. ***Time-varying Granger causality test of Rossi and Wang [2019]***

We implement the time-varying parameter robust Granger-causality method (TVP-GC) of Rossi and Wang [2019] to check the causal relationship between connectedness measures and COVID-19 induced uncertainty over time. The main advantage of the TVP-GC method is that it is more robust than the standard Granger causality test in the presence of instabilities and allows us to distinguish the periods when Granger causality exists or disappears in the data.[7] Given that our sample includes the COVID-19 periods leading to a destabilizing effect on agricultural commodity future returns, the TVP-GC method enables us to examine the time-varying causal relationships over time. Hence, it is more optimal to use the TVP-GC method to obtain a more appropriate estimation of the relationship than a constant parameter Granger causality method.

In particular, we consider a VAR model with time-varying parameters as follows:

$$y_t = \Phi_{1,t} y_{t-1} + \Phi_{2,t} y_{t-2} + \cdots + \Phi_{p,t} y_{t-p} + \epsilon_t, \tag{8}$$

where $y_t = [y_{1,t}, y_{2,t}, \ldots, y_{n,t}]'$ is an n×1 vector, $\Phi_{j,t}$, $j = 1, \ldots, p$ are functions of time-varying coefficient matrices, and ϵ_t denotes idiosyncratic shocks which are assumed to be heteroscedastic and serially correlated. The endogenous variables vector y_t in the VAR model includes alternatively total connectedness of agricultural futures return, agricultural sentiment indices or both agricultural sentiment indices & futures return; EMVID, ADS, DXY, EQUITY, VOL and EPU.

We test the null hypothesis that the lags of EMVID index do not Granger cause the total connectedness of agricultural futures return (alternatively, agricultural sentiment indices or both agricultural sentiment indices & futures return) for a given maturity, where θ_t denotes an appropriate subset of vec $(\Phi_{1,t}, \Phi_{2,t}, \ldots, \Phi_{p,t})$:

$$H_0 : \theta_t = 0, \quad \forall t = 1, 2 \ldots T. \tag{9}$$

In doing so, we report test statistics such as the mean Wald (MeanW) test, exponential Wald (ExpW) test, Nyblom test, and Quandt likelihood-ratio (SupLR) test following from Rossi and Wang [2019].[8] The lag length of the VAR model is selected

[7] Rossi [2005] suggests that traditional VAR-based test statistics do not yield coherent inferences about statistical significance in case of parameter instability.

[8] The TVP-GC test is implemented using the gcrobustvar command of STATA as provided by

one based on the Schwarz Information Criterion (SIC).

To further study the out-of-sample forecasting capacity of the EMVID index, we utilize a direct multi-step VAR-LP (VAR - Local projections) model with time-varying parameters in conjunction with time-varying parameters, which is estimated via Local Projections. By iterating Eq.(8), y_{t+h} can be projected onto the linear space generated by $(y_{t-1}, y_{t-2}, \ldots, y_{t-p})'$ by means of the following formula:

$$\mathrm{y}_{t+h} = \Phi_{1,t}\mathrm{y}_{t-1} + \Phi_{2,t}\mathrm{y}_{t-2} + \cdots + \Phi_{p,t}\mathrm{y}_{t-p} + \epsilon_{t+h} \tag{10}$$

Now, for h= 1, 5, 22, which represents h-step ahead forecasts i.e. 1-day-ahead, 1-week-ahead and 1-month-ahead forecasts, respectively, we again test the null hypothesis that the lags of EMVID index do not Granger cause the total connectedness of agricultural futures return (alternatively, agricultural sentiment indices or both agricultural sentiment indices & futures return) for a given h - step ahead forecast horizon, where θ_t denotes an appropriate subset of vec $(\Phi_{1,t}, \Phi_{2,t}, \ldots, \Phi_{p,t})$:

$$H_0 : \theta_t = 0, \quad \forall t = 1, 2 \ldots T \tag{11}$$

There are a variety of different approaches to modeling Granger causality in multivariate settings, including the use of directed acyclic graphs (DAGs) where each variable is represented as a node in the Granger network with directed edges signifying a causal relationship [Imbens, 2020]. It has been shown that DAGs can be used to describe causal hypotheses as well as to encode the independence and conditional independence requirements imposed by those hypotheses [Lauritzen and Richardson, 2002]. The PC algorithm is the most often utilized in the DAGs framework since it reduces the amount of conditional independence relations that must be examined, thereby yielding computational efficiency. However, it is very unstable because minor errors in input may produce significant inaccuracies in output. It performs well when

Rossi and Wang [2019]. Following the extant structural break literature, we choose the standard trimming parameter as 0.10 since the potential break dates are usually trimmed to omit the beginning and end of the sample period.

the number of variables is large, and the vanishing partial correlations are "faithful," created by the causal structure. On the other hand, in the case of a VAR with a contemporaneous causal structure, vanishing partial correlations that are "unfaithful" (unrelated to the causal structure) are more likely to be found. Furthermore, DAGs notation depicts relationships as one-way causal chains. The DAGs do not have any cycles. Multiple nodes would be needed to demonstrate reverse causality, most likely with two copies of the same node separated by a time index [Cunningham, 2021]. It is also challenging to deal with simultaneity (as in supply-and-demand models) using DAGs framework [Heckman and Pinto, 2015].

4.3. *Determinants of directional spillovers: Fixed effects panel regression model*

To examine the determinants of the directional spillovers across agricultural commodities, we estimate a panel fixed effect regression of the form:

$$Spillover_{i,t} = \alpha_i + \beta_1' VOL_{i,t} + \beta_2' ADS_t + \beta_3' EMVID_t + \beta_4' EQUITY_t + \beta_5' EPU_t + \beta_6' DXY_t + e_{i,t} \tag{12}$$

where $Spillover_{i,t}$ alternatively represents the total directional connectedness to others (TO) and the total directional connectedness from others (FROM), $VOL_{i,t}$ is 30-day realized volatility, ADS_t is Arouba-Diebold-Scotti business conditions index, $EMVID_t$ is the logarithm of (1+EMVID Index), $EQUITY_t$ is the Bloomberg World agriculture index return, EPU_t is the logarithm of the US economic policy uncertainty and DXY_t denotes the return of US Dollar index. Some heterogeneity between agricultural commodities is introduced through the time-invariant country fixed effects α_i.

5. Results

5.1. *Time-varying connectedness among agricultural commodity returns and sentiments*

To identify the connectedness among agricultural commodity returns and sentiment indices, we first estimate two connectedness networks separately for commodity returns and sentiments. Then we estimate a single aggregate connectedness network that includes both commodity returns and sentiment indices. The return- and sentiment-specific networks allow us to examine closely how agricultural commodity returns interact with one another and how agricultural commodity sentiments interact with one another. Meanwhile, the aggregate connectedness network enables us to identify the interactions between commodity market returns and sentiments.

5.1.1. Return connectedness among agricultural commodities

In this section, we consider the connectedness among agricultural commodity returns by estimating the TVP-VAR connectedness network among our return variables. Figure 1 presents the total spillover index between agricultural commodity returns. The total spillover index ranges from 15% to 40% and is time-varying. We find that the total spillover index experiences an upward trend in 2015, 2019, and early 2020. These increases in total connectedness are driven by the oil price glut in 2015, the U.S.-China trade war in 2019, and the COVID-19 crisis in 2020. These events increase the uncertainty in financial and commodity markets, thereby increasing the contagion among agricultural commodities.

Next, we analyze the pairwise connectedness among agricultural commodities. Table 2 provides the average connectedness network among agricultural commodity returns, which is obtained from averaging the TVP-VAR connectedness networks for all days in our sampling period. The diagonal elements of the table range from 54.79% to 89.79%. This indicates that agricultural commodity returns are mainly driven by their own shocks, while the cross-market spillovers are limited. Most of the cross-market return spillovers are less than 5%, except for the corn, soybean, soybean oil, and wheat returns. Specifically, wheat, soybean, and soybean oil account for 18.26% , 15.37%, and 5.57% of the total variance in corn returns, respectively. While soybean oil receives the largest spillovers from corn and soybean (6.29% and 14.54%), soybean gets the largest amount of spillovers from corn and soybean oil (15.71% and 12.99%). Finally, wheat receives the largest amount of spillovers from corn and soybean (20.55% and 7.25%). One explanation for the larger connectedness among these commodities is that corn and soybean are the primary inputs to the production of biofuel and biodiesel. Moreover, the high connectedness between wheat and corn stems from the fact that both these crops are essential in linking among various crops and between crop and livestock in the agricultural sectors [Westcott and Hoffman, 1999]. Table 2 also shows a significant spillover from soybean oil to palm oil, where soybean oil accounts for 12.11% of the total variance in palm oil returns. Finally, the "Net" connectedness row of the table suggests that corn, soybean, and soybean oil are the net transmitters of shocks while other commodities are the net receivers of shocks.

Figure 2 presents the findings in Table 2 in the form of a network. The size of each node is determined by the absolute values of the net spillovers. Red (green) nodes indicate net transmitters (receivers) of shocks. The thickness of the edges represents the strength of the directional spillovers. The arrows represent the pairwise directions of spillovers between any two commodities. The figure shows that corn, soybean, and soybean oil are the main shock transmitters, while other commodities are shock receivers. In addition, cocoa, coffee, and cattle are the least connected to other commodities. Finally, the figure shows a strong connection among corn, wheat, soybean, and soybean oil.

