Common Drivers of Commodity Futures*

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Abstract

This paper analyzes potential return drivers for a large cross-section of commodity futures using mixed-frequency Granger causality tests. We find that (de-)financialization affects linkages of financial and economic indicators to commodity futures returns over time with dissipating impact in recent years. As our results strongly differ from traditional low-frequency Granger causality tests under temporal aggregation of futures returns, we show the economic value of accessing information at a higher frequency in an out-of-sample trading study. Our findings emphasize the importance of using mixed data sampling techniques to uncover relationships between monthly-published macroeconomic variables and commodity prices.

Keywords: Commoditiy futures, VAR, Granger Causality, Mixed data sampling

JEL classification: C58; G17; Q02

*We are thankful for the comments and remarks of participants of the British Accounting & Finance Association Doctoral Masterclass 2021 (best finance PhD paper), the International Ruhr Energy Conference 2021, the Econometric Research in Finance Workshop 2021 (Warsaw), the Finance Research Seminar at Utrecht University, the HVB-UniCredit doctoral seminar 2021, the 6th Vietnam Symposium in Banking and Finance, and the 5th Commodity Markets Winter Workshop.

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1. Introduction

Prices of commodities do not only depend on individual supply and demand shocks as there is strong evidence for co-movement across prices of various "unrelated" commodities (Pindyck & Rotemberg 1990; Byrne et al. 2013; Chen et al. 2014; West & Wong 2014; Ohashi & Okimoto 2016; Delle Chiaie et al. 2017; Alquist et al. 2020; Ma et al. 2021). This phenomenon can be partly explained by the influence of financial markets on the one hand, and by fundamental variables that affect aggregate supply and demand for commodities on the other hand (Adams et al., 2020). It is well-known that the increased interest of financial investors to gain commodity exposure and associated capital flows into commodity futures markets since the early 2000s fundamentally changed their behavior (Adams & Glück, 2015). This ongoing process of financialization has been extensively surveyed in the academic literature (e.g., Cheng & Xiong 2014; Adams et al. 2020; Natoli 2021). Financial investors have been attracted by favorable risk-return characteristics commodity investments offered at this time such as diversification potential for stock portfolios (e.g., Gorton & Rouwenhorst 2006; Belousova & Dorfleitner 2012; Adams & Glück 2015). According to current perceptions (Büyükahin & Robe 2014; Adams & Glück 2015; Adams et al. 2020; Bianchi et al. 2020), financialization commenced around 2004 with rising open interest and net long positions in commodity futures yielding increases in prices, volatility, correlations between individual commodities, and correlations to equity markets (Basak & Pavlova, 2016). The degree of co-movement between commodities and other financial asset classes was further exacerbated by the onset of the global financial crisis in 2008 and remained particularly high over the following years (Büyükahin & Robe 2014; Adams & Glück 2015). Increased correlations to other asset classes consequently diminished the diversification abilities of commodities (Silvennoinen & Thorp, 2013).

According to Adams et al. (2020), commodity markets have entered a period of de-financialization around 2014 with dissipating influence of financial factors—albeit still different from pre-financialization levels. This is also supported by the results of other studies such as Aromi & Clements (2019). Bianchi et al. (2020), for instance, find de-financialization effects for metals and agricultural commodities after major investment

banks terminated their commodity trading activities in 2013.

Due to this dynamically changing behavior of commodity markets over the past two decades, it is crucial to investors and researches alike to understand the main time-varying driving forces of commodity futures returns. Next to financial markets, a wide range of commodities is also affected by fundamental variables. In the Theory of Storage (Working, 1949), prices of commodity futures are affected by the interest rate through the cost of carry. Furthermore, changes to the global economic activity cause shifts in aggregate supply and demand as well as shifts in expectations of market participants about future supply and demand and thereby influencing prices of of commodities among different groups (Pindyck & Rotemberg 1990; Kilian 2009). Several articles, hence, investigate if the co-movement in commodity spot or futures prices is explainable by common fundamental drivers (Pindyck & Rotemberg 1990; Byrne et al. 2013; Chen et al. 2014; West & Wong 2014; Daskalaki et al. 2014; Gao & Süss 2015; Andreasson et al. 2016; Ohashi & Okimoto 2016; Shang et al. 2016; Delle Chiaie et al. 2017; Alquist et al. 2020; Ma et al. 2021). Our study adds to this stream of the literature by exploring the changing relation of commodity futures and putative fundamental drivers in a Mixed Data Sampling (MIDAS) framework that allows to access information at distinct frequency levels. Since macroeconomic variables (as potential fundamental return drivers affecting global commodity supply and demand) are typically published at low-frequency levels, such as monthly or even quarterly, while price data for commodity futures is readily available at daily or even higher frequency, we thereby do not need to temporally aggregate the data to a common low-frequency level. This prevents us from disregarding information contained in the higher-frequency data.

To ascertain common fundamental drivers of commodity futures returns, we implement an empirical research design that consists of two parts. Based on bivariate mixed-frequency Vectorautoregressive (MF-VAR) models (Ghysels, 2016) for each pair of commodity and potential monthly driver we, firstly, study in-sample Granger causalities (Ghysels et al., 2016) from the driver variables to weekly commodity futures returns. Secondly, we run out-of-sample trading simulations for a broad commodity futures index based on

directional forecasts stemming from the MF-VAR models. Though Granger causality tests indicate that measures of global economic activity affect commodity futures returns across different groups, we find no variable that drives the entire cross-section of commodity returns. Accounting for the different stages of the financialization, our results, however, show that the relations fundamentally change over time with dissipating impact of macroeconomic variables in recent years. We further compare our results to those obtained in a commonly used low-frequency setting under temporal aggregation of commodity futures returns to the lower monthly level. As Ghysels et al. (2016) point out, temporal aggregation can cause spurious (non-)causality. This is strongly supported by our empirical results, showing that the frequency at which the data is sampled can lead to misinterpretation of the relations between low-frequency macroeconomic variables and commodity prices. Furthermore, our out-of-sample trading study shows that utilizing higher frequency information through our mixed-frequency approach increases the economic value of return predictions.

The contribution our paper makes to the existing literature is two-fold. First, we provide new evidence on the time-varying relation of fundamental variables and commodity futures. To the best of our knowledge, this is the first work that studies common drivers of commodity futures with mixed-frequency Granger causality. Chen et al. (2010) examine in-sample (low-frequency) Granger causality between commodity prices and exchange rates of currencies that are closely related to commodity exports. They find that these "commodity exchange rates" have predictive power for global commodity prices, however, their analysis is based on quarterly aggregated data. Similarly, Andreasson et al. (2016) also apply Granger causality tests with data at the common weekly frequency. Bevilacqua et al. (2019) analyzes mixed-frequency Granger causalities of macroeconomic and financial indicators to US stock market volatility and find that it unveils linkages that remain hidden in a low-frequency framework. Using a variety of models and evaluation methods, previous work, in contrast, either aggregates commodity returns to match the lower frequency of macroeconomic variables (Pindyck & Rotemberg 1990; Chen et al. 2010; Byrne et al. 2013; Chen et al. 2014; Daskalaki et al. 2014; West & Wong 2014; Shang et al.

2016; Ohashi & Okimoto 2016; Delle Chiaie et al. 2017; Alquist et al. 2020) or limit their analysis to a small set of potential macroeconomic variables as only very few are available on a daily or weekly basis (Gao & Süss 2015; Andreasson et al. 2016; Ma et al. 2021). A MIDAS approach comes with two advantages here: it avoids temporal aggregation which possibly distorts empirical findings (Ghysels et al. 2016; Bevilacqua et al. 2019) and also enables us to test a large set of potential low-frequency fundamental drivers. Also, our MF-VAR approach as proposed by Ghysels (2016) is purely observation-driven and, hence, does not require to include latent variables as in state space models such as the Bayesian MF-VARs suggested by Eraker et al. (2015) and Schorfheide & Song (2015) among others. In addition to most existing studies, we explicitly focus on the time variation of commodity drivers by running a sub-sample analysis that accounts for the changing behavior of commodity futures markets during different periods of the financialization. Particularly little evidence exists for the stage of de-financialization since samples of most related studies end around 2014 when this most recent era of financialization just began. Lastly, through studying futures instead of spot commodity prices, we can measure the economic value of our model by utilizing return predictions in trading rather than merely comparing statistical forecast errors.

The second contribution relates to the literature on MIDAS. By comparing the mixed-frequency to low-frequency results, we underpin findings of Ghysels et al. (2016) and Bevilacqua et al. (2019) that temporal aggregation and associated disregard of information can lead to different—potentially erroneous—conclusions. Moreover, in our trading application, we show that MF-VARs improve directional prediction accuracy compared to traditional low-frequency VARs and result in higher (risk-adjusted) returns—provided the difference in sampling frequencies is not too large.

The remainder of the paper is organized as follows. Section 2 gives a brief review of the related literature. We describe our methodology in Section 3 and our data on commodity futures as well as their potential drivers in Section 4. Section 5 presents our empirical results. Section 6 adds concluding remarks.

2. Related literature

One strand of the extant literature focuses on co-movement of commodity spot prices—mostly by employing factor models. Pindyck & Rotemberg (1990) examine correlations of commodity prices and state that the co-movement should be explained by changes in macroeconomic variables. They find, however, that it is not entirely explainable by changes in macroeconomic factors such as industrial production, interest rates, and inflation—leaving a degree of "excess co-movement". After controlling for macroeconomic shocks, this excess co-movement is found to increase from 1983–2011 by Ohashi & Okimoto (2016), who attribute this to the financialization in commodity markets. Byrne et al. (2013) are able to locate a common factor in commodity spot prices that is related to real interest rates and stock market uncertainty. Using a factor augmented Vector Autoregressive (VAR) model, they find that both the real interest rate and stock market uncertainty are inversely related to commodity prices. Also Chen et al. (2014) identify a common component in a broad sample of commodity spot price movements but relate this component to the nominal trade-weighted exchange rate of the US-Dollar. These results can be partly corroborated by findings of West & Wong (2014) who extract a common factor for distinct commodities within a static factor model. This common factor, however, is only weakly connected to global economic activity and the US-Dollar exchange rate. Delle Chiaie et al. (2017) aims at identifying common latent factors of a large set of spot commodity prices by using a dynamic factor model for disentangling the common component, components that are specific to a certain commodity market, and commodity-specific, i.e. idiosyncratic components. Their results indicate that a single common (latent) factor associated with global economic activity drives the returns in the cross-section of commodities. In contrast to Pindyck & Rotemberg (1990), they conclude that there is no puzzling excess co-movement in commodity prices that is not explainable by fundamental factors. Instead, their findings suggest that this co-movement is largely traceable to shifts in global demand induced by changes in global economic activity. Likewise, Alquist et al. (2020) find that non-commodity shocks, i.e., changes to aggregate economic activity and income, are primarily driving spot price fluctuations in

the cross-section of commodities. Compared to this, commodity-specific shocks directly affecting supply and demand through, e.g., input prices in commodity production, play a minor role in historical price movements on the commodity spot markets. With the most recent data set covering all stages of the financialization in contrast to the aforementioned studies, Ma et al. (2021) analyze the effect of fundamental and non-fundamental drivers on commodity spot returns via a connectedness network. They show that—next to financialization—market sentiment, as proxied by the VIX, contributes to commodity return co-movement.

Also for the futures markets, evidence has been found that market sentiment affects commodity return co-movement (Gao & Süss, 2015). Evidence for other common macroeconomic drivers of commodity futures is, however, scarce. A positive correlation of commodity futures to inflation has been found by Gorton & Rouwenhorst (2006). Daskalaki et al. (2014) examine the usefulness of commodity and equity-motivated asset pricing factor models as well as asset pricing models using principal components as factors for commodity futures returns. As no model performs reasonably well, they conclude that the commodity market is separated from the equity market and heterogeneous in the cross-section. Contradicting to these results, Shang et al. (2016) construct a four-factor asset pricing model including the market factor as well as unexpected real interest rate, real exchange rate and inflation as macroeconomic factors, and show that real exchange rate risk is indeed priced in the cross-section of commodity futures returns. Andreasson et al. (2016) use linear and non-linear causality tests to analyze potential financial and fundamental drivers of commodity futures. They provide evidence that futures returns are not driven by speculation. Moreover, energy futures show linear causation of exchange rates. Other studies analyze macroeconomic drivers of the return volatility in commodity futures markets. In a MIDAS framework, Nguyen & Walther (2020) find that global real economic activity, consumer sentiment, industrial production, and economic policy uncertainty are often drivers of long-term commodity volatility. Also using MIDAS techniques, Dinh et al. (2021) find that—next to stock markets—money supply, inflation, and the interest rate affect return volatility and correlation among precious metals futures.

3. Methodology

3.1. Mixed-Frequency Vector Autoregression

Ghysels (2016) introduces a new class of observation-driven MF-VAR models that can be applied to an n-dimensional process consisting of $K_L < n$ low-frequency processes and $K_H = n - K_L$ high-frequency processes. Since we focus on the bivariate case, we set $K_H = K_L = 1$, i.e., we apply the MF-VAR model to two time series sampled at different frequencies. Consider a univariate low-frequency process $x_L(\tau_L)$ with time index τ_L representing a potential driver variable that is available monthly such as world steel production or inflation. The log return of a commodity futures contract is described by the univariate high-frequency process $x_H(\tau_L, k_H)$ that is sampled m times between two observations of the low-frequency variable x_L such that $k_H = 1, ..., m$.[1] Usually, the high-frequency variable is aggregated to match the sampling frequency of the low-frequency variable such that $m = 1$. For instance, we can aggregate log returns of daily oil prices to monthly log returns by:

$$x_H^a(\tau_L) = \sum_{k_H=1}^{m} x_H(\tau_L, k_H).$$

We call a VAR(P) with the low-frequency and aggregated high-frequency variable a low-frequency VAR (LF-VAR), which reads as follows:

$$\begin{bmatrix} x_H(\tau_L) \\ x_L(\tau_L) \end{bmatrix} = \boldsymbol{A}_0 + \sum_{j=1}^{P} \boldsymbol{A}_j \begin{bmatrix} x_H(\tau_L - j) \\ x_L(\tau_L - j) \end{bmatrix} + \boldsymbol{\epsilon}(\tau_L).$$

Instead of losing valuable information of the high-frequency variable through aggregation, Ghysels (2016) proposes to form a "stacked" vector that contains all available observations of both the low-frequency and the high-frequency variable. Assuming that observations of the low-frequency series are made at the very end of each low-frequency period, τ_L, yields the stacked vector $\boldsymbol{X}(\tau_L) = [x_H(\tau_L, 1), ..., x_H(\tau_L, m), x_L(\tau_L)]'$.[2] If $\boldsymbol{X}$

[1] We set $m(\tau_L) = m \ \forall \tau_L$, i.e., we assume there is a fixed number of high-frequency observations during each low-frequency period.