Figure 1: Time varying total connectedness of agricultural commodity futures returns

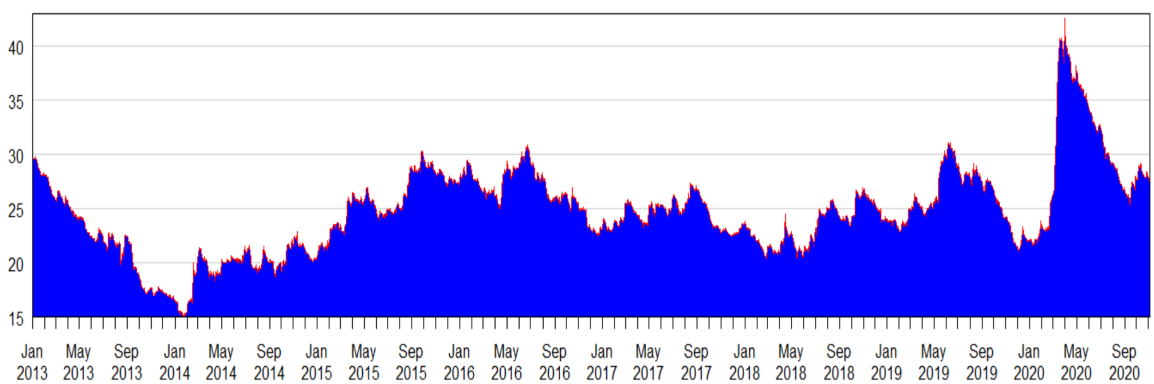
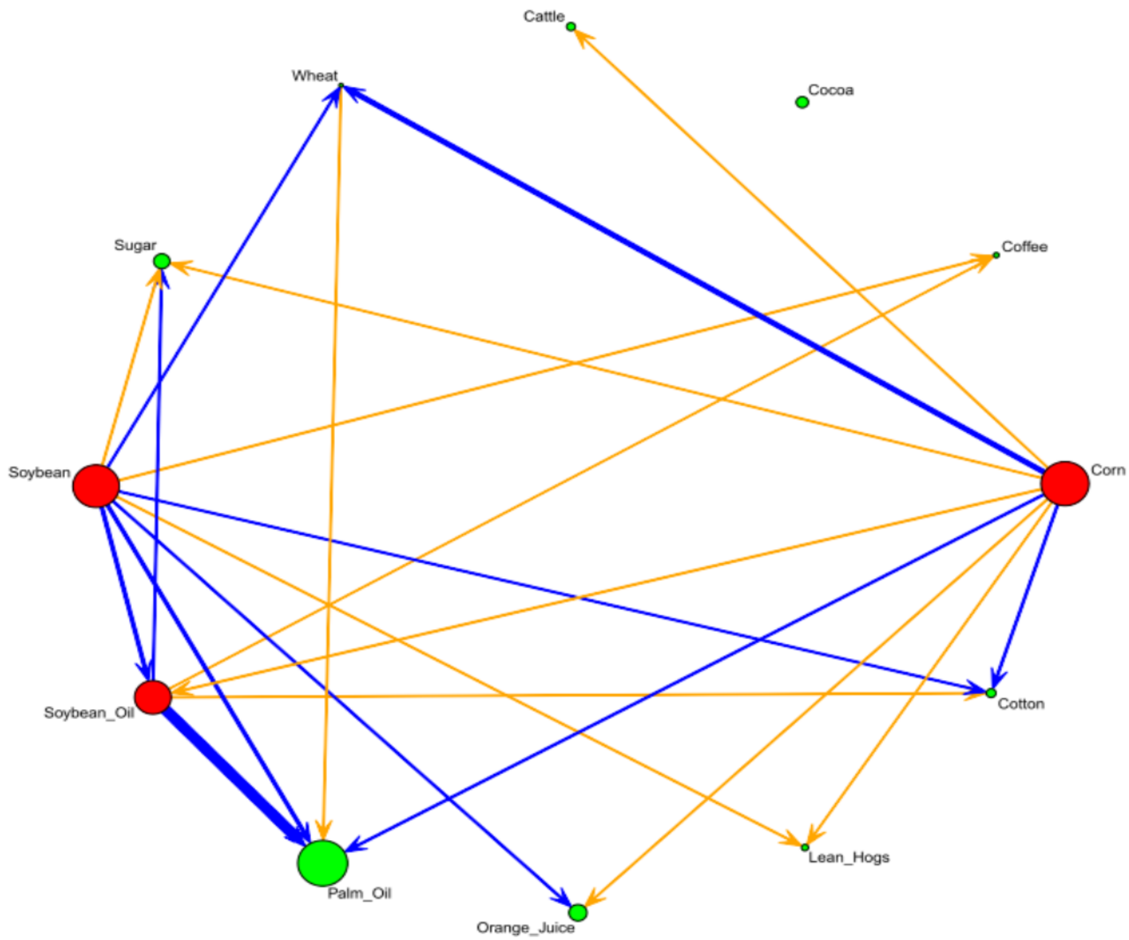


Figure 2: Network of agricultural commodity futures returns



Notes: For the purpose of better visualization, we put a 70% threshold on the edge values after ordering the net directional spillover values from smallest to largest. Put differently, we only visualize the top 30% of the values. Hence, the cut-off point is calculated as 0.04. Accordingly, we only use the edge values greater than 0.04. We also highlight the edges with blue color if the value of the edge is greater than 0.06.

Table 2: Agricultural commodity market futures return connectedness

		1	2	3	4	5	6	7	8	9	10	11	12	From
Cattle	1	87.25	0.74	1.24	1.28	1.04	1.25	0.98	0.93	1.67	1.08	1.10	1.44	1.06
Cocoa	2	0.74	89.21	2.18	0.72	1.12	0.69	0.69	0.91	1.00	0.90	1.04	0.80	0.90
Coffee	3	1.09	1.94	79.28	1.74	1.47	0.79	0.99	1.02	2.79	2.83	4.31	1.75	1.73
Corn	4	0.71	0.42	1.28	53.50	1.98	0.63	0.89	0.55	5.57	15.37	0.86	18.26	3.87
Cotton	5	0.85	1.03	1.57	2.92	82.18	0.46	1.05	0.74	2.68	3.31	1.35	1.85	1.48
Lean_Hogs	6	1.22	0.54	0.77	1.16	0.48	89.79	0.47	1.11	0.88	1.76	0.88	0.94	0.85
Orange_Juice	7	1.09	0.77	1.17	1.48	1.29	0.54	87.76	0.74	0.94	1.88	0.85	1.48	1.02
Palm_Oil	8	1.28	0.62	1.05	1.45	1.08	1.24	0.71	76.03	12.11	2.64	0.58	1.22	2.00
Soybean_Oil	9	1.43	0.79	2.28	6.29	2.01	0.60	0.65	6.82	60.22	14.54	1.27	3.11	3.31
Soybean	10	0.75	0.40	2.12	15.71	2.54	1.11	1.01	1.14	12.99	54.79	0.98	6.47	3.77
Sugar	11	1.11	0.92	4.53	1.47	1.41	0.93	0.75	0.82	2.05	1.63	82.86	1.52	1.43
Wheat	12	0.97	0.55	1.59	20.55	1.75	0.78	0.97	0.62	3.39	7.25	1.14	60.45	3.30
To		0.94	0.73	1.65	4.56	1.35	0.75	0.76	1.28	3.84	4.43	1.20	3.24	24.72
Net		-0.13	-0.17	-0.08	0.69	-0.14	-0.10	-0.26	-0.71	0.52	0.67	-0.23	-0.06	

Note: The rows and columns are numbered from 1 to 12, each of which corresponds to the variable listed in the left-hand side of the table. The table cells are the average spillovers from the column to the row variables, where diagonal elements indicate own-variable spillovers. The column "From" indicates the average spillovers from all other variables to the row variable, while the column "To" indicates the average spillovers from the column variable to all other variables. Finally, the row "Net" captures the net spillovers, which identifies whether a variable is a net transmitter or receiver of shocks.

5.1.2. Connectedness among agricultural commodity sentiments

In this section, we consider the connectedness among agricultural commodity sentiment indices by estimating the TVP-VAR connectedness network among our sentiment variables. Figure 3 presents the total spillover index among agricultural commodity sentiments. We find that the total spillover among the sentiment variables ranges from 10% to 20%, and the average total sentiment spillover index is 13.96%. In addition, the total sentiment spillover index peaks in 2015, 2019, and 2020, which is similar to our findings in section 5.1.1.

Table 3 presents the average connectedness network among agricultural commodity sentiments, which is calculated by averaging the daily TVP-VAR connectedness networks. Note that the diagonal elements of the table are all larger than 80%, which suggests that own-market sentiments explain the majority of sentiments in each market. On the other hand, cross-market sentiment spillovers are more limited (less than 5%). The low cross-market sentiment spillovers in the agricultural commodity market could suggest that investors view these markets separately from one another. Therefore, their sentiments toward one market are less likely to influence their sentiments toward other markets.

Figure 4 presents the network of sentiment spillovers. Soybean, wheat, cocoa, coffee, and corn sentiments are the main transmitters of shocks, while other market sentiments are the main receiver of shocks. The strongest directional spillovers are from soybean sentiment to soybean oil, wheat, cotton, lean hogs, and palm oil, from wheat and cattle to sugar and from corn to cotton. Moreover, orange juice sentiments are the least connected to other market sentiments, as indicated by the small number of connections to and from orange juice sentiments in Figure 4.

In summary, our findings so far show that the connectedness among agricultural returns and sentiments is time-varying. However, the pattern of spillovers is different between return and sentiment connectedness. We find that the total sentiment spillover index tends to be lower than the total return spillover index. This has several implications. First, it suggests that investors view agricultural commodity markets as separate from one another, and hence, sentiments in one market are less likely to spill over to other market sentiments. Second, sentiment spillovers may underestimate the actual return spillovers among agricultural commodities. Therefore, when making investment decisions, investors in agricultural commodities should rely on the analyses of the return relationships among agricultural commodities in addition to analyzing the impact of market sentiments.

Figure 3: Time varying total connectedness of agricultural commodity sentiments

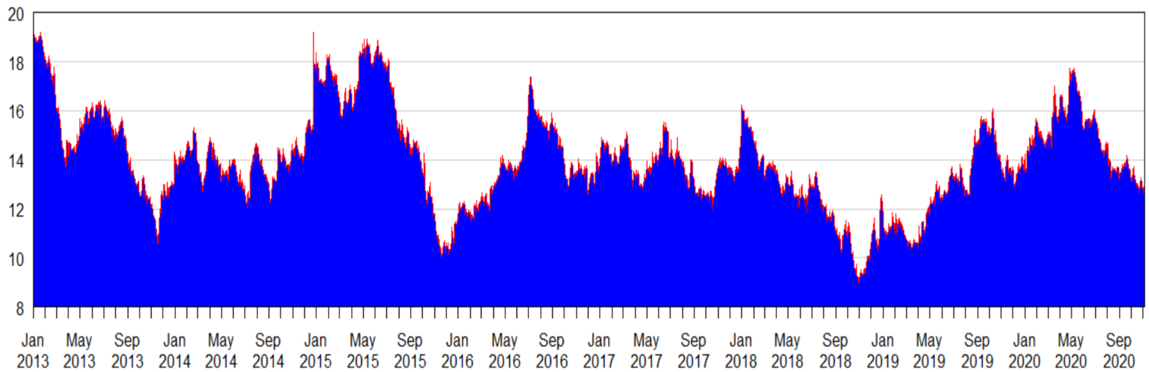
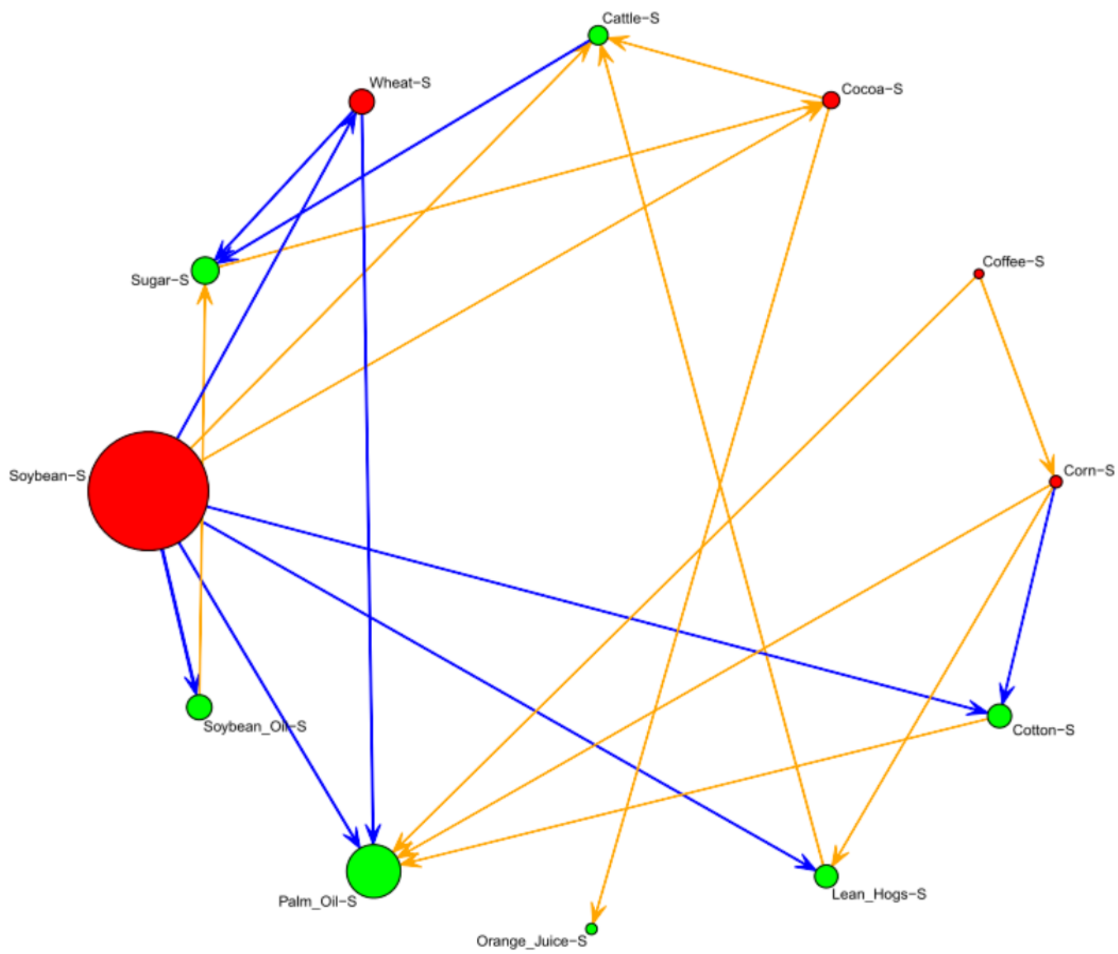


Figure 4: Network of agricultural commodity market sentiment



Notes: See notes to Fig. 2. The level corresponding to 70% threshold is calculated as 0.02. Accordingly, we only use the edge values bigger than 0.02. We also highlight the edges with blue color if the value of the edge is greater than 0.04.

Table 3: Agricultural commodity market sentiment connectedness

		1	2	3	4	5	6	7	8	9	10	11	12	From
Cattle-S	1	87.23	1.51	1.29	0.73	0.82	1.75	0.87	1.34	1.09	1.39	0.99	1.00	1.06
Cocoa-S	2	1.14	86.96	1.21	0.66	1.60	0.73	1.93	1.31	0.65	1.55	1.05	1.21	1.09
Coffee-S	3	1.46	1.16	88.53	0.93	0.80	0.97	0.85	0.75	1.13	1.00	1.21	1.21	0.96
Corn-S	4	0.71	0.89	1.37	82.72	0.86	1.13	0.75	0.94	1.45	4.69	1.06	3.45	1.44
Cotton-S	5	0.99	1.54	0.72	1.35	88.13	0.65	1.20	0.87	0.88	1.53	1.05	1.10	0.99
Lean_Hogs-S	6	1.31	0.97	0.82	1.47	0.71	88.46	0.79	1.17	0.64	1.89	0.53	1.24	0.96
Orange_Juice-S	7	1.00	2.30	0.67	0.84	1.03	0.57	89.19	0.81	0.71	0.86	0.81	1.21	0.90
Palm_Oil-S	8	1.11	1.20	1.03	1.24	1.18	1.17	0.86	84.43	2.76	2.08	1.14	1.81	1.30
Soybean_Oil-S	9	0.90	0.92	1.38	1.34	0.82	0.74	0.67	2.84	83.72	4.37	1.18	1.11	1.36
Soybean-S	10	1.02	1.27	1.06	4.62	1.00	1.32	0.77	1.42	3.31	81.00	0.91	2.31	1.58
Sugar-S	11	1.62	0.69	0.95	1.23	0.95	0.61	0.57	1.00	1.53	1.15	88.29	1.39	0.98
Wheat-S	12	0.81	1.21	1.31	3.33	1.23	1.04	1.14	1.15	1.20	2.91	0.78	83.88	1.34
To		1.01	1.14	0.98	1.48	0.92	0.89	0.87	1.13	1.28	1.95	0.89	1.42	13.96
Net		-0.06	0.05	0.03	0.04	-0.07	-0.07	-0.03	-0.17	-0.08	0.37	-0.08	0.08	

Note: See notes to table 2

5.1.3. Connectedness among returns and sentiments

Next, we consider the connectedness between agricultural commodity returns and sentiments. We do this by estimating a single aggregate connectedness network that includes both returns and sentiment variables. The total spillover index, presented in Figure 5, range between 25 and 40%, with peaks around the same time as in Figures 1-3. [9]

Table 4 summarizes the connectedness network among returns and sentiments, which is obtained by averaging the daily connectedness networks throughout the sampling period. The upper-left and lower-right quadrants of the table capture the connectedness among returns and among sentiments separately. The diagonal elements of these quadrants represent own-variable spillovers, and the off-diagonal elements of these quadrants represent cross-variable spillovers. Consistent with our findings in sections 5.1.1-5.1.2, we find that the largest return spillovers are among corn, soybean and soybean oil returns. In addition, the majority of the total variance in sentiments are explained by own-variable shocks instead of cross-variable shocks.