[2] For our analysis, it is reasonable to assume that the low-frequency variable is observed at the end of each low-frequency period. Think of, e.g., world steel production as the monthly available low-frequency

follows a VAR(P) process, we can write the stacked vector as:

$$\boldsymbol{X}(\tau_L) = \boldsymbol{A}_0 + \sum_{j=1}^{p} \boldsymbol{A}_j \boldsymbol{X}(\tau_L - j) + \boldsymbol{\epsilon}(\tau_L) \tag{1}$$

$$\begin{bmatrix} x_H(\tau_L, 1) \\ \vdots \\ x_H(\tau_L, m) \\ x_L(\tau_L) \end{bmatrix} = \boldsymbol{A}_0 + \sum_{j=1}^{P} \boldsymbol{A}_j \begin{bmatrix} x_H(\tau_L - j, 1) \\ \vdots \\ x_H(\tau_L - j, m) \\ x_L(\tau_L - j) \end{bmatrix} + \boldsymbol{\epsilon}(\tau_L),$$

where $\boldsymbol{A}_j$ is the $K \times K$ coefficient matrix for lag $j = 1, ..., P$, with $K = K_L + m \cdot K_H$, and $\boldsymbol{\epsilon}(\tau_L)$ the $K \times 1$ vector of errors. The bivariate MF-VAR model from (1) is a traditional finite order VAR model of dimension $K = m + 1$.

3.2. Mixed-Frequency Granger causality

Based on the MF-VAR model suggested by Ghysels (2016), Ghysels et al. (2016) develop a methodology to test for linear mixed-frequency Granger causality. For $K_H = K_L = 1$, we extract $\tilde{\boldsymbol{x}}_H(\tau_L) = [x_H(\tau_L, 1), ..., x_H(\tau_L, m)]'$ and $x_L(\tau_L)$ separately from $\boldsymbol{X}(\tau_L)$ and define $\ell(\tau_L) := \boldsymbol{X}(-\infty, \tau_L] = \tilde{\boldsymbol{x}}_H(-\infty, \tau_L] + x_L(-\infty, \tau_L]$ as the mixed-frequency reference information set in period τ_L. Adopting the notation of Ghysels et al. (2016), we can formulate the null hypothesis of non-causality from (i) the low to the high-frequency variable or (ii) the high to the low-frequency variable at the low-frequency forecasting horizon $h \in \mathbb{N}$ as:

(i) $H_0^{(1)}(h)$: $x_L \nrightarrow_h x_H \mid \ell$, if:

$$P\big[\tilde{\boldsymbol{x}}_H(\tau_L + h) \mid \tilde{\boldsymbol{x}}_H(-\infty, \tau_L]\big] = P\big[\tilde{\boldsymbol{x}}_H(\tau_L + h) \mid \ell(\tau_L)\big] \ \forall \tau_L \in \mathbb{Z}.$$

(ii) $H_0^{(2)}(h) : x_H \nrightarrow_h x_L \mid \ell$, if:

$$P\big[x_L(\tau_L + h) \mid x_L(-\infty, \tau_L]\big] = P\big[x_L(\tau_L + h) \mid \ell(\tau_L)\big] \ \forall \tau_L \in \mathbb{Z},$$

variable. As this indicator measures the amount of steel produced within one month, the first possible point in time this number theoretically can be calculated would be at the end of the last day of that month. Note that we are interested in the linkage between changes in macroeconomic indicators and commodity futures markets and not on the reaction of commodity prices to public releases of these numbers.

where $P\left[z(\tau_L + h) \mid \ell(\tau_L)\right]$ describes the best linear h-step ahead forecast of some variable z given the information ℓ at period τ_L. Our main interest is to test the null hypothesis formulated in (i). It states that the low-frequency variable does not Granger cause the high-frequency variable at horizon h, if the h-step ahead forecast of the high-frequency variable, x_H, based on available information on x_H up to period τ_L remains the same whether or whether not information about the past of the low-frequency variable, x_L, up to period τ_L is included. To put it simply, the prediction of the high-frequency variable cannot be improved by looking at past values of the low-frequency variable.

Ghysels et al. (2016) propose to test the null of non-causality at horizon h based on the Wald statistic, for which we need to introduce a few notations. Assuming that the stacked vector follows a VAR(P) process and all elements of the stacked vector are demeaned, we obtain the following (P,h)-autoregression based on Dufour et al., 2006:

$$\boldsymbol{X}(\tau_L + h) = \sum_{j=1}^{P} \boldsymbol{A}_j^{(h)} \boldsymbol{X}(\tau_L + 1 - j) + \boldsymbol{u}^{(h)}(\tau_L), \tag{2}$$

where $\tau_L = 0, ..., T_L - h$ and

$$\boldsymbol{A}^{(h)} = \begin{cases} \boldsymbol{A}_j & \text{for } h = 1 \\ \boldsymbol{A}_{j+h-1} + \sum_{i=1}^{h-1} \boldsymbol{A}_{h-i} \boldsymbol{A}_j^{(i)} & \text{for } h \geq 2 \end{cases}$$

$$\boldsymbol{u}^{(h)}(\tau_L) = \sum_{j=0}^{h-1} \boldsymbol{\Psi}_j \boldsymbol{\epsilon}(\tau_L - j).$$

The matrices $\boldsymbol{\Psi}_j$ contain impulse response coefficients with $\boldsymbol{\Psi}_0 = \boldsymbol{I}_K$ (Dufour et al., 2006).[3] In the bivariate case (i.e., $K_L = K_H = 1$), x_L does not Granger cause x_H at any horizon $h > 0$ if x_L does not Granger cause x_H at $h = 1$ (Dufour & Renault, 1998). Hence, we only test for non-causality at horizon $h = 1$, which simplifies the (P,h)-autoregression from (2) to:

$$\boldsymbol{X}(\tau_L + 1) = \sum_{j=1}^{P} \boldsymbol{A}_j \boldsymbol{X}(\tau_L + 1 - j) + \boldsymbol{\epsilon}(\tau_L),$$

[3]See Dufour & Renault (1998) and Dufour et al. (2006) on how to obtain $\boldsymbol{\Psi}_j$ for $j > 0$.

which is the MF-VAR(P) presented in (1).

Next, we define

$$\boldsymbol{B}(h) = \left[\boldsymbol{A}_1^{(h)}, ..., A_P^{(h)}\right]' \in \mathbb{R}^{PK \times K}$$

as the parameter set of the MF-VAR coefficients and can, therefore, write the null hypothesis of non-causality at horizon h as

$$H_0(h) : \boldsymbol{R}\,\mathrm{vec}\left[\boldsymbol{B}(h)\right] = \boldsymbol{r}, \tag{3}$$

where $\boldsymbol{R}$ is a $q \times PK^2$ selection matrix and $\boldsymbol{r}$ is a column-vector of zeros with length q. The number of MF-VAR coefficients q that are relevant for testing the null hypothesis, depends on the direction of Granger causality that is being tested. As our primary interest is Granger causality from the low to the high-frequency variable (see $H_0^{(1)}(h)$ from (3)), we will henceforth focus on this specific case, where $q = m$ and $K_H = K_L = 1$, and furthermore set $P = 1$.[4]

Recall the form of the demeaned stacked vector in the bivariate case with the low-frequency variable $x_L(\tau_L)$ being observed at the very end of each low-frequency period: $\boldsymbol{X}(\tau_L) = [x_H(\tau_L, 1), ..., x_H(\tau_L, m), x_L(\tau_L)]'$. For $P = 1$, we then obtain

$$\boldsymbol{B}(h) = \boldsymbol{A}_1^{(h)\prime} \in \mathbb{R}^{K \times K} \quad \text{and} \quad \boldsymbol{A}_1^{(h)} = \begin{bmatrix} a_{11}^{(h)} & \cdots & a_{1K}^{(h)} \\ \vdots & \ddots & \vdots \\ a_{K1}^{(h)} & \cdots & a_{KK}^{(h)} \end{bmatrix}.$$

The influence of the low-frequency variable $x(\tau_L)$ on the high-frequency variable x_H, represented in the stacked vector through $x_H(\tau_L, 1), ..., x_H(\tau_L, m)$, at horizon h is given by the first $m = K - 1$ coefficients in the K-th column of $\boldsymbol{A}_1^{(h)}$. Thus, the null hypothesis

[4] To test the null of non-causality from the high to the low-frequency variable, $\boldsymbol{r}$ is a row-vector of zeros. For a more general formulation of mixed-frequency Granger Causality with $n \geq 2$ (non-bivariate), including mixed-frequency Granger causality from low to low, high to high, all high to all low, and all low to all high-frequency variables, please refer to Ghysels et al. (2016).

from (3) is equivalent to

$$H_0^{(1)}(h) : a_{1K} = a_{2K} = \cdots = a_{mK} = 0$$

if we set

$$\boldsymbol{R} = [\boldsymbol{\Lambda}(\delta_1)', ..., \boldsymbol{\Lambda}(\delta_m)'] \quad \text{and} \quad \boldsymbol{r} = \mathbf{0}_{m\times 1},$$
$$\delta_k \in \{1 \cdot K, 2 \cdot K, ..., m \cdot K\}, k = 1, ..., m,$$

where the δ_k-th element of the $1 \times K^2$-dimensional vector $\boldsymbol{\Lambda}(\delta_k)$ is 1 and zero otherwise. For instance, when we want to test for non-causality from the potential monthly driver variable to weekly commodity returns, assuming that we always observe four weekly returns per month, i.e. $m(\tau_L) = 4\,\forall\tau_L$ and $K = 5$, the 4×25 selection matrix has the form:

$$\boldsymbol{R} = [\boldsymbol{\Lambda}(5)', \boldsymbol{\Lambda}(10)', \Lambda(15)', \Lambda(20)'] = \begin{bmatrix} \mathbf{0}_{1\times 4} & 1 & \mathbf{0}_{1\times 4} & 0 & \mathbf{0}_{1\times 4} & 0 & \mathbf{0}_{1\times 4} & 0 & \mathbf{0}_{1\times 4} \\ \mathbf{0}_{1\times 4} & 0 & \mathbf{0}_{1\times 4} & 1 & \mathbf{0}_{1\times 4} & 0 & \mathbf{0}_{1\times 4} & 0 & \mathbf{0}_{1\times 4} \\ \mathbf{0}_{1\times 4} & 0 & \mathbf{0}_{1\times 4} & 0 & \mathbf{0}_{1\times 4} & 1 & \mathbf{0}_{1\times 4} & 0 & \mathbf{0}_{1\times 4} \\ \mathbf{0}_{1\times 4} & 0 & \mathbf{0}_{1\times 4} & 0 & \mathbf{0}_{1\times 4} & 0 & \mathbf{0}_{1\times 4} & 1 & \mathbf{0}_{1\times 4} \end{bmatrix}$$

and $\boldsymbol{r} = \mathbf{0}_{4\times 1}$.[5]

We follow the non-causality testing scheme as suggested by Ghysels et al. (2016). First, we fit the (P,h)-autoregression from (2) for MF-VAR lag order $P = 1$ and forecasting horizon $h = 1$ to the underlying data of one high-frequency ($K_H = 1$) and one low-frequency variable ($K_L = 1$). The high-frequency variable represents the commodity futures log return and the low-frequency variable is—whatever is applicable to the variable at hand and ensures stationarity—either the level or log growth rate of an economic or financial indicator considered as a potential driver of commodity returns. Estimating the (P,h)-autoregression via OLS yields the OLS estimator $\hat{\boldsymbol{B}}(h)$ for the MF-VAR parameter

[5]Again, for a more general representation of the selection matrix, see Ghysels et al. (2016, Section 3.3).

set $\boldsymbol{B}(h)$. Under the assumptions that the process $\boldsymbol{X}(\tau_L)$ follows a VAR(P), $P \geq 1$, and $\boldsymbol{X}(\tau_L)$ as well as that $\boldsymbol{\epsilon}(\tau_L)$ are stationary and ergodic (α-mixing), Ghysels et al. (2016) derive a consistent OLS estimator for $\boldsymbol{B}(h)$ that is asymptotically normal with

$$\sqrt{T_L^*}\,\mathrm{vec}\left[\hat{\boldsymbol{B}}(h) - \boldsymbol{B}(h)\right] \xrightarrow{d} N\big(\boldsymbol{0}_{K^2\times 1}, \boldsymbol{\Sigma}(h)\big),$$

where $T_L^* = T_L - h + 1$ denotes the effective sample size for the (P,h)-autoregression. Ghysels et al. (2016) propose an almost surely positive semi-definite (for $T_L^* \geq 0$) and consistent estimator $\hat{\boldsymbol{\Sigma}}(h)$ for the covariance matrix $\boldsymbol{\Sigma}(h)$ based on the HAC estimator of Newey & West (1987) (see Ghysels et al. (2016, Section 3.2) for details). After we obtained the estimates $\hat{\boldsymbol{B}}(h)$ and $\hat{\boldsymbol{\Sigma}}(h)$, we can construct the selection matrix $\boldsymbol{R}$ and $\boldsymbol{r}$, and calculate the Wald statistic $W_{T_L^*}[H_0(h)] \xrightarrow{d} \chi^2_q$ under $H_0(h)$:[6]

$$W_{T_L^*}[H_0(h)] = T_L^*\Big(\boldsymbol{R}\,\mathrm{vec}\left[\hat{\boldsymbol{B}}(h)\right] - \boldsymbol{r}\Big)'\Big(\boldsymbol{R}\hat{\boldsymbol{\Sigma}}(h)\boldsymbol{R}'\Big)^{-1}\Big(\boldsymbol{R}\,\mathrm{vec}\left[\hat{\boldsymbol{B}}(h)\right] - \boldsymbol{r}\Big).$$

Eventually, we calculate the p-values for the Granger causality test at horizon $h = 1$ based on the parametric bootstrap of Gonçalves & Kilian (2004) with $N = 10{,}000$ replications according to the procedure as is described in Ghysels et al. (2016, Section 6.1):[7]

1) We fit an unrestricted MF-VAR(P) to the underlying data for $h = P = 1$ in order to obtain $\hat{\boldsymbol{B}}(1) = \hat{\boldsymbol{A}}(1)'$ and calculate the Wald statistic $W_{T_L^*}[H_0(1)]$

2) Based on the actual errors $\hat{\boldsymbol{\epsilon}}(\tau_L)$, $\tau_L = 1, ..., T_L^*$, of the fitted MF-VAR from Step 1, we simulate N samples of artificial errors through $\tilde{\boldsymbol{\epsilon}}_i = \hat{\boldsymbol{\epsilon}}(\tau_L) \circ \boldsymbol{\xi}_i(\tau_L)$ with $\boldsymbol{\xi}_i(\tau_L) \overset{i.i.d}{\sim} N(\boldsymbol{0}_{K\times 1}, \boldsymbol{I}_K)$, $i = 1, ..., N$, where $\circ$ denotes the element-wise multiplication operator.

3) Using the simulated errors from Step 2, we simulate N MF-VAR(p) processes (the ($P, h = 1$)-autoregression from (2)) with $\boldsymbol{B}(1) = \hat{\boldsymbol{B}}(1)$ under the assumption that

[6] Proof can be found in Ghysels et al. (2016).