The lower-left quadrant of Table 4 summarizes the spillover indexes from agricultural commodity returns to sentiments. The diagonal elements of this quadrant capture spillovers from returns to sentiments in the same market, while the off-diagonal elements capture cross-market spillovers. First, the diagonal elements tend to be the largest in each row and column. This means that commodity market returns contribute the largest amount to their own market sentiments. The own market spillovers from returns to sentiments are largest for soybeans (10.43%), palm oil (7.13%), wheat (6.68%), soybean oil (6.10%), and corn (5.61%). In contrast, the spillovers from one market's returns to another market's sentiments tend to be small.

The upper-right quadrant of Table 4 summarizes the spillover indexes from agricultural commodity sentiments to returns, with the diagonal elements capturing

[9] As a robustness check, we calculate the total connectedness index using the approach developed by Diebold and Yilmaz [2009], which is based on the constant parameter VAR model. Figure A5 in the Appendix shows that although there are some differences between total connectedness indices from both approaches, they are in general move together and capture the structural break points well. However, as pointed out by Diebold and Yilmaz [2012], the method of Diebold and Yilmaz [2009] depends on the Cholesky-factor identification of VARs hence the resulting variance decomposition relies on the variable ordering.

spillovers in the same market and the off-diagonal elements capturing cross-market spillovers. Similar to our findings above, the spillovers from sentiments to returns are mostly contained within each market since the diagonal elements are the largest components in each row and column. Moreover, we find that the diagonal elements in the upper right quadrant tend to be smaller than their corresponding diagonal elements in the lower left quadrant. Thus, for each commodity market, the spillovers from returns to sentiments are larger than the spillovers in the opposite directions.

Figure 6 presents the connectedness network among agricultural commodity returns and sentiments. First, this figure shows that corn returns, soybean oil returns, soybean returns, and wheat returns are the main transmitters of shocks to other market returns and sentiments. Second, orange juice sentiments and sugar sentiments are the least connected to other market returns and sentiments. Finally, the spillovers from returns to sentiments tend to be stronger when the returns and sentiments considered are from the same market.

In the Appendix, we plot the time-varying net connectedness of agricultural commodity market returns and sentiments derived from the aggregate TVP-VAR connectedness model for all commodities returns and sentiments. These figures show that returns in the corn, soybean oil, soybean, and wheat markets tend to have positive net directional connectedness, suggesting that these market returns are the net shock transmitters. On the other hand, the net return connectedness in other markets tends to alternate between positive and negative values. Finally, net directional spillover of sentiment indices tends to be negative throughout the sampling period. This implies that the directional spillovers from returns to sentiments are stronger than those in opposite directions. Note that the absolute values of the net connectedness tend to increase at the beginning of 2020, which suggests the increasing spillover effects in agricultural commodity markets during the COVID-19 pandemic. We will explore this point in more detail in the following sections.

Figure 5: Time varying total connectedness of agricultural commodities futures returns and sentiments

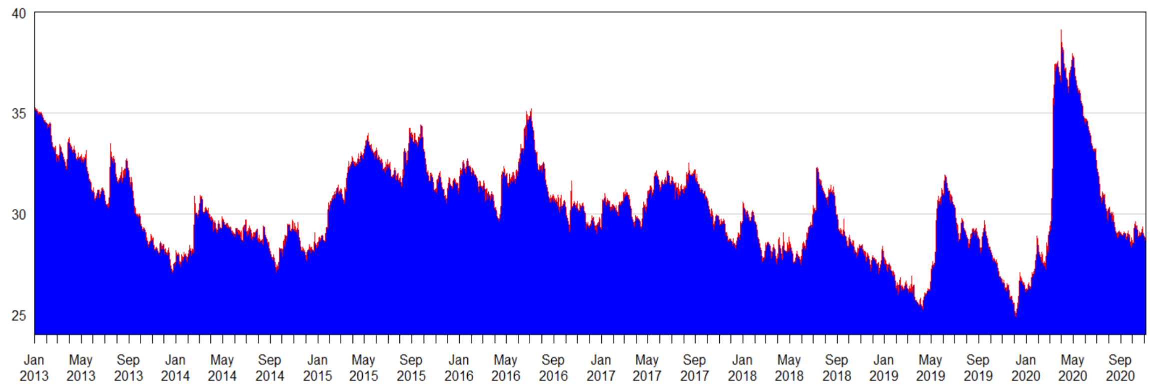
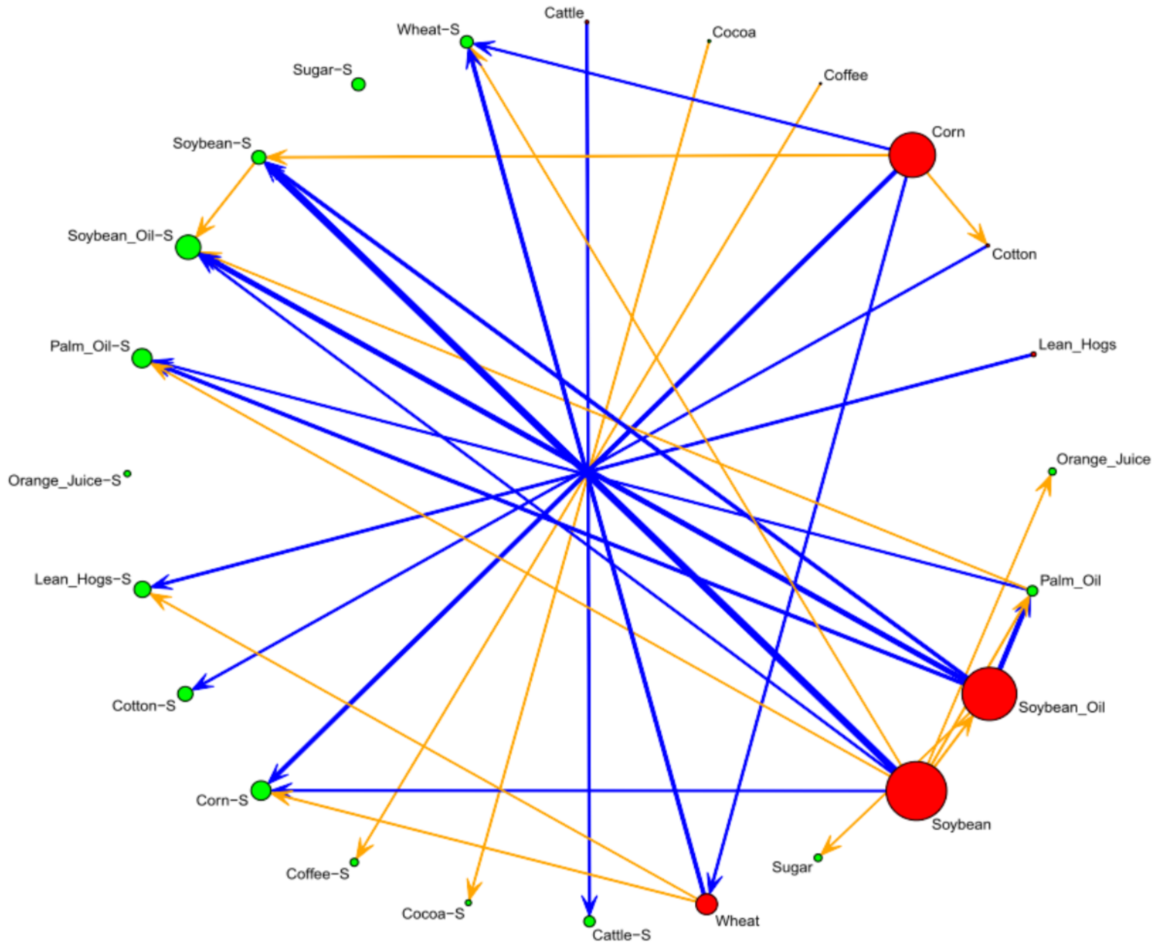


Table 4: Agricultural commodity market futures return and sentiment connectedness

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	From
Cattle	1	78.55	0.68	1.12	1.19	0.97	1.12	0.88	0.81	1.54	0.97	1.11	1.29	1.27	0.43	0.87	0.73	0.63	1.01	0.92	0.90	0.65	1.12	0.53	0.72	0.89
Cocoa	2	0.67	78.47	1.97	0.63	0.97	0.60	0.62	0.89	0.95	0.80	0.88	0.77	0.61	3.37	0.66	0.63	0.60	0.42	0.93	0.79	0.98	0.88	1.03	0.88	0.90
Coffee	3	1.02	1.81	71.33	1.57	1.29	0.72	0.92	0.86	2.57	2.53	3.95	1.57	0.58	1.20	1.17	1.09	0.62	0.55	0.47	0.59	1.02	1.19	0.66	0.72	1.19
Corn	4	0.64	0.43	1.15	48.38	1.85	0.59	0.78	0.50	5.08	14.11	0.83	16.53	0.40	0.57	0.66	2.02	0.47	0.46	0.38	0.44	0.46	1.31	0.36	1.56	2.15
Cotton	5	0.78	0.97	1.42	2.71	74.14	0.43	1.01	0.67	2.30	3.01	1.23	1.66	0.75	0.75	0.83	0.76	0.82	0.78	0.51	0.62	0.82	1.26	0.82	0.93	1.08
Lean_Hogs	6	1.09	0.46	0.68	1.09	0.43	79.82	0.43	1.10	0.76	1.60	0.81	0.92	0.95	0.78	0.93	1.05	0.70	2.06	0.96	0.92	0.60	0.77	0.54	0.56	0.84
Orange_Juice	7	1.04	0.74	1.07	1.29	1.16	0.50	78.96	0.68	0.98	1.76	0.78	1.25	0.73	0.82	0.67	0.82	0.58	0.67	1.46	0.85	0.92	0.87	0.68	0.72	0.88
Palm_Oil	8	1.02	0.54	0.87	1.23	0.88	1.11	0.62	63.59	9.72	2.29	0.55	1.05	0.58	0.83	0.57	0.97	0.58	0.67	0.48	5.49	2.76	1.90	0.66	1.05	1.52
Soybean_Oil	9	1.21	0.71	2.03	5.51	1.65	0.51	0.64	5.60	52.67	12.72	1.08	2.69	0.74	0.54	0.43	0.93	0.44	0.65	0.65	1.90	1.57	3.06	0.65	1.43	1.97
Soybean	10	0.61	0.37	1.85	14.14	2.25	0.98	0.91	1.02	11.50	48.60	0.83	5.77	0.51	0.50	0.61	1.38	0.40	0.54	0.36	0.66	0.78	4.10	0.43	0.89	2.14
Sugar	11	1.02	0.82	4.13	1.40	1.21	0.90	0.72	0.83	1.84	1.48	74.14	1.26	0.71	1.09	0.74	0.64	0.59	0.76	0.94	0.71	0.94	1.24	1.30	0.59	1.08
Wheat	12	0.84	0.55	1.42	18.37	1.53	0.70	0.82	0.53	3.01	6.53	0.91	53.83	0.60	0.65	0.75	1.53	0.51	0.37	0.45	0.58	0.39	1.21	0.42	3.49	1.92
Cattle-S	13	3.18	0.71	0.58	0.75	0.79	1.37	0.63	0.58	0.84	0.88	0.84	0.80	77.26	1.20	1.11	0.62	0.73	1.52	0.74	1.10	0.90	1.11	0.88	0.88	0.95
Cocoa-S	14	0.53	4.48	1.13	0.74	0.92	0.70	1.16	0.76	0.66	0.82	0.85	0.96	1.01	75.01	1.05	0.61	1.35	0.62	1.59	1.19	0.56	1.43	0.90	0.97	1.04
Coffee-S	15	1.23	0.73	2.12	0.88	0.66	1.21	0.60	0.94	0.81	0.95	1.12	1.02	1.24	1.00	77.78	0.89	0.72	0.78	0.73	0.69	1.00	0.90	0.99	1.02	0.93
Corn-S	16	0.57	0.84	1.29	5.61	0.89	0.90	0.91	0.89	1.66	2.92	0.64	2.73	0.62	0.80	1.18	65.96	0.73	0.80	0.56	0.73	1.09	4.18	0.89	2.62	1.42
Cotton-S	17	1.07	0.71	0.71	0.78	2.54	0.75	0.70	0.61	0.64	0.83	0.45	0.98	0.94	1.42	0.70	1.31	78.24	0.62	1.12	0.83	0.81	1.36	0.95	0.94	0.91
Lean_Hogs-S	18	1.07	0.51	0.81	0.85	0.88	4.41	0.66	0.65	1.03	1.27	0.66	1.25	1.10	0.76	0.69	1.16	0.61	76.33	0.68	1.07	0.65	1.49	0.47	0.93	0.99
Orange_Juice-S	19	0.65	0.64	0.68	0.71	0.72	1.08	1.94	0.60	0.93	0.60	0.77	0.66	0.84	1.93	0.62	0.70	0.92	0.56	80.54	0.76	0.56	0.76	0.78	1.04	0.81
Palm_Oil-S	20	0.94	0.57	0.58	0.76	0.63	0.91	0.70	7.13	4.88	1.53	0.69	0.96	0.92	1.06	0.93	0.93	0.95	0.99	0.75	67.81	1.67	1.32	0.88	1.52	1.34
Soybean_Oil-S	21	0.64	0.74	0.94	1.22	1.22	0.61	0.64	3.72	6.10	2.45	0.74	0.81	0.72	0.75	1.21	1.11	0.82	0.71	0.52	1.75	67.98	2.98	0.80	0.85	1.33
Soybean-S	22	1.04	0.69	1.16	2.74	1.49	0.77	0.79	1.51	6.09	10.43	1.05	1.39	0.72	0.89	0.92	3.46	0.82	0.99	0.62	0.81	1.91	57.48	0.67	1.55	1.77
Sugar-S	23	0.92	1.00	0.91	0.80	1.19	0.52	0.77	0.80	1.16	0.95	1.73	0.82	1.52	0.64	0.83	1.12	0.81	0.49	0.50	0.87	1.22	0.91	78.32	1.20	0.90
Wheat-S	24	0.90	0.85	0.67	3.23	0.86	0.52	0.53	0.94	1.86	1.68	0.61	6.68	0.68	0.91	1.20	2.45	0.93	0.69	0.86	0.89	0.85	2.16	0.66	68.39	1.32
To		0.94	0.86	1.22	2.84	1.12	0.91	0.77	1.36	2.79	3.05	0.96	2.24	0.78	0.95	0.81	1.12	0.68	0.74	0.72	1.05	0.96	1.56	0.71	1.13	30.27
Net		0.05	-0.04	0.03	0.69	0.05	0.07	-0.11	-0.16	0.82	0.90	-0.12	0.32	-0.17	-0.09	-0.12	-0.30	-0.23	-0.25	-0.09	-0.29	-0.37	-0.21	-0.20	-0.19	

Note: See notes to Table 2

Figure 6: Network of agricultural commodity market futures returns and sentiments



Notes: See notes to Fig. 2. The level corresponding to 90% threshold is computed as 0.03. Accordingly, we only use the edge values bigger than 0.03. We also highlight the edges with blue color if the value of the edge is greater than 0.06.

5.2. *Time-varying Granger causality between agricultural commodities and COVID-19*

In summary, our results of the TVP-VAR connectedness models indicate that the connectedness among agricultural commodity returns and sentiments varies over time and across individual commodity markets. A common theme in all our connectedness models is that the spillover effects in agricultural commodity markets tend to increase at the beginning of 2020, at the onset of the COVID-19 pandemic. To further investigate this point, we employ the time-varying Granger causality test of Rossi and Wang [2019] to test the causal effects between COVID-19 induced uncertainty and the returns and sentiments connectedness in the agricultural commodity market.

The TVP-GC test results are presented in Table 5. For all cases, regardless of the test-statistic considered (ExpW, MeanW, Nyblom, SupLR), there exists a consensus among findings that the EMVID index Granger-causes the connectedness of agricultural commodities and their sentiment when time-varying instabilities are considered. In other words, the null hypothesis of the robust Granger causality test can be rejected at the 1% significance level. This implies that the EMVID index has predictive power for the connectedness of the agricultural market and their sentiments even if we control for the macroeconomic conditions and economic policy uncertainty. Figure 7 plots the Wald test statistics of the Granger causality tests between the COVID-19 induced uncertainty and total return connectedness (figure 1), total sentiment connectedness (figure 3) and total return and sentiment connectedness (figure 5). The results show that the causal relationship from the COVID-19 induced uncertainty to agricultural commodity returns and sentiments significantly strengthens around March 2020. This corresponds to the WHO's declaration of a global COVID-19 pandemic and the implementation of travel restrictions and lockdowns in many countries all over the world. The uncertainty associated with these events leads to increasing contagion among financial markets. While the causal link between COVID-19 uncertainty and agricultural commodity returns weakens toward the end of the sampling period, the causal link between COVID-19 uncertainty and sentiments remains strong. This suggests that the COVID-19 induced uncertainty has a more lingering effect on investor sentiment than on commodity returns in the agricultural commodity markets. This highlights the importance of complementing the analysis of market sentiments with an analysis of the actual price movements when making investment decisions in the agricultural commodity market.

Our findings also include robust Granger causality tests based on direct multi-step VAR-LP forecasting over short (1-day), medium (1-week), and long (1-month) horizons to examine whether the EMVID index has an informative value in predicting the return connectedness of agricultural commodities and their sentiments. Since it permits heteroskedastic and serially correlated idiosyncratic shocks in the VAR model to consider unstable patterns in the variables during the highly volatile episodes, the VAR-LP model is chosen as a basis for the analysis [Jordà, 2005]. The results in Table 6 show that the EMVID index has a stronger predictive ability for future return dynamics of agricultural commodities and their sentiments. There might be several underlying mechanisms both from the supply and demand view to explain the predictive power of COVID-19-related uncertainty in the agricultural commodity market. Due to the abrupt restriction of movement across borders and within countries, the significant slowdown during the COVID-19 pandemic affected the countries where the agriculture-food industry heavily relies upon seasonal migrant workers. This has resulted in labor shortages, which in turn have influenced food supply and pricing internationally. On the other hand, a sudden drop in family incomes due to the pandemic has led to a decrease in gross calorie demand, particularly in low- and middle-income countries (LDC), and put downward pressure on agricultural prices and production.