[7] The bootstrapping procedure described above does only apply for the specific case considered in this work, i.e., $P = h = 1$ and $K_H = K_L = 1$. For non-bivariate MF-VARs, an MF-VAR lag order greater one, and/or Granger causality at forecasting horizons greater one, see Ghysels et al. (2016).

the null hypothesis $H_0(1)$ from (3) is true, i.e., we set $a_{1K} = \cdots = amK = 0$ in $\hat{\boldsymbol{A}}(1)$. We calcuate the Wald test statistic $W_i\left[H_0(1)\right]$ for each $i \in \{1, ..., N\}$.

4) At level α, we reject the null hypothesis $H_0(1)$ of non-causality at horizon $h = 1$ if $\hat{p_N}\left(W_{T_L^*}\left[H_0(1)\right]\right) \leq \alpha$, where

$$\hat{p}_N\big(W_{T_L^*}\left[H_0(1)\right]\big) = \frac{1}{N+1}\left(1 + \sum_{i=1}^{N} \mathbb{1}\big(W_i\left[H_0(1)\right] \geq W_{T_L^*}\left[H_0(1)\right]\big)\right).$$

Ghysels et al. (2016) recommend to use bootstrapping for smaller sample sizes regarding the number of low-frequency observations T_L in order to avoid size distortions. The wild bootstrap of Gonçalves & Kilian (2004) allows for conditional heteroskedasticity.

4. Data

We collect settlement prices of 37 front-month commodity futures from various exchanges via Bloomberg at daily frequency from January 1998 to December 2019.[8] Our data set covers a wide range of agricultural and energy commodities as well as industrial and precious metals. Since our methodology requires a fixed number of high-frequency observations per low-frequency observation (i.e., m is constant independent of the low-frequency period $\boldsymbol{\tau}_L$), we only consider the last 20 trading days of each month, which is the minimum number of trading days per month in our sample. In doing so, we drop at most the first three daily observations of a given month. To avoid parameter proliferation, we choose an MF-VAR lag order of $P = 1$ and aggregate daily commodity futures prices to weekly log returns over non-overlapping 5-day intervals through $100 \times [\ln(p_t) - \ln(p_{t-5})]$.[9]

[8] Bloomberg tickers (PX_SETTLE): KC1 Comdty, CC1 Comdty, JO1 Comdty, SB1 Comdty, CT1 Comdty, OL1 Comdty, LB1 Comdty, OR1 Comdty, DL1 Comdty, C 1 Comdty, W 1 Comdty, O 1 Comdty, RR1 Comdty, S 1 Comdty, SM1 Comdty, BO1 Comdty, FC1 Comdty, LH1 Comdty, LC1 Comdty, PB1 Comdty, CO1 Comdty, CL1 Comdty, HO1 Comdty, NG1 Comdty, XB1 Comdty, QS1 Comdty, LP1 Comdty, LN1 Comdty, LCO1 Comdty, GC1 Comdty, PL1 Comdty, PA1 Comdty, SI1 Comdty, LT1 Comdty, LA1 Comdty, LL1 Comdty, LX1 Comdty

[9] One weekly return covers the period of five trading days except for the first weekly return of the first month of a futures series, which covers only 4 days. For instance, the first weekly return of February is calculated from the settlement price of the last trading day of January to the settlement price of the fifth trading day of February. Note that this does not include the first trading days of the month that may have been removed from our data set. The remaining weekly returns are calculated from the 5th–10th, 10th–15th, and 15th–20th trading day of February. If January is the starting month of the futures series,

We, therefore, end up with four weekly log returns per month, such that $m = 4$, and a total of 5^2 estimated parameters for each bivariate MF-VAR. Using daily instead of weekly log returns would increase the number of parameters to 21^2 and presumably result in unstable MF-VAR estimations and misleading Granger causalities. Findings of Ghysels et al. (2016) also suggest that a small difference in sampling frequencies is preferable for estimating MF-VARs.[10] Summary statistics of our final commodity futures sample and equally-weighted commodity portfolios are presented in Table 1.[11]

Using weekly log returns in our empirical analysis results in the stacked vector of the following form:

$$\begin{bmatrix} x_H(\tau_L, 1) \\ x_H(\tau_L, 2) \\ x_H(\tau_L, 3) \\ x_H(\tau_L, 4) \\ x_L(\tau_L) \end{bmatrix},$$

where the high-frequency variable $x_H(\tau_L, k_H)$ denotes the log return of a continuous front-month commodity futures for week k_H in month τ_L. The low-frequency variable $x(\tau_L)$ represents a monthly available macroeconomic indicator that we consider ex-ante as a potential commodity return driver. Potential drivers include seasonally adjusted USD inflation (INFL) calculated as year-on-year log-differences in US CPI, consumers' inflation expectation (INFLE) surveyed by the University of Michigan, USD effective exchange rate (USDEER) published by the Bank for International Settlements, three-month USD Treasury Bill rate (TBILL) as the short-term interest rate, the TED spread (TED), global crude steel production (STEEL) published by the World Steel Association, the Baltic Dry Index (BDI) as published by the London Baltic Exchange[12] , World Industrial Production

the first weekly return is calculated from the settlement price of the first to the fifth trading day.

[10] Götz et al. (2016) propose techniques involving reduced rank regressions or Bayesian VAR estimation to reduce the number of parameter estimations in MF-VARs with a larger difference in sampling frequencies (such as daily-monthly) before running Granger causality tests.

[11] Summary statistics of the full commodity futures sample with monthly returns are provided in Table A.10.

[12] We also considered to include the index of Global Real Economic Activity (GREA) from Kilian (2009) in the set of potential drivers as, e.g., Nguyen & Walther (2020) show that the GREA index is a long-term driver of commodity market volatility. For our sample period, however, the ADF, PP, and

Table 1: Sample statistics of commodity futures for weekly (5-day) log returns, 1998–2019

	Obs.	Mean	Std.Dev.	Skewn.	Ex.Kurt.	J.B.	ADF	PP	KPSS
Agriculture (Softs)									
Cocoa (ICE)	1056	0.042	4.543	0.178	1.646	0.000	-10.290^{***}	-925.317^{***}	0.061
Coffee (ICE)	1056	−0.021	4.842	0.327	1.368	0.000	-9.244^{***}	-1023.794^{***}	0.131
Cotton (ICE)	1056	0.003	4.248	−0.378	3.995	0.000	-9.564^{***}	-923.139^{***}	0.045
Ethanol (CBOT)	700	0.017	5.028	−1.460	9.782	0.000	-9.443^{***}	-665.940^{***}	0.108
Lumber (CME)	1056	0.032	4.864	0.080	1.012	0.000	-9.910^{***}	-1021.886^{***}	0.034
Orange Juice (ICE)	1056	0.018	4.952	0.341	2.450	0.000	-9.456^{***}	-997.246^{***}	0.082
Rubber (SGX)	1056	0.065	3.959	−1.143	9.095	0.000	-9.055^{***}	-953.870^{***}	0.162
Sugar (ICE)	1056	0.009	4.788	0.029	1.524	0.000	-9.509^{***}	-1081.916^{***}	0.070
Wool (ASX)	720	0.058	2.966	0.287	2.719	0.000	-7.717^{***}	-719.204^{***}	0.086
Portfolio (Softs)	1056	0.020	2.037	−0.363	3.043	0.000	-8.436^{***}	-1040.804^{***}	0.118
Agriculture (Grains)									
Corn (CBOT)	1056	0.037	4.094	−0.220	3.547	0.000	-9.368^{***}	-1087.932^{***}	0.063
Oats (CBOT)	1056	0.063	5.153	−0.140	1.865	0.000	-10.918^{***}	-1020.563^{***}	0.041
Rough Rice (CBOT)	1056	0.020	3.985	0.213	6.579	0.000	-9.516^{***}	-902.526^{***}	0.119
Soy Bean	1056	0.034	3.624	−0.969	5.938	0.000	-9.388^{***}	-1073.929^{***}	0.069
Soybean Meal (CBOT)	1056	0.039	4.288	−0.806	5.766	0.000	-10.094^{***}	-995.482^{***}	0.046
Soybean Oil (CBOT)	1056	0.031	3.399	−0.120	1.921	0.000	-9.021^{***}	-1037.910^{***}	0.087
Wheat (CBOT)	1056	0.050	4.392	0.276	0.794	0.000	-10.620^{***}	-1020.920^{***}	0.051
Portfolio (Grains)	1056	0.039	2.797	−0.239	1.695	0.000	-9.305^{***}	-1025.571^{***}	0.094
Agriculture (Livestock)									
Feeder Cattle (CME)	1056	0.063	2.389	−0.468	4.490	0.000	-8.987^{***}	-1194.923^{***}	0.064
Lean Hogs (CME)	1056	0.020	5.734	−0.299	3.847	0.000	-11.019^{***}	-1035.006^{***}	0.014
Live Cattle (CME)	1056	0.062	2.810	−0.530	2.416	0.000	-9.835^{***}	-1104.615^{***}	0.032
Pork Bellies (CME)	624	0.118	6.605	0.184	8.140	0.000	-9.231^{***}	-579.250^{***}	0.024
Portfolio (Livestock)	1056	0.055	2.780	−0.406	1.886	0.000	-11.122^{***}	-1032.449^{***}	0.040
Energy									
Brent (ICE)	1056	0.132	4.968	−0.474	3.105	0.000	-9.362^{***}	-1186.024^{***}	0.144
Gasoil (NYMEX)	1056	0.134	4.701	−0.462	2.150	0.000	-9.121^{***}	-1093.413^{***}	0.134
Gasoline (NYMEX)	684	−0.016	5.652	−0.257	4.486	0.000	-7.645^{***}	-792.766^{***}	0.038
Heating Oil (NYMEX)	1056	0.134	5.052	−0.374	2.612	0.000	-9.303^{***}	-1042.040^{***}	0.133
Natural Gas (NYMEX)	1056	0.002	7.401	0.095	1.124	0.000	-10.694^{***}	-1013.340^{***}	0.116
WTI (NYMEX)	1056	0.119	5.316	−0.220	2.399	0.000	-9.283^{***}	-1114.968^{***}	0.129
Portfolio (Energy)	1056	0.108	4.432	−0.283	1.799	0.000	-9.082^{***}	-1080.172^{***}	0.174
Industrial Metals									
Aluminium (LME)	1056	0.014	2.977	0.096	2.210	0.000	-9.060^{***}	-1091.361^{***}	0.062
Cobalt (LME)	472	−0.055	3.798	−0.341	3.502	0.000	-6.588^{***}	-506.552^{***}	0.147
Copper (LME)	1056	0.120	3.569	−0.814	6.186	0.000	-8.546^{***}	-1116.661^{***}	0.148
Lead (LME)	1056	0.116	4.500	−0.238	2.945	0.000	-9.491^{***}	-1012.827^{***}	0.111
Nickel (LME)	1056	0.080	5.167	−0.276	2.472	0.000	-9.439^{***}	-1088.691^{***}	0.117
Tin (LME)	1056	0.110	3.842	−0.558	4.242	0.000	-8.488^{***}	-1092.765^{***}	0.130
Zinc (LME)	1056	0.070	4.026	−0.430	2.239	0.000	-9.020^{***}	-1077.933^{***}	0.074
Portfolio (Industrial Metals)	1056	0.083	2.961	−0.569	3.582	0.000	-8.695^{***}	-1053.068^{***}	0.147
Precious Metals									
Gold (COMEX)	1056	0.157	2.440	−0.179	2.716	0.000	-10.167^{***}	-924.486^{***}	0.178
Palladium (NYMEX)	1056	0.212	5.020	−0.111	3.187	0.000	-9.927^{***}	-1041.536^{***}	0.109
Platinum (NYMEX)	1056	0.092	3.242	−0.584	3.005	0.000	-8.912^{***}	-1001.061^{***}	0.264
Silver (COMEX)	1056	0.104	4.252	−0.749	5.308	0.000	-10.479^{***}	-938.532^{***}	0.121
Portfolio (Precious Metals)	1056	0.141	2.979	−0.692	3.149	0.000	-9.591^{***}	-1002.686^{***}	0.072

Notes: Summary statistics for single futures are provided for non-overlapping 5-day returns calculated as $r_t = 100 \times [\ln(p_t) - \ln(p_{t-5})]$, where $\{p_t\}_{t=1}^{T}$ is the front month continuous futures series which contains daily settlement prices (in USD) of the last 20 trading days of each month. Portfolio log returns are calculated as $n^{-1}\sum_{i=1}^{n} r_{i,t}$, where $i = 1, \ldots, n$ are the futures in the respective portfolio for which returns are available on trading day t. Daily futures data spans the period of 1998:1–2019:12 except for Ethanol (2005:6–2019:12), Wool (1998:1–2012:12), Pork Bellies (1998:1–2010:12), Gasoline (2005:10–2019:12), and Cobalt (2010:3–2019:12). Asterisks indicate the rejection of the null hypothesis that the time series has a unit root (ADF, PP) or is level stationary (KPSS) at the ***1%, **5%, and *10% level for the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests for stationarity.

(WIP) from Baumeister & Hamilton (2019), the Global Economic Conditions (GECON) index by Baumeister et al. (2020), the University of Michigan Consumer Sentiment index (CSENTI), the Cboe Volatility Index (VIX) as a proxy for investor sentiment, global Economic Policy Uncertainty (EPU) based on Baker et al. (2016), Geopolitical Risk (GPR) from Caldara & Iacoviello (2018), Geopolitical Volatility (GEOVOL) as proposed in Engle

KPSS tests consistently indicate that the GREA time series is non-stationary, and conducting Granger causality tests with non-stationary variables is likely to produce misleading results.

& Campos-Martins (2020)[13] , and Macro (MUNCERT), Financial (FUNCERT) as well as Real uncertainty (RUNCERT) indices based on the work of Jurado et al. (2015) and Ludvigson et al. (2018).[14] Descriptions and data sources of each variable can be found in Table A.19. Table 2 provides summary statistics for all variables. We use log-differenced data except for inflation expectation (already expected year-on-year change in US CPI), and GECON, which are already stationary in levels.