Table 5: Time-varying Granger causality test results

	ExpW	MeanW	Nyblom	SupLR
EMVID → Return TCI	249.4	100.6	567.8	509.4
	(0.000)	(0.000)	(0.000)	(0.000)
EMVID → Sentiment TCI	218.2	142.5	225.6	446.1
	(0.000)	(0.000)	(0.000)	(0.000)
EMVID → All TCI	223.6	84.3	333.8	457.8
	(0.000)	(0.000)	(0.000)	(0.000)

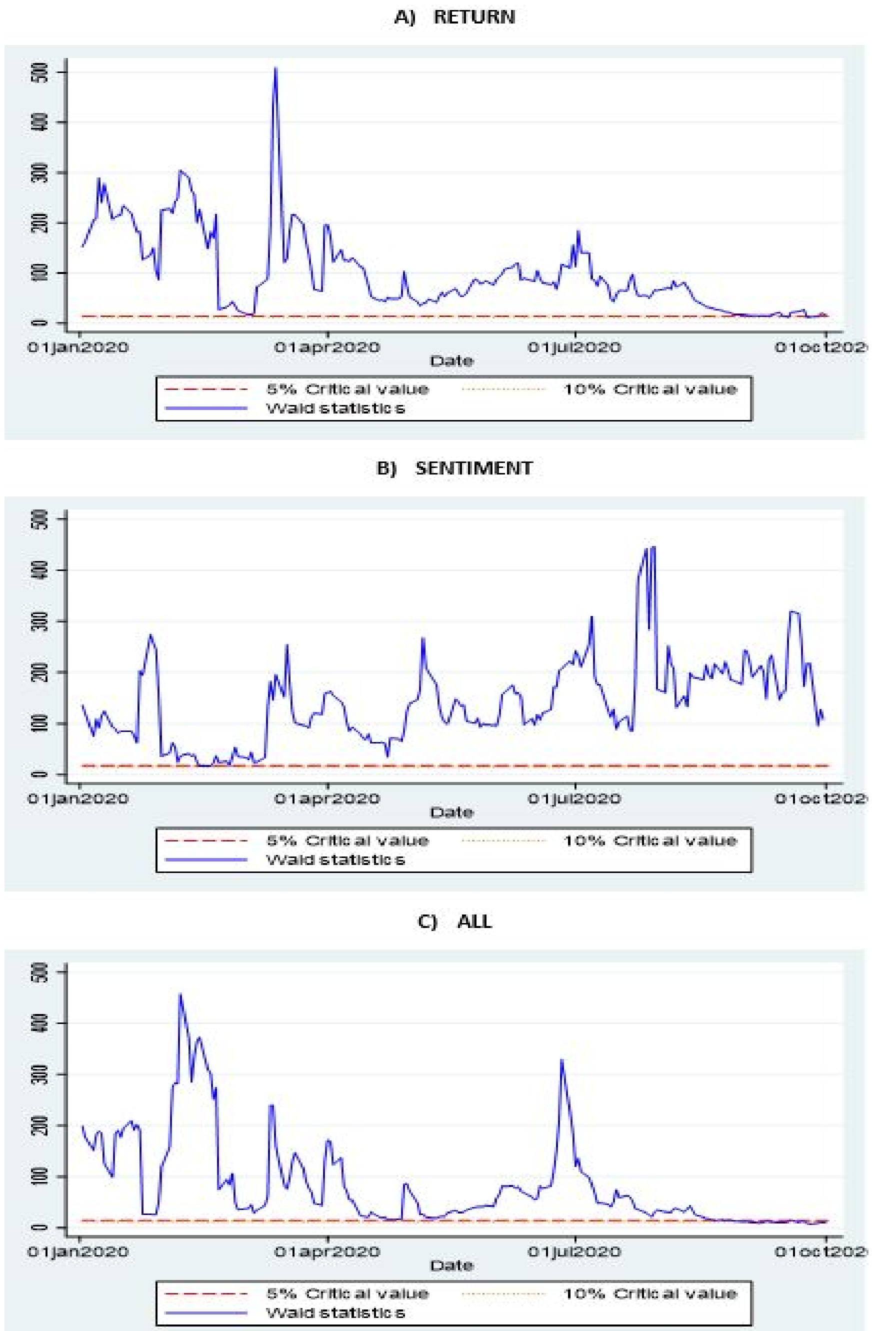
Note: The table presents the test statistics based on time-varying robust Granger causality test of Rossi and Wang [2019]. The corresponding p-values are reported in parenthesis. ***, **, and * denote 1%, 5%, and 10% statistical significance levels, respectively.

5.3. *Determinants of directional spillovers*

In this section, we further explore the determinants of directional spillovers in the agricultural commodity market using a panel regression approach, as described in Section 4.3. Table 7 presents our estimation results. Columns (1) and (2) present the estimation results for the return spillover indexes. Columns (3) and (4) present the results for the sentiment spillover indexes. Columns (5) and (6) present the results for a panel that includes both return and sentiment spillover indexes.

The table shows that the financial market volatility significantly influences the connectedness in agricultural commodity markets, COVID-19 induced uncertainty, and economic policy uncertainty. Specifically, a 1% increase in the realized volatility index increases the "TO" and "FROM" return connectedness by 9.060% and 11.006%, respectively. Similarly, a 1% increase in the realized volatility index increases the 'TO" and "FROM" sentiment connectedness by 3.617% and 7.499%, respectively. These results suggest that the realized volatility exhibits a larger influence on the "FROM" connectedness, which is the amount of shocks each commodity receives from other variables. In contrast, the impact of realized volatility on the "TO" connectedness, which captures the amount of shocks each commodity transmits to other variables, is smaller but still statistically significant. Similar conclusions can be reached when we consider the impact of the COVID-19 induced uncertainty (EMVID) and the EPU indexes on the return and sentiment connectedness. However, the

Figure 7: Time-varying Granger causality test - Wald statistics



Notes: The blue line depicts the time-varying Wald statistics based on time-varying robust Granger causality test of Rossi and Wang [2019], testing whether the lags of EMVID index do not Granger cause the total connectedness of agricultural futures return (alternatively, agricultural sentiment indices or both agricultural sentiment indices & futures return). The dotted red line show the critical test statistics.

Table 6: VAR-LP forecasting results

	ExpW	MeanW	Nyblom	SupLR
		1-day		
EMVID → Return TCI	249.39	138.02	1684.90	509.29
	(0.000)	(0.000)	(0.000)	(0.000)
EMVID → Sentiment TCI	487.8	203.0	249.6	986.1
	(0.000)	(0.000)	(0.000)	(0.000)
EMVID → All TCI	165.3	118.8	1389.2	341.2
	(0.000)	(0.000)	(0.000)	(0.000)
		1- week		
EMVID → Return TCI	378.8	216.7	2514.9	768.1
	(0.000)	(0.000)	(0.000)	(0.000)
EMVID → Sentiment TCI	553.6	194.9	231.7	1117.7
	(0.000)	(0.000)	(0.000)	(0.000)
EMVID → All TCI	452.2	218.9	2035.5	914.9
	(0.000)	(0.000)	(0.000)	(0.000)
		1- month		
EMVID → Return TCI	662.0	376.1	3219.4	1775.6
	(0.000)	(0.000)	(0.000)	(0.000)
EMVID → Sentiment TCI	1650.5	632.4	215.5	2899.3
	(0.000)	(0.000)	(0.000)	(0.000)
EMVID → All TCI	583.2	322.2	1617.4	3079.5
	(0.000)	(0.000)	(0.000)	(0.000)

Note: Entries reports test statistics based on time-varying robust Granger causality test of Rossi and Wang [2019], which is based on the VAR-LP forecasting model. The corresponding p-values are given in parenthesis. We assume heteroskedastic and serially correlated idiosyncratic shocks. ***, **, and * denote 1%, 5%, and 10% statistical significance levels, respectively.

magnitudes of the coefficients on the EMVID and EPU indexes are smaller compared to those on the VOL index.

With respect to the marginal impact of the Arouba-Diebold-Scotti business conditions (ADS) index, we find that an increase in the ADS index lowers the returns and sentiment connectedness in agricultural commodity markets. Thus, as business conditions improve, shocks are less contagious in agricultural commodity markets, which reduces the level of connectedness. Finally, our results show that the impact of the EQUITY and DXY indexes are statistically insignificant.