Table 2: Sample statistics of monthly macroeconomic variables, 1998–2019

	Obs.	Mean	Std.Dev.	Min	Max	Skewn.	Ex.Kurt.	J.B.	ADF	PP	KPSS
Global Economic Activity											
STEEL	264	0.319	4.477	−13.723	13.456	0.581	0.904	0.000	-6.543^{***}	-388.256^{***}	0.034
BDI	264	0.024	19.436	−101.249	70.348	−0.657	3.889	0.000	-8.070^{***}	-162.775^{***}	0.048
GECON	264	−0.046	0.393	−2.203	0.885	−1.997	7.795	0.000	-3.688^{**}	-50.426^{***}	0.097
WIP	264	0.200	0.606	−3.265	1.842	−1.629	7.405	0.000	-5.130^{***}	-264.803^{***}	0.101
Sentiment/Uncertainty											
VIX	264	−0.249	16.500	−37.925	71.918	1.198	3.161	0.000	-8.691^{***}	-217.326^{***}	0.022
CSENTI	264	−0.011	4.925	−19.925	12.762	−0.384	1.194	0.000	-7.534^{***}	-218.613^{***}	0.126
EPU	264	0.402	17.721	−45.853	70.585	0.529	1.143	0.000	-8.116^{***}	-249.979^{***}	0.067
RUNCERT	264	0.109	2.140	−5.444	7.775	0.329	0.977	0.000	-5.483^{***}	-118.481^{***}	0.072
MUNCERT	264	0.110	2.272	−5.550	8.284	0.487	1.066	0.000	-4.870^{***}	-74.841^{***}	0.069
FUNCERT	264	0.082	3.314	−9.143	9.933	0.277	0.445	0.062	-6.069^{***}	-100.028^{***}	0.075
GPR	264	0.299	33.228	−102.940	175.819	0.550	2.922	0.000	-7.121^{***}	-269.733^{***}	0.033
GEOVOL	234	−0.704	46.683	−176.673	150.359	−0.298	1.430	0.000	-9.864^{***}	-261.767^{***}	0.028
Others											
INFL	264	2.115	1.168	−1.978	5.352	−0.328	0.910	0.001	-4.300^{***}	-28.980^{***}	0.590^{**}
INFLE	264	2.914	0.563	0.400	5.200	0.842	4.901	0.000	-3.649^{**}	-47.286^{***}	0.407^{*}
USDEER	264	0.038	1.230	−3.586	6.422	0.488	2.282	0.000	-6.516^{***}	-161.720^{***}	0.187
TBILL	264	−0.459	31.470	−174.392	214.472	0.843	14.631	0.000	-6.065^{***}	-201.747^{***}	0.198
TED	264	−0.257	21.743	−54.318	86.690	0.267	0.810	0.006	-5.803^{***}	-194.206^{***}	0.049

Notes: Summary statistics are provided for 100× log-differenced data except for GECON, INFL, and INFLE (in levels). Monthly data spans the period of 1998:1–2019:12 except for GEOVOL (2000:7–2019:12). Asterisks indicate the rejection of the null hypothesis that the time series has a unit root (ADF, PP) or is level stationary (KPSS) at the ***1%, **5%, and *10% level for the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests for stationarity.

As our full sample period comprises different stages of the financialization as elaborated in Section 1, we divide the sample into subperiods accounting for the distinct behavior of commodity futures markets over time. Figure 1 illustrates different phases of financialization including pre-financialization (1998–2003), financialization (2004–2013), and de-financialization (2014–2019). As Adams et al. (2020) points out that there is no clearly identifiable breakpoint between the periods of pre-financialization and financialization, we further split the financialization period into emerging financialization (2004–2007) and the global financial crisis including the years after the crisis (2008–2013). The latter period marks the height of financialization in commodity futures markets. Summary statistics for commodity futures as well as potential drivers for each of the four subsamples can be found in the Appendix (Tables A.6–A.14 and A.15–A.18).

[13]We are grateful to Susana Martins and Brian Reis for providing us with the GEOVOL time series.
[14]VIX, GEOVOL, TBILL, and TED are calculated as monthly averages from daily data.

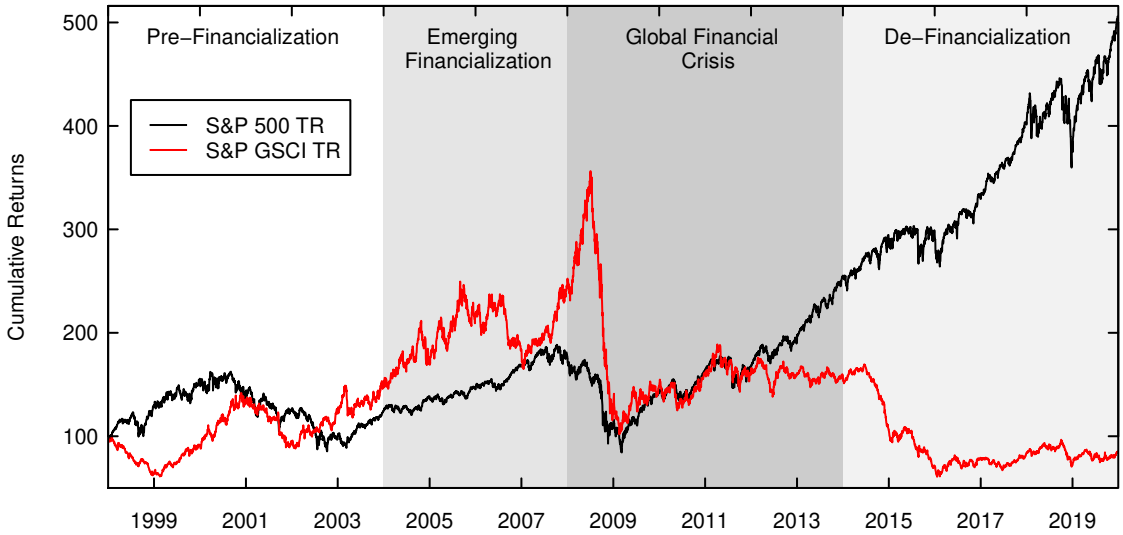

Figure 1: Different stages of the financialization of commodity futures markets illustrated by cumulative returns of the S&P 500 Total Return and the S&P GSCI Total Return indices. These stages (1998–2003, 2004–2007, 2008–2013, 2014–2019) serve as subsamples in our in-sample Granger causality analysis. Data is obtained from Refinitiv Datastream.

5. Results

The discussion of our results focuses on two aspects. Since our data set consists of 37 commodity futures, six equally-weighted commodity portfolios, and 17 potential drivers, we first estimate a total of 731 bivariate MF-VAR models in order to test for non-causality from potential drivers to commodity futures (portfolios). To account for a possible time-varying relationship between macroeconomic variables and commodity futures, we repeat this analysis within five subsamples—each of which covers a distinct stage of the ongoing (de-)financialization of commodity futures markets. We additionally compare the results to low-frequency Granger causality tests involving the temporal aggregation of commodity returns to the common monthly frequency.

As we encounter clear discrepancies in Granger causalities between the mixed-frequency and the low-frequency approach, our second subsection shifts the focus of our analysis towards a comparison of both approaches with an out-of-sample VAR-based trading study.

5.1. In-sample Granger causality analysis over the full sample

To identify common drivers of commodity futures, we evaluate p-values of the pairwise Granger causality tests based on bivariate VAR models. We are not concerned about

accumulation of alpha errors as single significances do not draw our attention. We solely focus on cases where one macroeconomic variable Granger causes at least a large subset of commodity futures. For the full sample of 1998–2019, Figure 2 depicts rejections of the null hypothesis of non-causality from the potential monthly driver (low-frequency) to the commodity futures (high-frequency) up to the 10% level:[15]

$$H_0^{(1)}(h=1): \text{ Driver } (x_L) \nrightarrow \text{Commodity } (x_H).$$

Additionally, Table 3 shows the number of times the null of non-causality is rejected relative to the total number of bivariate Granger causality tests per driver (which is 43 for the full sample). We will first put our attention on the results of the mixed-frequency analysis.

Not surprisingly, measures of global economic activity, especially World Industrial Production (WIP) and Global Economic Conditions (GECON) appear to be "common" drivers of many commodity futures across a range of different commodity classes, yet not all of them. Given the significance level of 5% (10%), the null non-causality for WIP and GECON is rejected in 37.21% (46.51%) and 34.88% (53.49%) of all bivariate cases, respectively. We can find the most pronounced effects for energies and industrial metals but also the majority of grains seems to be affected by GECON. Changes in WIP and GECON indicate changes in global economic activity which affect aggregate demand for a wide range of commodities, particularly for energies and industrial metals that are most intensively used in the industry. This corresponds to findings of Delle Chiaie et al. (2017) and Alquist et al. (2020) showing that commodity spot prices are commonly driven by aggregate demand shocks related to changes in global economic activity. Industrial metals seem to be furthermore driven by Financial and Macro Uncertainty (FUNCERT, MUNCERT). Precious metals (except Palladium), in contrast, are Granger caused by Geopolitical Volatility (GEOVOL), while common drivers of softs and livestock cannot be clearly identified. In sum, even though indicators of economic activity Granger cause a

[15] Tables A.20 and A.25 provide p-values of all mixed-frequency and low-frequency Granger causality tests for the full sample.

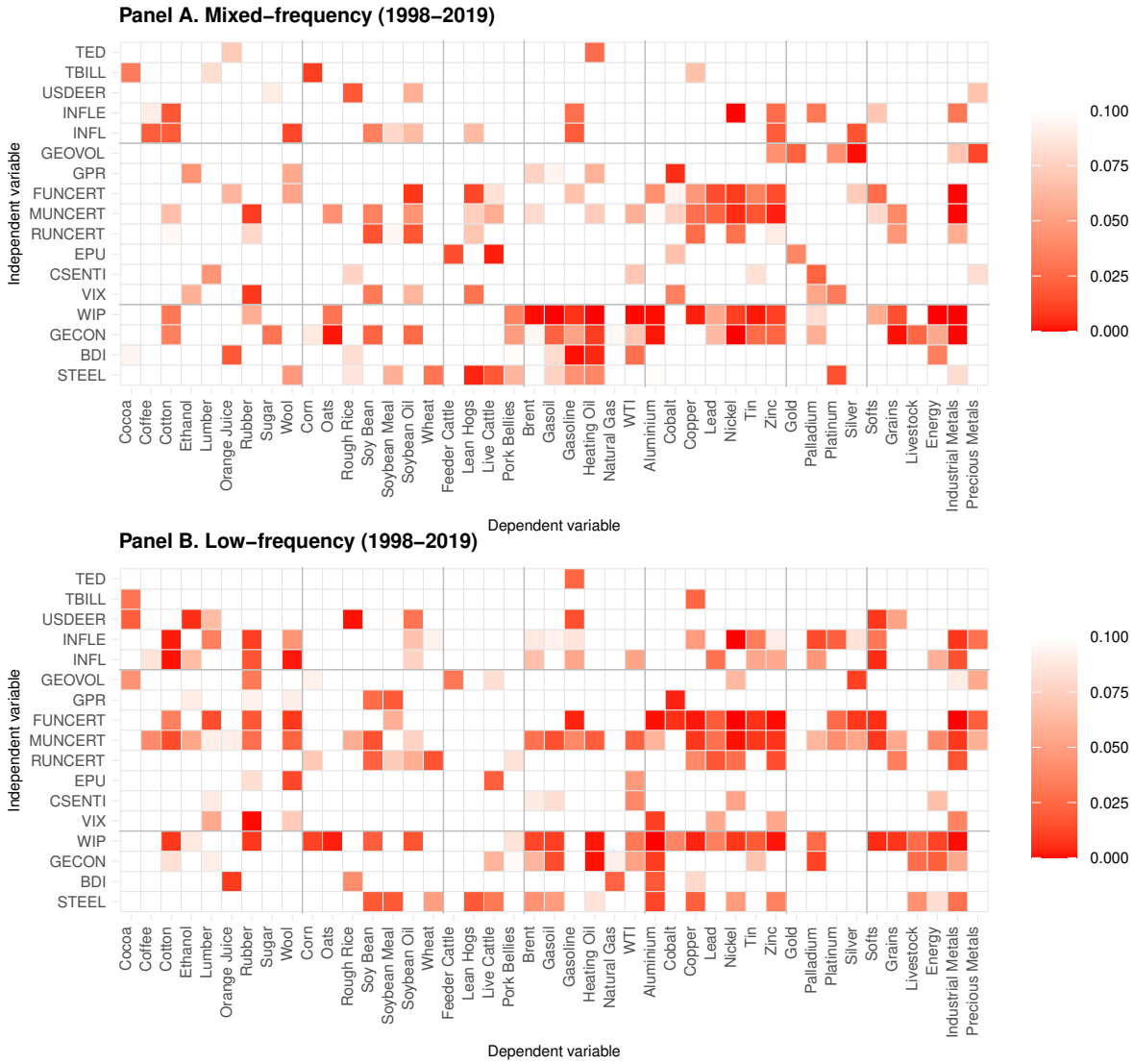

Figure 2: Bootstrapped p-values of mixed-frequency and low-frequency Granger causality tests for the null hypothesis of non-causality from potential drivers to commodity futures at the low-frequency prediction horizon $h = 1$: $H_0^{(1)}(h = 1)$: Driver $(x_L) \nrightarrow$ Commodity (x_H). Granger causality tests are based on bivariate MF-VAR (LF-VAR) models using weekly (monthly) commodity returns. i.e., $m = 4$ $(m = 1)$. The period covers the full sample from 1998–2019.

large fraction of commodities, we cannot determine a single common driver for the entire cross-section.

The lower panel of Figure 2 and Table 3 depict results of low-frequency Granger causality under temporal aggregation of commodity returns to the monthly level. In contrast to GECON, WIP is also recognized as a driver of many commodity futures where non-causality to even five out of six commodity portfolios (except precious metals) is rejected at the 5% level. Considering all pairwise driver-commodity combinations it is, however,

striking that the null of non-causality is generally more often rejected than for mixed-frequency Granger causality. In the low-frequency setting, it is indicated that MUNCERT not only drives the returns of industrial metals, but also of most of the energy, softs, and precious metals futures. Based on low-frequency Granger causality, MUNCERT is recognized as a return driver for 44.19% (69.77%) of all commodities (including portfolios) at the 5% (10%) level, while this proportion amounts to 53.49% (58.14%) for WIP. Next to MUNCERT and WIP, the null of non-causality from FUNCERT, inflation (INFL), and expected inflation (INFLE) to futures across different commodity classes is also often rejected. While GEOVOL was identified as a driver of most of the precious metals futures in the mixed-frequency case, the low-frequency approach instead does only indicate a causal link from GEOVOL to silver.

These differences in low-frequency and mixed-frequency Granger causality are in accordance with findings of Ghysels et al. (2016) and Bevilacqua et al. (2019). Since Ghysels et al. (2016) show that mixed-frequency Granger causality tests have higher asymptotic power and temporal aggregation is likely to lead to either spurious causality or spurious non-causality, we henceforth focus on the results of mixed-frequency Granger causality tests. We report low-frequency results for comparison reasons and show in the next section that differences are also present in the subsamples. In Section 5.3, we provide further evidence that the underlying VAR model prediction accuracy suffers from temporal aggregation.[16]

[16] We also rely on temporal aggregation by using weekly instead of daily commodity returns. However, as Ghysels et al. (2016) points out, a large difference in sampling frequencies will adversely affect the forecast performance of an unrestricted MF-VAR model, which we confirm in Section 5.3.

Table 3: Share of rejections of the null of non-causality per driver

		1998–2019			**1998–2003**			**2004–2007**			**2008–2013**			**2014–2019**		
		<0.01	<0.05	<0.10	<0.01	<0.05	<0.10	<0.01	<0.05	<0.10	<0.01	<0.05	<0.10	<0.01	<0.05	<0.10
Global Economic Activity																
STEEL	$m = 4$	0.0233	0.1628	0.3023	0.0000	0.0500	0.1250	0.0000	0.0476	0.0714	0.0000	0.0465	0.1628	0.0000	0.0244	0.1220
	$m = 1$	0.0000	0.2791	0.3488	0.0500	0.1750	0.2250	0.0238	0.0714	0.1190	0.0000	0.0698	0.1163	0.0000	0.0976	0.2439
BDI	$m = 4$	0.0465	0.1163	0.2093	0.0000	**0.1750**	**0.2500**	0.0000	0.0476	0.1190	0.0000	0.0698	0.1860	0.0488	0.1463	0.1707
	$m = 1$	0.0233	0.0930	0.1163	0.0250	0.2000	0.3000	**0.0952**	0.1429	0.1905	0.0698	0.2093	0.2791	0.0244	0.0976	0.0976
GECON	$m = 4$	0.1163	0.3488	**0.5349**	0.0250	0.0750	0.2000	0.0238	0.0476	0.1667	0.0465	0.2558	0.4186	0.0244	0.0488	0.1463
	$m = 1$	0.0465	0.1395	0.3488	**0.1250**	**0.2250**	**0.3500**	0.0238	0.0238	0.0952	0.0698	0.2093	0.3488	0.0000	0.0244	0.1220
WIP	$m = 4$	**0.2326**	**0.3721**	0.4651	0.0000	0.0750	0.1750	0.0000	0.0238	0.0714	0.2326	0.3721	0.4186	0.0000	0.0244	0.0488
	$m = 1$	**0.2558**	**0.5349**	0.5814	0.0250	0.1750	0.2500	0.0000	0.0714	0.1429	0.1163	0.3953	0.5116	0.0000	0.1463	0.2195
Sentiment/Uncertainty																
CSENTI	$m = 4$	0.0000	0.0465	0.1395	0.0000	0.0500	0.1250	0.0000	0.0714	0.0952	0.0233	0.1163	0.1628	0.0000	0.0000	0.0732
	$m = 1$	0.0000	0.0233	0.1395	0.0750	0.2000	0.3000	0.0238	0.0952	0.1190	0.0000	0.0000	0.0465	0.0244	0.1463	0.2195
TBILL	$m = 4$	0.0000	0.0465	0.0930	0.0000	0.0500	0.1000	0.0476	0.1667	0.2619	0.0000	0.0000	0.0465	0.0488	0.1220	0.2927
	$m = 1$	0.0000	0.0465	0.0465	0.0000	0.0500	0.1000	**0.0952**	**0.2381**	**0.3333**	0.0000	0.0233	0.0698	0.0000	0.0732	0.1220
TED	$m = 4$	0.0000	0.0233	0.0698	0.0000	0.0750	0.1250	0.0000	0.0476	0.1429	0.0000	0.0465	0.0465	0.0000	0.0000	0.0244
	$m = 1$	0.0000	0.0233	0.0233	0.0250	0.0750	0.0750	0.0238	0.0952	0.2619	0.0465	0.2093	0.3721	**0.0732**	**0.1951**	**0.2927**
VIX	$m = 4$	0.0233	0.1163	0.1860	0.0000	0.0500	0.1500	0.0000	0.0476	0.0476	0.0233	0.1395	0.3023	0.0000	0.0732	0.0976
	$m = 1$	0.0233	0.0698	0.1628	0.0250	0.0500	0.1250	0.0000	0.0714	0.0952	0.0465	0.1163	0.3023	0.0000	0.0488	0.0488
EPU	$m = 4$	0.0233	0.0698	0.0930	0.0000	0.0250	0.1000	0.0000	0.0000	0.0238	0.0000	0.0233	0.0233	0.0244	0.1951	0.2683
	$m = 1$	0.0000	0.0698	0.0930	0.0000	0.1250	0.2500	0.0000	0.0000	0.0952	0.0000	0.0000	0.0698	0.0000	0.0732	0.0732
FUNCERT	$m = 4$	0.0698	0.2326	0.3721	0.0000	0.0250	0.1000	0.0000	0.0000	0.0952	0.0465	0.2791	0.4186	0.0732	0.1951	0.3171
	$m = 1$	**0.2558**	0.3953	0.4186	0.0500	0.1000	0.2000	0.0476	0.0952	0.1905	0.0930	0.3721	0.6279	0.0244	0.0976	0.1220
MUNCERT	$m = 4$	0.0930	0.2558	0.4651	**0.0500**	0.1000	0.2000	0.0000	0.0476	0.1190	0.1163	0.3256	0.4651	0.0244	0.0976	0.1463
	$m = 1$	0.1395	0.4419	**0.6977**	0.0500	**0.2250**	0.2750	0.0000	0.0714	0.0952	0.2558	0.5581	0.6977	0.0244	0.0488	0.0488
RUNCERT	$m = 4$	0.0000	0.1163	0.2558	0.0000	0.0500	0.1500	0.0000	0.0714	0.1190	0.0233	0.1628	0.2093	0.0244	0.0732	0.1220
	$m = 1$	0.0000	0.1860	0.2791	0.0250	0.0500	0.1250	0.0000	0.0952	0.1667	0.0233	0.2558	0.3953	0.0000	0.0488	0.0732
Others																
GPR	$m = 4$	0.0233	0.0465	0.1395	0.0250	0.1000	**0.2500**	0.0000	0.0000	0.0476	0.0465	0.1395	0.1628	0.0000	0.0488	0.0488
	$m = 1$	0.0233	0.0698	0.1395	0.0000	0.0250	0.1750	0.0238	0.1190	0.1667	0.0465	0.1163	0.1860	0.0000	0.0244	0.0244
GEOVOL	$m = 4$	0.0233	0.1163	0.1395	0.0000	0.0250	0.0750	0.0000	0.0476	0.1429	0.0000	0.0233	0.0930	0.0244	0.1220	0.1707
	$m = 1$	0.0000	0.0930	0.2093	0.0500	0.1000	0.1250	0.0000	0.0000	0.0000	0.0233	0.1163	0.2326	0.0000	0.0000	0.0244
INFL	$m = 4$	0.0000	0.1628	0.2326	**0.0500**	0.0750	0.1750	0.0476	**0.2143**	0.2619	**0.2791**	**0.5349**	**0.6744**	**0.1707**	**0.3171**	**0.4390**
	$m = 1$	0.0698	0.1628	0.3721	0.0000	0.1000	0.1500	0.0714	**0.2381**	0.2381	**0.3953**	**0.6744**	**0.7209**	0.0000	0.0976	0.1463
INFLE	$m = 4$	0.0233	0.1395	0.1860	**0.0500**	0.1250	0.2250	**0.1190**	0.1905	**0.2857**	0.0698	0.2791	0.3721	0.0244	0.0732	0.1951
	$m = 1$	0.0698	0.2791	0.4419	0.0500	0.2000	0.2750	**0.0952**	0.1905	0.2381	0.2326	0.4419	0.5814	0.0488	0.1220	0.1951
USDEER	$m = 4$	0.0000	0.0233	0.0930	0.0000	0.0000	0.0250	0.0000	0.0238	0.0476	0.0000	0.0930	0.1628	0.0244	0.0976	0.1951
	$m = 1$	0.0698	0.1395	0.2093	0.0000	0.0000	0.0250	0.0238	0.0952	0.1190	0.0000	0.1628	0.2093	0.0488	0.1220	0.2195
total	$m = 4$	0.0410	0.1409	0.2339	0.0118	0.0662	0.1500	0.0140	0.0644	0.1246	0.0534	0.1710	0.2544	0.0301	0.0976	0.1693
	$m = 1$	0.0575	0.1792	0.2722	0.0338	0.1221	0.1956	0.0322	0.1008	0.1569	0.0834	0.2312	0.3393	0.0158	0.0861	0.1349

Notes: This table shows the proportion of all bivariate Granger Causality tests for a given potential driver in which the null hypothesis of non-causality from the driver to the commoditiy futures ($h = 1$: $H_0^{(1)}(h = 1)$: Driver $(x_L) \nrightarrow$ Commodity (x_H)) is rejected at the 1%, 5%, and 10% level, respectively. Granger causality tests are based on bivariate MF-VAR (LF-VAR) models using weekly (monthly) commodity returns, i.e., $m = 4$ ($m = 1$).

5.2. In-sample Granger causalitiy analysis over subsamples

We now split our sample period into four subsamples to cover for pre-financialization (1998–2003), emerging financialization (2004–2007), the global financial crisis (2008–2013), and de-financialization (2014–2019) as illustrated in Figure 1. The proportion of rejections of the null of non-causality are reported in Table 3. Figures 3–6 display heatmaps of p-values of mixed-frequency and low-frequency Granger causality tests.[17] It is worth noting that stationary tests, particularly for the potential driver variables, often show equivocal results (see Tables A.15–A.18), i.e., we cannot unambiguously determine if the variables are stationary over subsamples. Two exceptions are GECON (2008–2013) and INFL (2014–2019) that are non-stationary as indicated by all three tests. This might imply that supposedly causal links could be of spurious nature.[18]

The key findings from the subsample analysis are threefold. First, the relationships between potential drivers and commodity futures change over time and results for the full sample do not hold for each of the subsamples. Second, the total number of detected Granger causalities is—compared to the full sample results—relatively small during pre- and emerging financialization, substantially increases during the core of financialization beginning with the global financial crises, and shrinks again with the ongoing de-financialization. Third, clear differences between results of mixed and low-frequency Granger causalities are also apparent during each of the subsamples emphasizing the importance of choosing appropriate analysis tools for data sets involving frequency mismatches.

During the stages of pre-financialization, i.e., before financial investors increasingly engaged in commodity futures markets, and emerging financialization, there appears to be no single macroeconomic variable significantly affecting price movements in the majority of commodity futures. At the 5% level, the null of non-causality was rejected only in roughly 6.5% of all pairwise tests during the first two subsamples compared to 14.1% over the full

[17] Tables A.21–A.24 and A.26–A.29 provide p-values of all mixed-frequency and low-frequency Granger causality tests over each subsample.

[18] One way to get around this issue might be provided by using mixed-frequency Granger causality tests for processes that are possibly cointegrated as suggested by Götz & Hecq (2019).

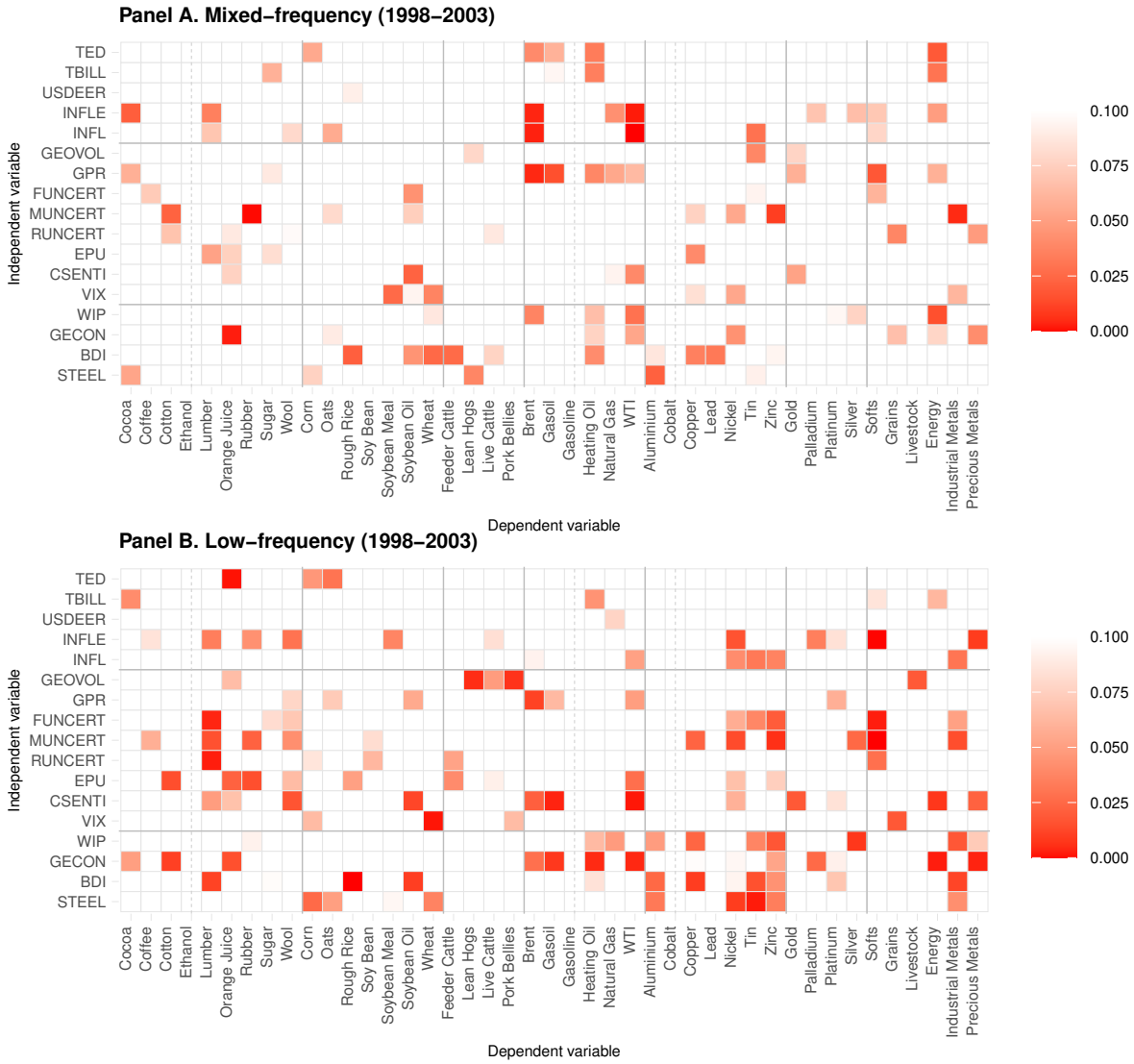

Figure 3: Bootstrapped p-values of mixed-frequency and low-frequency Granger causality tests for the null hypothesis of non-causality from potential drivers to commodity futures at the low-frequency prediction horizon $h = 1$: $H_0^{(1)}(h = 1)$: Driver $(x_L) \nrightarrow$ Commodity (x_H). Granger causality tests are based on bivariate MF-VAR (LF-VAR) models using weekly (monthly) commodity returns. i.e., $m = 4$ $(m = 1)$. The sample spans the period 1998:1–2003:12 (pre-financialization). If the data is not available over the sample, commodities are crossed out.

sample. Particularly changes in global economic activity—which Granger cause a large subset of commodities over the full sample as represented by WIP and GECON—play a far less prominent role for commodity futures returns from 1998–2007. Merely the class of energy commodities are jointly driven by Geopolitical Risk (GPR) from 1998–2003, which can be traced to the 9/11 terrorist attacks in 2001 and the subsequent "War on Terror" in the middle east with the invasion of Iraq by the U.S. military in 2003. GPR is not identified as a common driver in the low-frequency analysis. From 2004–2007, mixed-