Table 7: Determinants of connectedness: fixed effects panel regression results

	RETURN		SENTIMENT		ALL	
	TO (1)	FROM (2)	TO (3)	FROM (4)	TO (5)	FROM (6)
ADS	-0.020***	-0.022***	-0.004***	-0.002***	-0.004***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
EQUITY	0.003	0.002	0.003	0.001	0.001	0.001
	(0.004)	(0.004)	(0.003	(0.003)	(0.002)	(0.001)
DXY	0.012	-0.014	0.003	-0.009	-0.007	-0.011**
	(0.016)	(0.016)	(0.012)	(0.011)	(0.006)	(0.005)
VOL	9.060***	11.006***	3.617***	7.499***	1.586***	5.399***
	(0.481)	(0.466)	(0.405)	(0.378)	(0.203)	(0.167)
EMVID	0.255***	0.351***	0.049***	0.042***	0.008**	0.016***
	(0.009)	(0.009)	(0.007)	(0.007)	(0.004)	(0.003)
EPU	-0.009	0.083***	0.028***	0.049***	0.007	0.034***
	(0.013)	(0.012)	(0.009)	(0.009)	(0.005)	(0.004)
C	1.873***	1.644***	1.151***	0.945***	1.224***	1.107***
	(0.024)	(0.023)	(0.018)	(0.017)	(0.009)	(0.008)
R^2	0.81	0.84	0.30	0.28	0.75	0.79
F-statistic	6227.4	7780.8	626.5	572.7	5034.7	6671.1
Prob. F-statistic	0.00	0.00	0.00	0.00	0.00	0.00
Observations	24564	24564	24564	24564	24564	24564

Note: Standard errors in parentheses; *, **, ***: Significant at 10, 5, 1% significant levels.

6. Conclusion

This study examines the connectedness and directional spillovers among global agricultural commodity futures market returns and sentiments. We construct a dynamic time-varying connectedness network for agricultural commodity returns and sentiments. Next, we employ a time-varying Granger causality model to identify the causal relationship between the return-sentiment connectedness in agricultural commodity markets and the COVID-19 pandemic uncertainty. Furthermore, we use panel data regressions to evaluate whether the connectedness among these commodities and their corresponding sentiment is influenced by economic and financial uncertainty, and other macroeconomic variables, in addition to the global COVID-19 pandemic. We find that the connectedness among agricultural returns and sentiments is time-varying. Moreover, this connectedness strengthens significantly after the commodity market financialization and during the COVID-19 pandemic. We find that the COVID-19 induced uncertainty significantly impacts agricultural commodity markets, especially during the early phase of the pandemic in 2020. Finally, economic policy and financial market uncertainty also substantially influence the spillovers between agricultural commodity returns and sentiments.

Our results provide valuable insights for portfolio managers by identifying the potential spillover drivers of agricultural commodity returns and sentiments, further guiding their investment decisions. For example, they might invest in commodity pairs that are unlikely to spill over to each other to diversify their portfolio risks. Alternatively, they may group strongly connected agricultural commodities such as corn, wheat, soybean, and soybean oil to gain speculative profits during the bullish market times. Note that these strategies need to be constantly monitored, as our empirical evidence shows that the spillover patterns within the commodity market are variable over time.

Our findings also have important policy implications, particularly due to the increasing financialization of the agricultural commodity markets in recent years. Considering that agricultural commodities have a significant pass-through to food price inflation in many countries [Abbas and Lan, 2020] via the economic activity and international trade channels, monitoring the connectedness of agricultural commodities and investor sentiment enables policymakers to find the appropriate policy response for price stabilization. For instance, policymakers can incorporate investor sentiment into the design of agricultural subsidy programs and import taxes to effectively lower the effect of global agricultural commodity market fluctuations on domestic food inflation.

Given the increasing tendency for trade protectionism policies and trade tensions in the global markets, especially the US-China trade war, it would be interesting to investigate how geopolitical risks and increasing trade uncertainty in some countries affect the sentiment and return dynamics in the agricultural commodity market. We leave the exploration of this issue to future research.