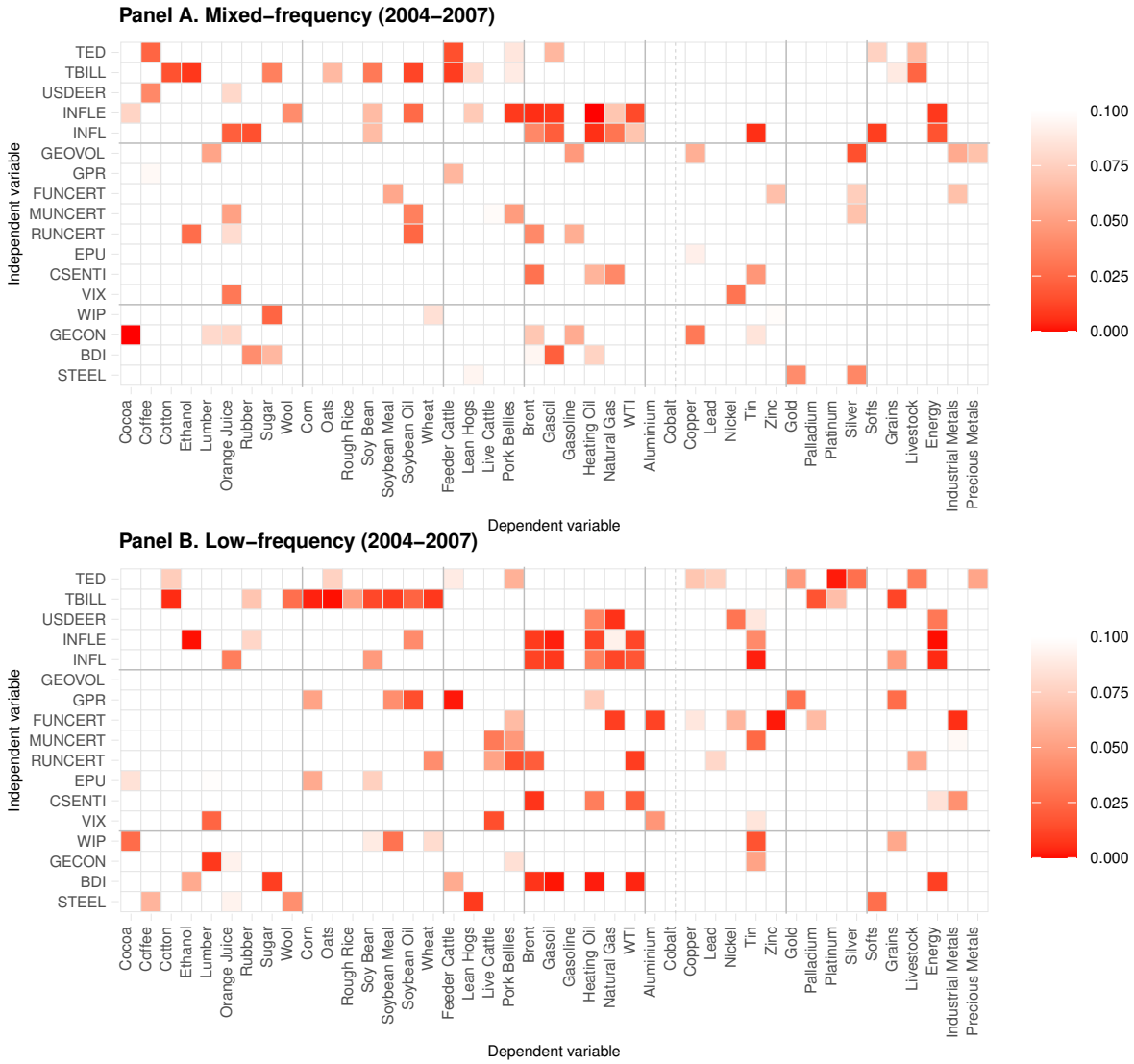

Figure 4: Bootstrapped p-values of mixed-frequency and low-frequency Granger causality tests for the null hypothesis of non-causality from potential drivers to commodity futures at the low-frequency prediction horizon $h = 1$: $H_0^{(1)}(h = 1)$: Driver $(x_L) \nrightarrow$ Commodity (x_H). Granger causality tests are based on bivariate MF-VAR (LF-VAR) models using weekly (monthly) commodity returns. i.e., $m = 4$ $(m = 1)$. The sample spans the period 2004:1–2007:12 (emerging financialization). If the data is not available over the sample, commodities are crossed out.

frequency Granger causality tests indicate that energy commodities were then driven by inflation (INFL) as well as inflation expectations (INFLE).

At the peak of financialization (2008–2013) beginning around the outburst of the global financial crisis, linkages between the fundamental variables and commodity returns intensified. With 17.10% of all pairs at the 5% level and 25.44% at the 10% level, this period shows the highest proportion of rejections of the null of non-causality. Most Granger causalities are found for (expected) inflation, various uncertainty measures, and indica-

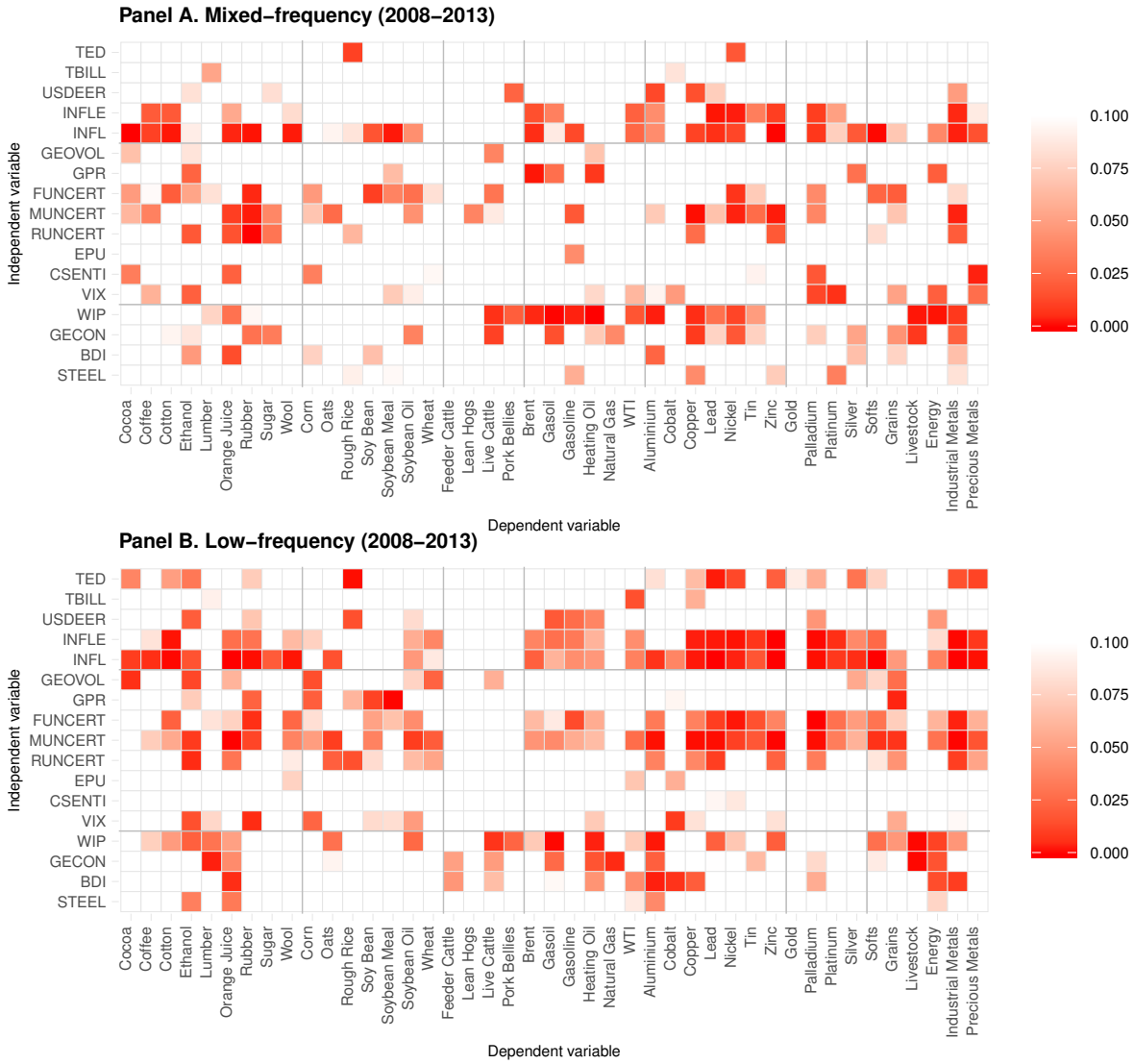

Figure 5: Bootstrapped p-values of mixed-frequency and low-frequency Granger causality tests for the null hypothesis of non-causality from potential drivers to commodity futures at the low-frequency prediction horizon $h = 1$: $H_0^{(1)}(h = 1)$: Driver $(x_L) \nrightarrow$ Commodity (x_H). Granger causality tests are based on bivariate MF-VAR (LF-VAR) models using weekly (monthly) commodity returns. i.e., $m = 4$ $(m = 1)$. The sample spans the period 2008:1–2013:12 (global financial crisis). If the data is not available over sample, commodities are crossed out.

tors of global economic activity. More precisely, the highest percentage of rejected null hypotheses of non-causality at the 5% resp. 10% level show INFL (53.49%, 67.44%), WIP (37.21%, 41.86%), MUNCERT (32.56%, 46.51%), INFLE (27.91%, 37.21%), FUNCERT (27.91%, 41.86%), and GECON (25.58%, 41.86%). Rejection rates for low-frequency tests are even higher. On a portfolio basis, INFL is a common driver of all commodity classes except livestock, whereas INFLE shows similar but less Granger causalities. Hardly surprising, uncertainty (FUNCERT, MUNCERT), and the global economic activity (WIP,

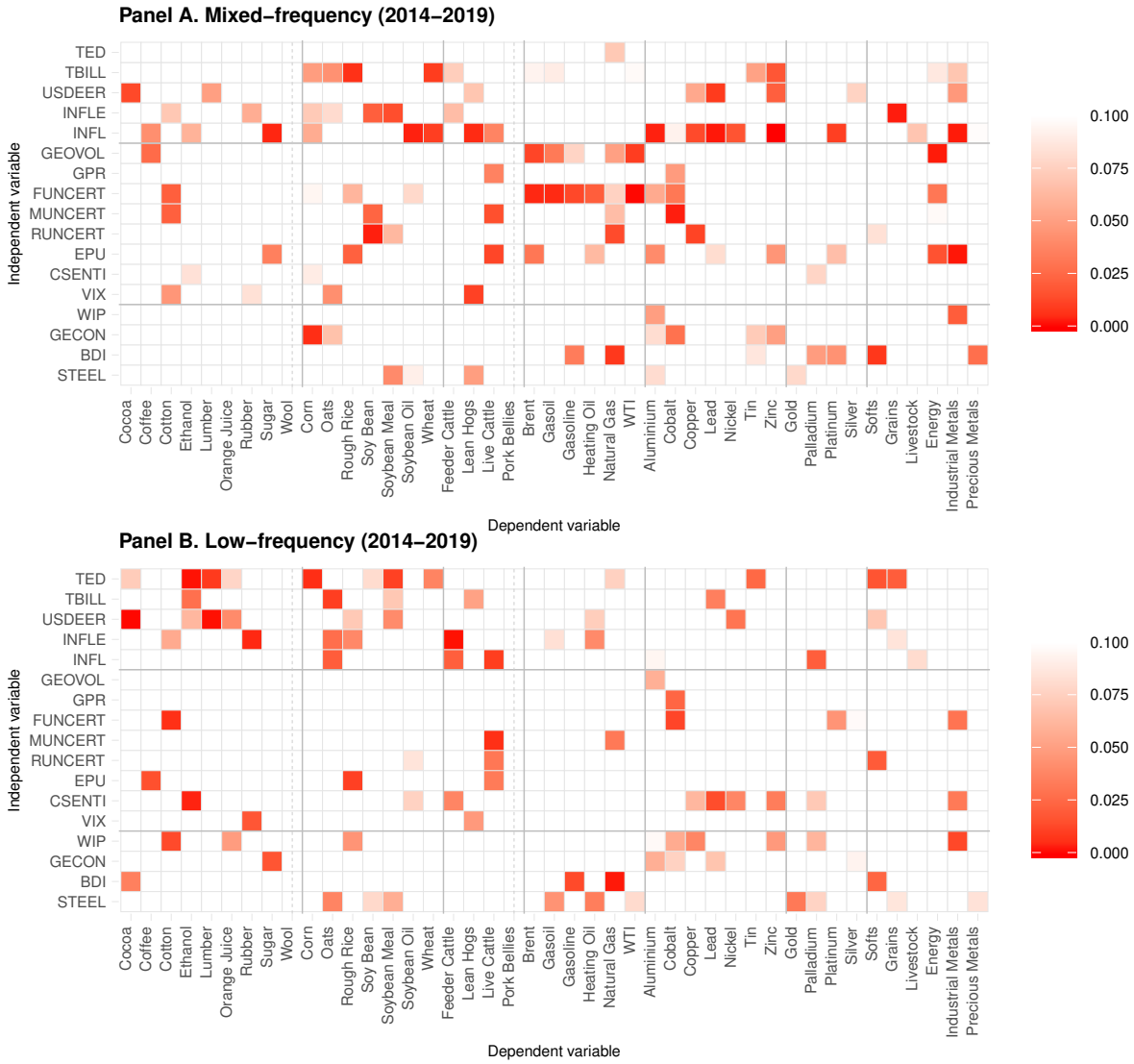

Figure 6: Bootstrapped p-values of mixed-frequency and low-frequency Granger causality tests for the null hypothesis of non-causality from potential drivers to commodity futures at the low-frequency prediction horizon $h = 1$: $H_0^{(1)}(h = 1)$: Driver $(x_L) \nrightarrow$ Commodity (x_H). Granger causality tests are based on bivariate MF-VAR (LF-VAR) models using weekly (monthly) commodity returns. i.e., $m = 4$ $(m = 1)$. The sample spans the period 2014:1–2019:12 (de-financialization). If the data is not available over sample, commodities are crossed out.

GECON) were important factors influencing commodity prices during the financial crisis that quickly emerged as an economic crisis globally. Delle Chiaie et al. (2017) also find that changes in global demand during the great recession affected a wide range of commodity spot prices more than usual. According to our results, particularly energy commodities and industrial metals are driven by WIP and GECON besides INFL(E), while uncertainty (FUNCERT and MUNCERT) played a more important role for prices of softs and grains. Next to measures of economic activity, also MUNCERT Granger causes the bulk of in-

dustrial metals. Energies, in contrast, show additional Granger causalities from GPR. Precious metals exhibit Granger causal links from INFL, stock market sentiment (VIX) and consumer sentiment (CSENTI).

What is, however, surprising is that we detect only very few Granger causalities from changes in monthly stock market sentiment as proxied by the average VIX level to single commodity futures. On a portfolio basis, non-causality is rejected for grains, energies, and precious metals, which cannot be deduced from results for individual commodities (except for industrial metals).

With the ongoing de-financialization that gradually started during 2014, the relationship of the potential drivers to commodities changes again. Compared with the preceding period involving the great recession, we observe an overall dissipating influence of macroeconomic indicators on commodity futures returns, howbeit the number of significant Granger causalities is still higher compared to pre-crisis levels. While INFL Granger causes the majority of industrial metals, GEOVOL and FUNCERT seem to drive the returns of energy commodities. None of these linkages are recognized by low-frequency Granger causality.

The subsample analysis not only shows that drivers of commodity futures vary over time and the relationships heavily depend on the stage of the financialization. It also provides additional evidence that results depend on the frequency of commodity futures returns that are fed into the VAR model. The overall number of rejections of the null of non-causality is consistently and remarkably higher for the LF approach as presented in Table 3. Vivid examples for this pattern are Granger causalities from TBILL to grains (2004–2007), BDI to energies (2004-2007), as well as TED (2008–2013) and CSENTI to industrial metals (2014–2019) among others. The only exception is the de-financialization subsample (2014–2019) where the total number of identified Granger causalities is higher for the mixed-frequency approach since low-frequency Granger causality fails to spot INFL, GEOVOL, and FUNCERT as drivers of a considerable subset of commodity futures.

5.3. Out-of-sample trading simulation

It is of great interest to investors whether the relationships between fundamental variables and commodity futures identified in the previous section can be utilized in commodities futures trading. Furthermore, the question arises if the mixed-frequency approach provides an economic value over the traditional low-frequency approach as the in-sample analysis shows that temporal aggregation often leads to substantially different conclusions. We also check whether using daily returns, and thereby more information at the expense of parameter proliferation, substantially reduces the performance of the model. Our trading strategy is straightforwardly constructed based on directional VAR return predictions of the S&P GSCI total return index (GSCI) that reflects the performance of investing in a series of liquid commodity futures. We choose the GSCI as the trading instrument since the index is investable through liquid and highly capitalized ETFs and ETNs. Using an index instead of futures also enables to easily calculate return figures that are independent of margin requirements. Sample statistics are provided in Table 4.

Table 4: Sample statistics of S&P GSCI index for daily, weekly (5-day), and monthly log returns

	Obs.	Mean	Std.Dev.	Min.	Max.	Skewn.	Ex.Kurt.	J.B.	ADF	PP	KPSS
Daily prices	5739	4173.24	1638.04	1860.66	10898.10	0.89	0.839	0.000	−1.849	−5.125	9.311^{***}
Daily returns	5280	−0.003	1.469	−15.613	7.617	−0.543	6.352	0.000	-15.807^{***}	-5475.936^{***}	0.220
Weekly returns	1056	−0.014	3.323	−22.295	12.320	−0.546	2.964	0.000	-8.364^{***}	-1141.649^{***}	0.194
Monthly returns	264	−0.063	6.529	−33.127	17.953	−0.649	1.984	0.000	-6.524^{***}	-225.772^{***}	0.144

Notes: Summary statistics for daily ($i = 1$) and non-overlapping weekly ($i = 5$) returns are provided for $r_t = 100 \times [\ln(p_t) - \ln(p_{t-i})]$, where $\{p_t\}_{t=1}^{T}$ is the time series of S&P GSCI closing prices of the last 20 trading days of each month. The sample period runs from 1998:1 to 2019:12. Asterisks indicate the rejection of the null hypothesis that the time series has a unit root (ADF, PP) or is level stationary (KPSS) at the ***1%, **5%, and *10% level for the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests for stationarity.

The implemented trading rules are as follows. (1) On the last day of each month, we estimate a bivariate VAR(1) model with either daily ($m = 20$), weekly ($m = 4$), or monthly ($m = 1$) GSCI returns and monthly observations of the respective driver variable over the last 50 months (approx. 1,000 trading days). (2) We forecast the GSCI log return over the next month. (3) We enter a long position if the predicted return is positive and exit an open long position if the predicted return is negative, i.e., we hold cash over the next month. If the return prediction has the same sign on two consecutive months, positions (long GSCI or cash) remain unchanged. Profits are fully reinvested. Transaction costs are not taken into account but should only play a minor role as trades

are executed on a monthly basis at most. Note that for some drivers this strategy uses only "pseudo"-out-of-sample forecasts as, e.g., monthly steel production or inflation is not readily available by the end of the month. In real world applications, one would need to rely on nowcasts of these variables for the last month of the rolling window.

We obtain monthly return forecasts from an MF-VAR model by forecasting the GSCI log return for each high-frequency period (days or weeks) during the one-step-ahead low-frequency period (month) and then aggregating log return forecasts to the monthly level. Consider a rolling window size of T_L with the low-frequency time index $\tau_L \in \{1, ..., T_L\}$ and an MF-VAR with weekly GSCI returns, i.e., $m = 4$. The forecast of the log return for the i-th week of the following month, i.e. one-step-ahead $(T_L + 1)$, within a bivariate MF-VAR(1) is given through:

$$\begin{aligned}\hat{x}_H(T_L + 1, k_H) \mid \ell(\tau_L) &= \mathbb{E}\big[x_H(T_L + 1, k_H) \mid \ell(T_L)\big] \\ &= \hat{a}_{11} x_H(T_L, 1) + ... + \hat{a}_{14} x_H(T_L, 4) + \hat{a}_{15} x_H(T_L, 4)\end{aligned}$$

where $k_H = 1, ..., 4$ and $\ell(T_L) = x_H(1, 1), ..., x_H(T_L, 1), ..., x_H(1, 4), ..., x_H(T_L, 4), x_L(1), ..., x_L(T_L)$. Then, we predict the log return over the next month by summing up the individually forecasted weekly log returns:

$$\hat{x}^a_H(T_L + 1) = \sum_{k_H=1}^{4} \hat{x}_H(T_L + 1, k_H).$$

For the sake of readability, we will henceforth denote the actual discrete return of month τ_L as $r_\tau := p_\tau / p_{\tau-1} - 1$, where p_τ denotes the settlement price of the last trading day of a month, and the predicted monthly log return as $\hat{r}_\tau := \hat{x}^a_H(\tau_L)$.

We measure the directional predictive accuracy of VAR return forecasts by the Success Ratio (SR):

$$SR = T^{-1} \sum_{\tau=1}^{T} I\{r_\tau \hat{r}_\tau > 0\},$$

where $I\{\cdot\}$ is the indicator function that is one if the condition in curly brackets is true and zero otherwise. The SR corresponds to the proportion of months for which the sign

of the return was correctly predicted. We follow Degiannakis et al. (2020) and apply the non-parametric test of Directional Accuracy (DA) proposed by Pesaran & Timmermann (1992), who suggest the following Hausman-type test statistic:

$$\frac{SR - SR^*}{\sqrt{\hat{\text{var}}(SR) - \hat{\text{var}}(SR^*)}} \overset{a}{\sim} N(0,1),$$

where $SR^* = P_r P_{\hat{r}} + (1 - P_r)(1 - P_{\hat{r}})$ is the estimated probability that $r_\tau \hat{r}_\tau > 0$, $P_r = T^{-1} \sum_{\tau=1}^{T} I\{r_\tau > 0\}$, $P_{\hat{r}} = T^{-1} \sum_{\tau=1}^{T} I\{\hat{r}_\tau > 0\}$, $\hat{\text{var}}(SR) = T^{-1} SR^*(1 - SR^*)$, and $\hat{\text{var}}(SR^*) = T^{-1}(2P_r - 1)^2 P_{\hat{r}}(1 - P_{\hat{r}}) + T^{-1}(2P_{\hat{r}} - 1)^2 P_r(1 - P_r) + 4T^{-2} P_r P_{\hat{r}}(1 - P_r)(1 - P_{\hat{r}})$.

While the DA test of Pesaran & Timmermann (1992) does only focus on the sign of the predicted and actual return, it does not allow to draw any conclusions about the profitability of a trading strategy that is build upon directional forecasts. The excess profitability (EP) test of Anatolyev & Gerko (2005) therefore takes both into account: the sign of the return forecast and the magnitude of the trading strategy's return that was either earned or avoided due to the forecast-based long or short signal. Let $y_\tau = \text{sign}(\hat{r}_\tau) r_\tau$, where $sign(\cdot)$ is -1 if its argument is negative and $+1$ otherwise. In order to test the null hypothesis of conditional mean independence, i.e., $\mathbb{E}[r_{\tau+1} | \ell(\boldsymbol{\tau})] = \text{const.}$, the authors propose the following Hausman-type test statistic:

$$\frac{A_T - B_T}{\sqrt{\hat{\text{var}}(A_T - B_T)}} \overset{a}{\sim} N(0,1),$$

where $A_T = T^{-1} \sum_{\tau=1}^{T} y_\tau$ represents the mean monthly strategy returns (including omitted negative and missed out positive returns), $B_T = \big(T^{-1} \sum_{\tau=1}^{T} \text{sign}(\hat{r}_\tau)\big)\big(T^{-1} \sum_{\tau=1}^{T} r_\tau\big)$, $\hat{\text{var}}(A_T - B_T) = 4T^{-2} p_{\hat{r}}(1 - p_{\hat{r}}) \sum_\tau (r_\tau - \bar{r})^2$, and $p_{\hat{r}} = 0.5\big(1 + T^{-1} \sum_\tau \text{sign}(\hat{r}_\tau)\big)$. If the null hypothesis holds, the actual strategy's mean return, A_T, is not significantly greater than the mean return generated by buy and sell signals that appear arbitrarily with ex-post probabilities of buys and sells induced by the trading strategy being tested.

We expect that the performance of the trading strategy and the additional value provided by including a potential fundamental driver through the VAR model will strongly depend on the time period due to the dynamically changing commodity-driver relation-

ships as observed in the preceding in-sample Granger causality analysis. If the differences in mixed and low-frequency Granger causalities are indeed due to spurious (non-)causality generated by temporal aggregation, a trading strategy that relies on MF-VAR return predictions should outperform the same strategy relying on LF-VAR return predictions. The MF-VAR using weekly returns ($m = 4$) should, moreover, produce higher (risk-adjusted) returns than the MF-VAR with daily returns ($m = 20$) as the latter is expected to suffer from parameter proliferation. Annualized return figures as well as results of the DA and EP tests are presented in Table 5 and Figure 7. Figure 8 shows the performance of the VAR-based strategies relative to a GSCI buy-and-hold benchmark strategy over time.

Table 5 and Figure 7 show that both annualized returns and annualized Sharpe ratios are consistently and mostly substantially higher for the MF-VAR using weekly GSCI returns (MF-VAR$_{m=4}$) than for the MF-VAR with daily returns (MF-VAR$_{m=20}$) and the LF-VAR with monthly returns (LF-VAR$_{m=1}$) across all drivers. In contrast to the other VAR-models, results of the EP test confirm that MF-VAR$_4$ return predictions generate both positive and significant mean returns for all drivers at least at the 10% level.

For the trading period running from the last trading day of February 2002, when the first trading signal was issued, through the end of December 2019, the highest Sharpe ratios are attained by the MF-VAR$_4$ for TED (0.624), STEEL (0.539), and TBILL (0.491) with annualized returns of 9.185%, 7.528%, and 7.286%, respectively. For the same three drivers, the LF-VAR generates remarkably lower Sharpe ratios (annualized returns) between -0.009 to 0.101 (-0.119% to 1.619%), whereas the MF-VAR with daily returns achieves Sharpe ratios (annualized returns) of 0.069 to 0.186 (0.799% to 2.927%). In comparison, a buy-and-hold investment in the GSCI over the same period yields an annualized Sharpe ratio of -0.005 with an annualized return of -2.416%. Figure 8 shows that the relative performance to the buy-and-hold benchmark was merely fluctuating around one until the GSCI reached is peak in 2008. When the index was heavily declining in value amid the global financial crisis most VAR models issued sell signals after prices began to shrink and thereby avoided sharper losses. Thereafter, the outperformance of the MF-VAR$_4$ against the buy-and-hold strategy continued to increase for most drivers.

Table 5: Trading results for the S&P GSCI index

	Global Economic Activity				Sentiment/Uncertainty								Others				
	STEEL	BDI	GECON	WIP	VIX	CSENTI	EPU	RUNCERT	MUNCERT	FUNCERT	GPR	GEOVOL	INFL	INFLE	USDEER	TBILL	TED
Annualized return																	
LF-VAR ($m = 1$)	−0.119	−1.434	1.627	0.789	2.089	3.110	5.490	−0.285	0.932	2.662	0.407	−0.635	3.746	−0.881	−0.489	1.619	0.269
MF-VAR ($m = 4$)	7.528	6.215	5.894	6.326	6.705	6.277	6.510	4.749	4.412	5.267	6.275	3.555	7.133	5.954	4.317	7.286	9.185
MF-VAR ($m = 20$)	2.927	−0.579	2.380	4.674	2.170	2.762	1.854	0.319	2.027	1.708	1.560	0.418	3.683	−2.241	0.821	1.130	0.799
Annualized Sharpe ratio																	
LF-VAR ($m = 1$)	−0.009	−0.090	0.103	0.054	0.133	0.235	0.378	−0.019	0.063	0.170	0.029	−0.045	0.268	−0.063	−0.029	0.101	0.016
MF-VAR ($m = 4$)	0.539	0.422	0.412	0.432	0.435	0.461	0.428	0.310	0.303	0.343	0.438	0.244	0.496	0.448	0.300	0.491	0.624
MF-VAR ($m = 20$)	0.186	−0.032	0.150	0.299	0.137	0.179	0.121	0.019	0.129	0.108	0.098	0.026	0.247	−0.144	0.052	0.069	0.049
Success Ratio (SR)																	
LF-VAR ($m = 1$)	0.472	0.505	0.533	0.509	0.505	0.528	0.575	0.523	0.547^{**}	0.547	0.495	0.543	0.561	0.481	0.505^{*}	0.528	0.509
MF-VAR ($m = 4$)	0.570^{**}	0.579^{**}	0.551^{*}	0.565^{**}	0.547^{*}	0.547^{*}	0.565^{**}	0.551	0.533^{**}	0.551^{*}	0.547	0.533^{*}	0.551	0.537	0.523^{*}	0.561	0.575
MF-VAR ($m = 20$)	0.584^{***}	0.542	0.561^{*}	0.589^{***}	0.556^{**}	0.561	0.575^{**}	0.556^{*}	0.547^{**}	0.556^{*}	0.561	0.571^{*}	0.561^{*}	0.509^{**}	0.561^{**}	0.537	0.561^{**}
Mean monthly strategy returns (A_T)																	
LF-VAR ($m = 1$)	−0.049	−0.189	0.312	0.146	0.385	0.493	0.905	−0.018	0.173^{**}	0.477	0.068	0.234	0.613	−0.151	0.001^{*}	0.325	0.114
MF-VAR ($m = 4$)	1.213^{***}	1.025^{**}	0.964^{**}	1.041^{***}	1.119^{**}	1.008^{***}	1.084^{***}	0.806^{***}	0.733^{***}	0.890^{**}	1.024^{*}	0.932^{**}	1.160^{**}	0.949^{**}	0.714^{***}	1.195^{**}	1.488^{*}
MF-VAR ($m = 20$)	0.526	0.018	0.440	0.804^{**}	0.403	0.489	0.338	0.116	0.378	0.328	0.304	0.465	0.625	−0.340	0.178^{*}	0.250	0.190

Notes: This table presents the results of a trading rule based on bivariate VAR-induced directional one-month-ahead return forecasts of the S&P GSCI index which is also used as the trading instrument. If the VAR model predicts a positive GSCI return over the next month (long signal), a long position is opened at the close and a buy-and-hold strategy is pursued over the next month. Open positions are closed in case of a negative GSCI return forecast (short signal). With short signals on two consecutive months, only cash is held over the next month. Profits are fully reinvested. Bivariate VAR(1) models are estimated over a rolling window spanning 50 months with daily ($m = 20$), weekly ($m = 4$), and monthly ($m = 1$) GSCI return data as well as monthly observations of the respective driver variable. The sample period lasts from 1998:1–2019:12 such that the first trading signal determining the position for the next month is generated at the end of 2002:2, except for the GEOVOL sample lasting from 2000:7–2019:12 such that the first return prediction is generated at the end of 2004:8. Return figures (annualized return and A_T) are stated in percent. The Sharpe ratio is calculated for a zero risk-free rate. Transaction costs are not taken into account. Asterisks denote the rejection of the null hypothesis of the DA and EP tests at the $10\%^{*}$,$5\%^{**}$, and $1\%^{***}$ level, respectively.