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Appendix

Figure A1: Net Connectedness Measures for all futures and sentiments

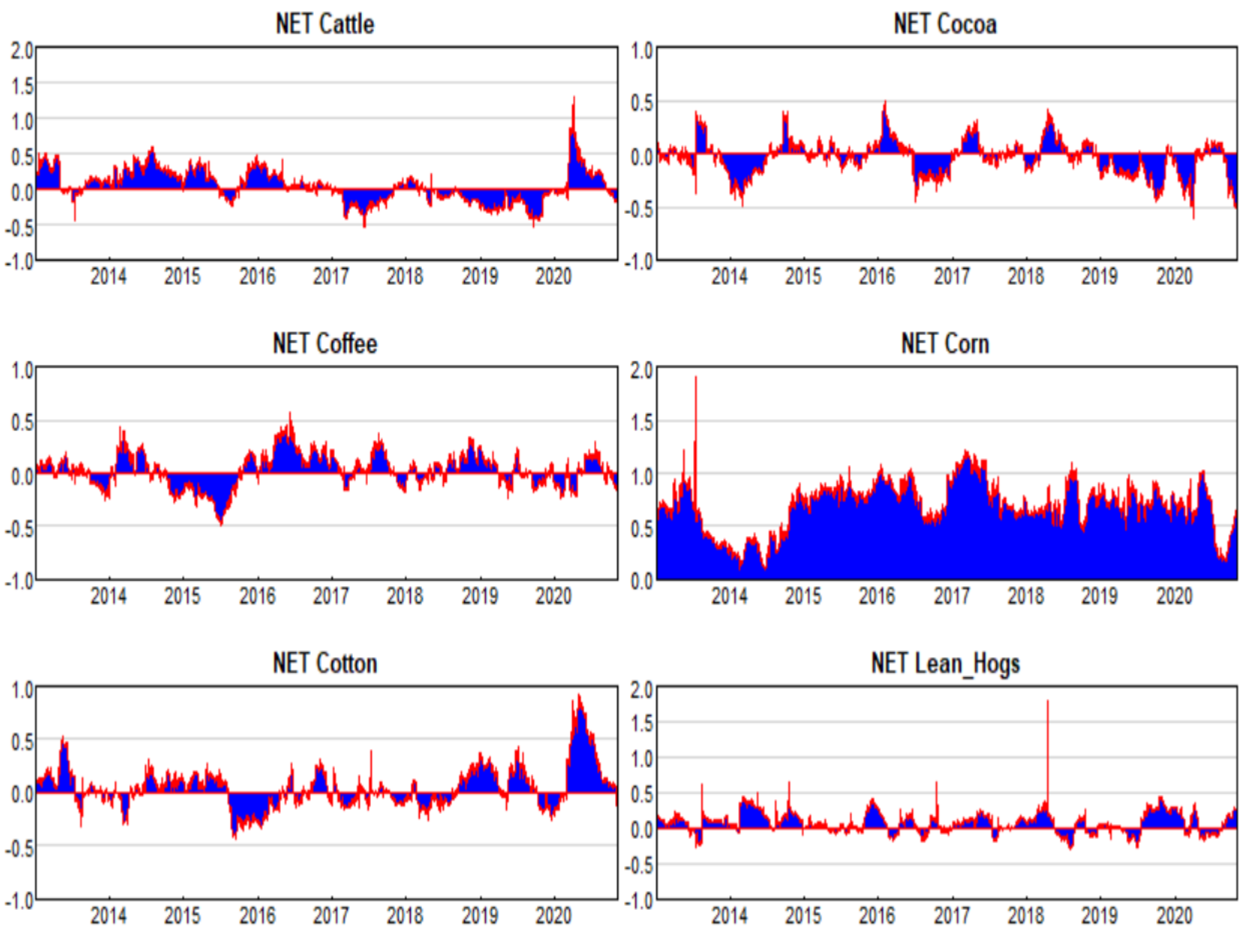

Figure A2: Net Connectedness Measures for all futures and sentiments

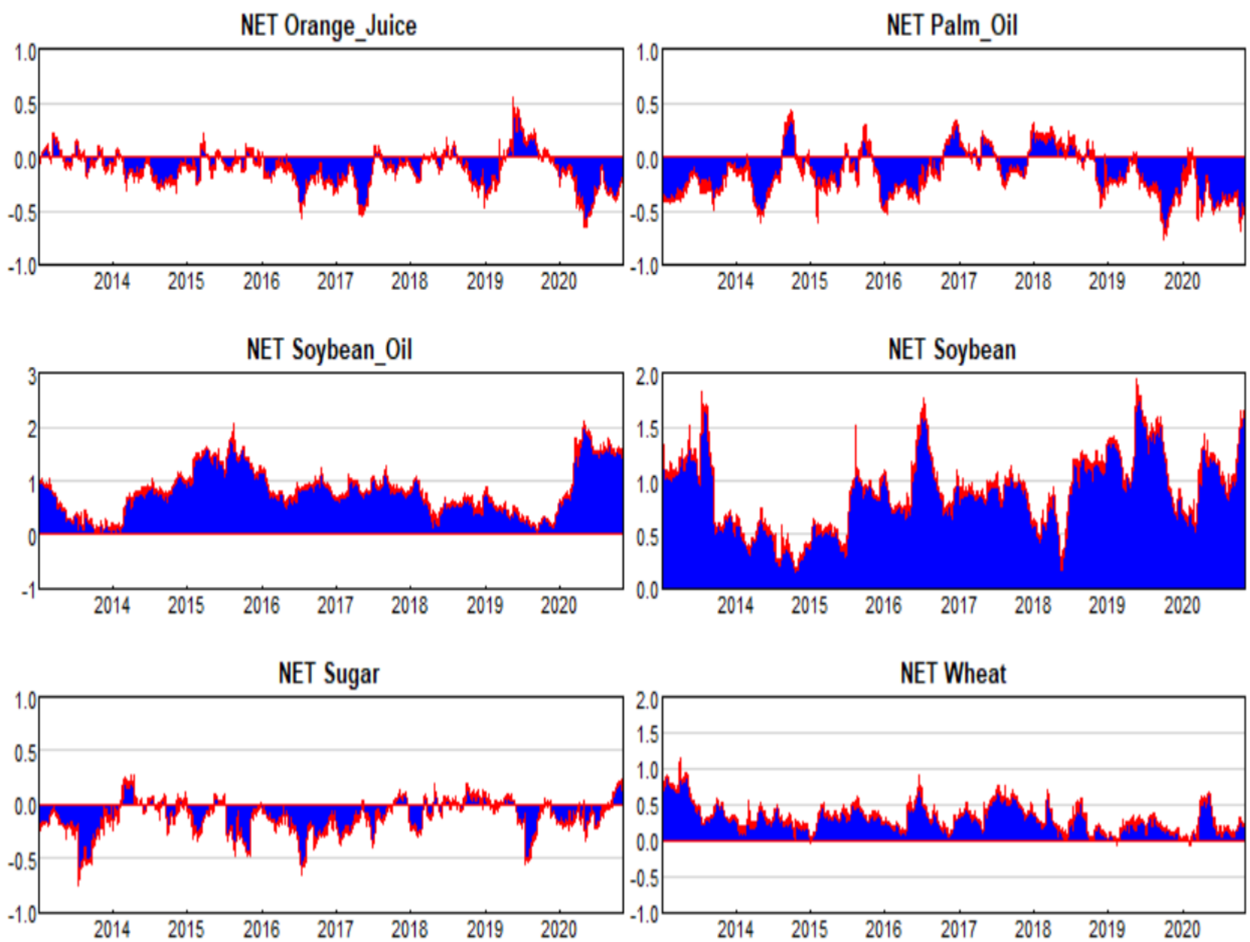

Figure A3: Net Connectedness Measures for all futures and sentiments

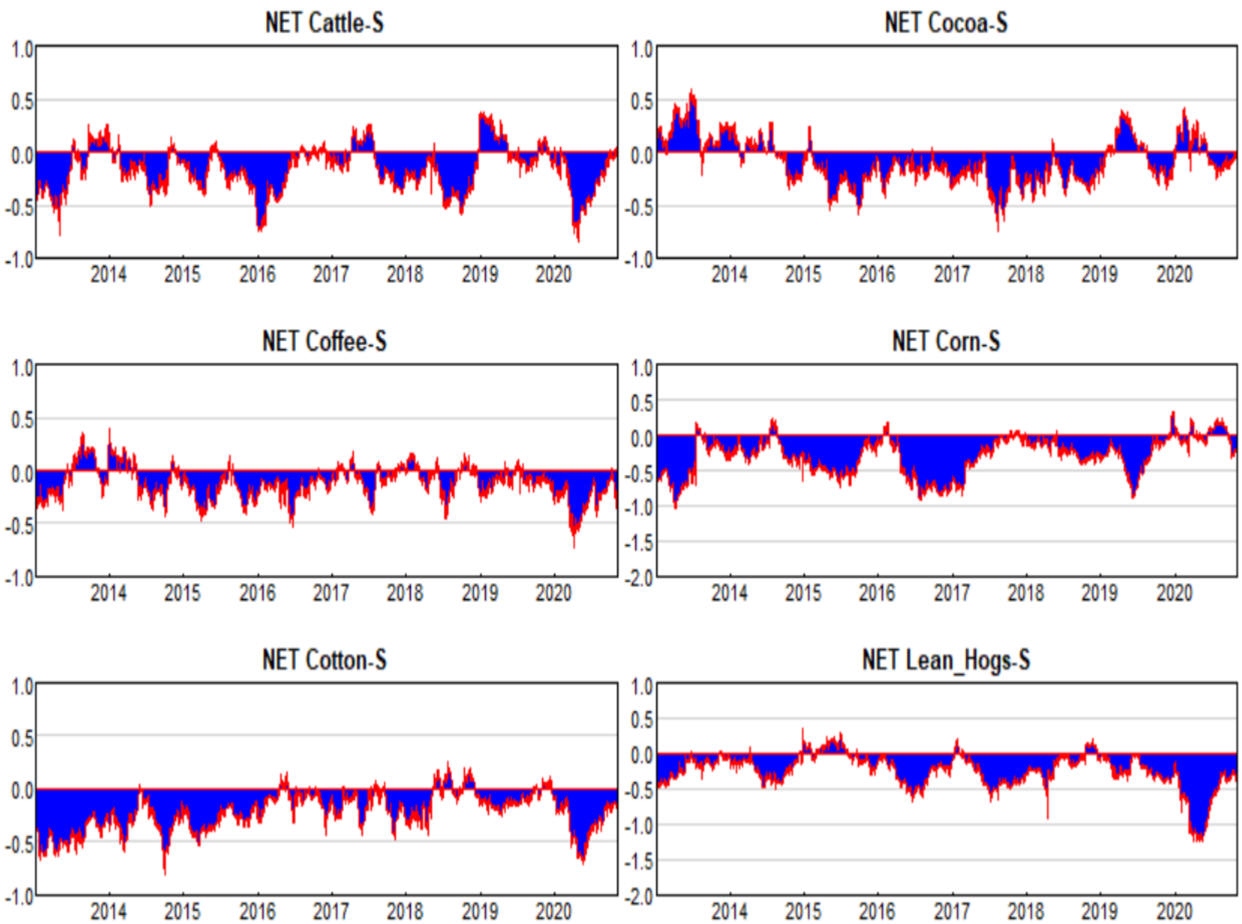

Figure A4: Net Connectedness Measures for all futures and sentiments

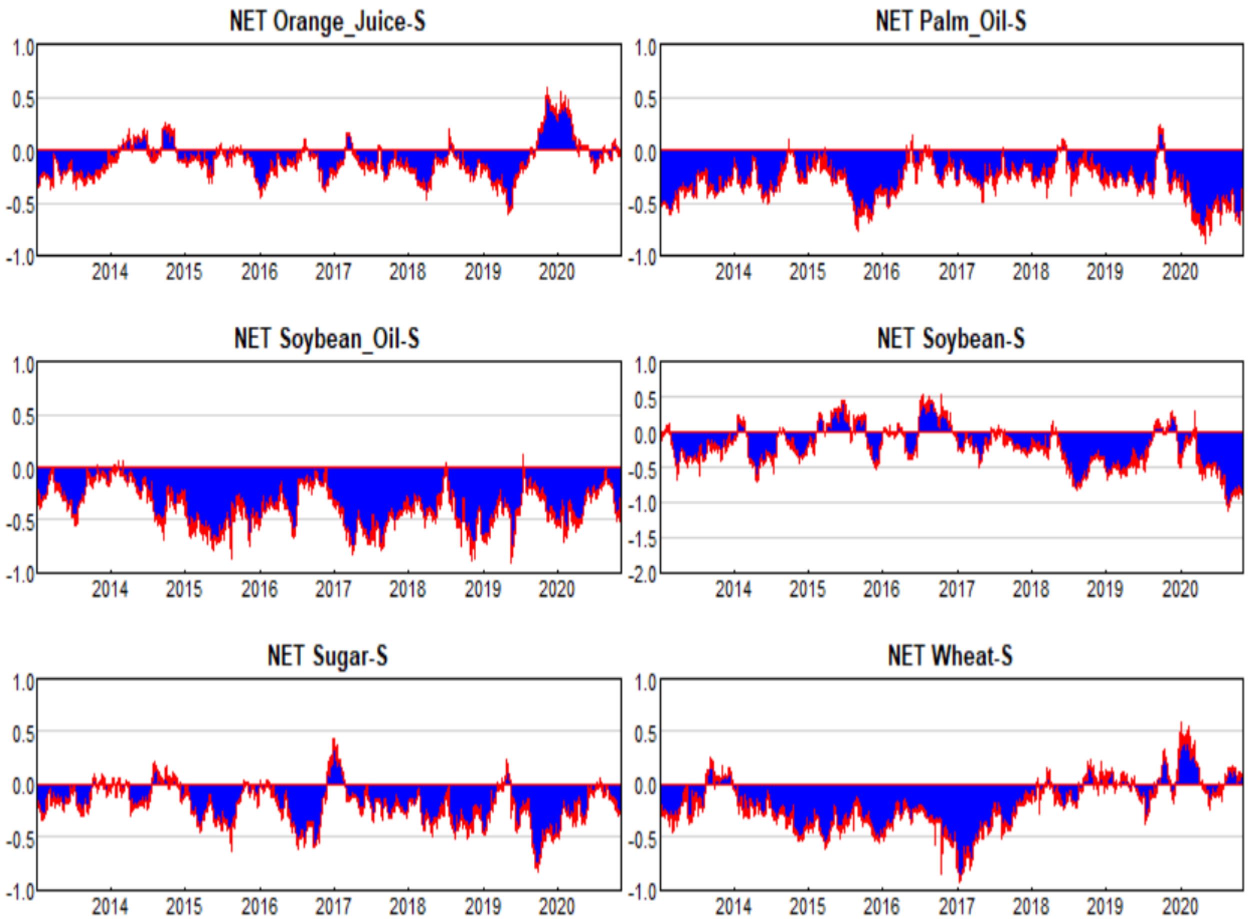

Figure A5: Comparison with Diebold and Yilmaz [2009] approach