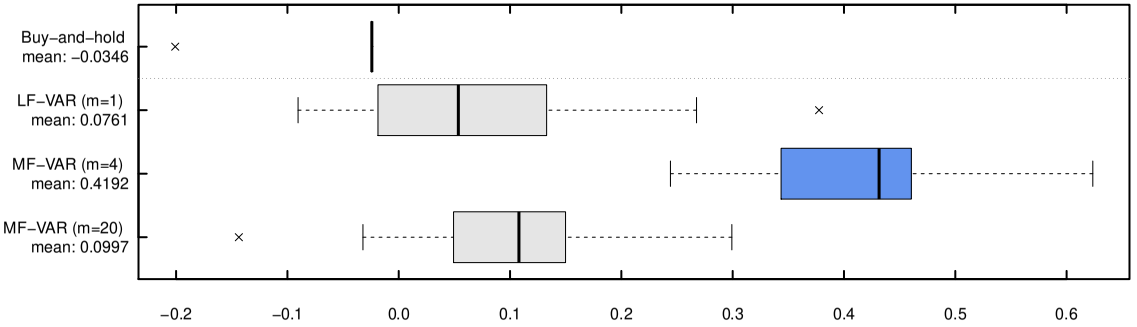

Figure 7: Distribution of annualized Sharpe ratios for trading the S&P GSCI index according to bivariate VAR-induced directional one-month-ahead return forecasts. Each boxplot comprises 17 backtests (one for each driver) with daily ($m = 20$), weekly ($m = 4$), or monthly ($m = 1$) GSCI return data as well as monthly observations of the respective driver variable. The trading period runs from the end of 2002:2 (2004:8 for GEOVOL) to 2019:12.

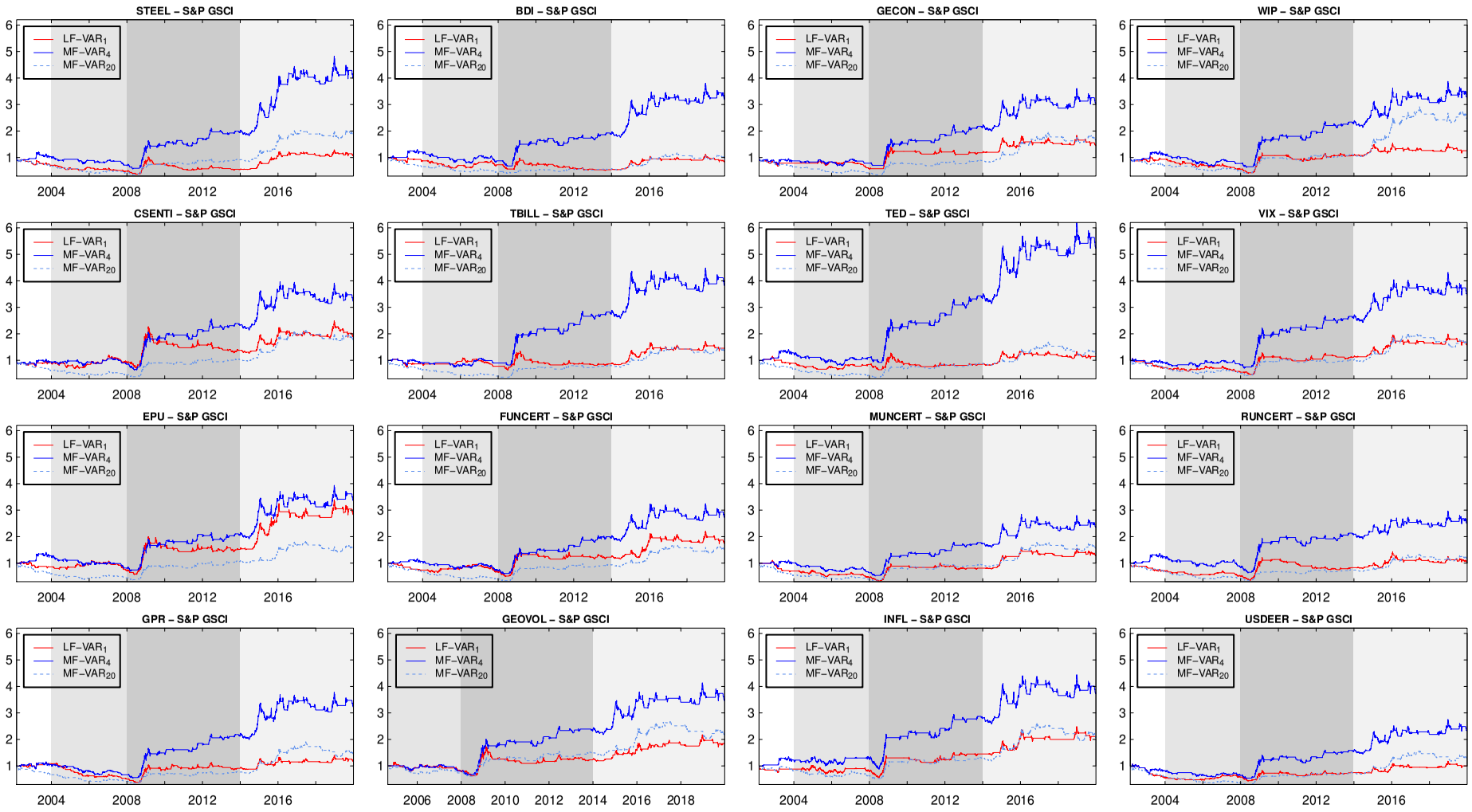

Figure 8: Cumulative returns for trading the S&P GSCI based on bivariate VAR-induced directional one-month-ahead return forecasts relative to a buy-and-hold strategy. The VAR_m model either uses daily ($m = 20$), weekly ($m = 4$), or monthly ($m = 1$) GSCI return data and monthly observations of the respective driver variable. The trading period runs from the end of 2002:2 (2004:8 for GEOVOL) to 2019:12. Shadings indicate the following periods: pre-financialization, emerging financialization, global financial crisis, de-financialization. INFLE is omitted.

The worst risk-adjusted performance for the MF-VAR$_4$ is caused by using GEOVOL as driver leading to an annualized Sharpe ratio of 0.244 and annualized returns of 3.555%, which is still far higher than the Sharpe ratios (annualized returns) of -0.045 and 0.026 (-0.635% and 0.418%) produced by the LF-VAR$_1$ and MF-VAR$_{20}$. The closest performance of the MF-VAR$_4$ and the LF-VAR$_1$ (MF-VAR$_{20}$) in terms of risk-adjusted returns is observed for EPU (WIP). Considering all bivariate VAR models, the average Sharpe ratio generated by MF-VAR$_4$ return predictions amounts to 0.4192 and is thus considerably higher than for the LF-VAR$_1$ (0.0761) and the MF-VAR$_{20}$ (0.0997). This superior trading performance is also not limited to the full sample period as Figure 9 demonstrates, which plots the 12-month rolling excess returns of the MF-VAR$_4$ over the LF-VAR$_1$.

Differences in the success ratios and DA test results, in contrast, are rather small and success ratios are often even higher for the MF-VAR$_{20}$ compared to the MF-VAR$_4$. The far higher monthly strategy returns from the EP test, hence, suggest that the MF-VAR$_4$ outperformance does not stem from more frequent correct directional return forecasts in general, but from more accurate directional forecasts of relatively high positive and negative returns. But is the MF-VAR$_4$'s ability to provide superior directional return forecasts due to the inclusion of fundamental economic indicators, or due to better accounting for interdependencies in weekly GSCI returns? The answer to this question, again, depends on the time period. As we know from the Granger causality analysis, dependencies of commodity prices on global economic activity, uncertainty, market sentiment, and other economic indicators are not constant over time since these relationships are possibly affected by different stages of the financialization. Likewise, the drivers' contribution to trading performance are different across drivers and also changes over time, as Figure A.10 shows with 12-month rolling excess returns of the MF-VAR$_4$ strategy over an equivalent MF-VAR that does not encompass the low-frequency driver variable. Periods in which macroeconomic variables improve returns alternate with periods in which the inclusion of a driver has a detrimental or no effect on directional GSCI return predictions.

In sum, our findings from the trading application are in line with expectations. They emphasize the adverse VAR model performance coming with either temporal aggregation

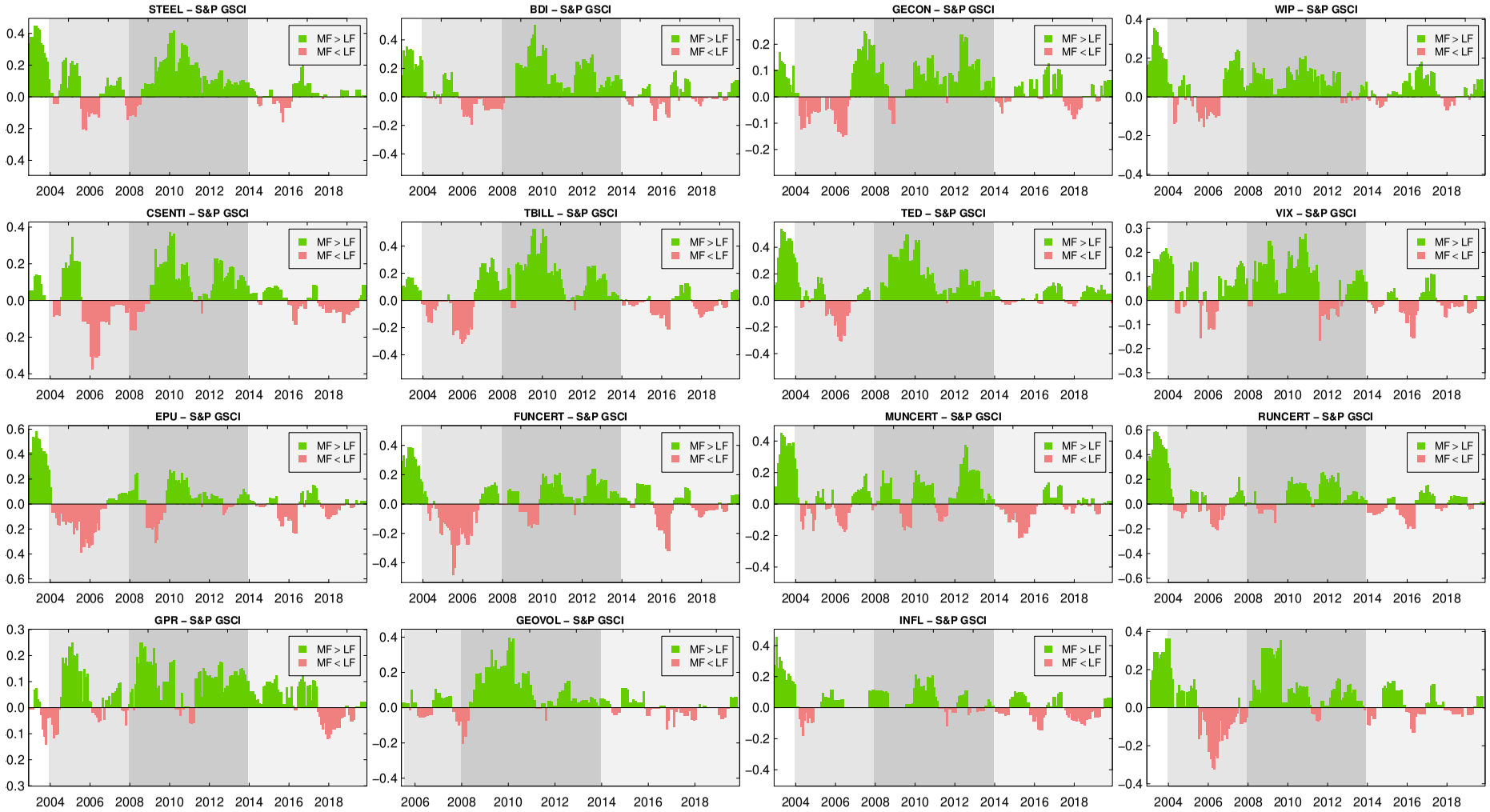

Figure 9: 12-month rolling excess returns of MF-VAR ($m = 4$) over LF-VAR ($m = 1$) on a monthly basis. The trading period runs from the end of 2002:2 (2004:8 for GEOVOL) to 2019:12. Shadings indicate the following periods: pre-financialization, emerging financialization, global financial crisis, de-financialization. INFLE is omitted.

and disregarding high-frequency information in a low-frequency environment or parameter proliferation in a mixed-frequency environment where the frequency mismatch is too large. The outcome of the trading study further supports the conclusion on common commodity drivers gained from the in-sample Granger causality analysis. We cannot identify fundamental economic variables driving returns consistently over time across the entire cross-section of commodity futures.

6. Conclusion

Our study contributes to the literature on commodity price co-movements on futures markets by investigating the presence of common fundamental drivers in the cross-section of commodities. Unlike previous studies, we use linear mixed-frequency Granger causality tests to access the information of higher frequency commodity returns. We use monthly data of macroeconomic indicators that serve as proxies for global economic activity, sentiment and uncertainty, as well as other variables such as inflation, the effective US-Dollar exchange rate, and the short-term interest rate. Over the full sample from 1998–2019 covering multiple periods of financialization, we find no single fundamental variable that drives (Granger causes) the entire cross-section of commodity futures returns. However, indicators of global economic activity, especially world industrial production and global economic conditions, seem to play an important role for many commodities across different groups, particularly for energies and industrial metals. Industrial metals seem to be furthermore driven by macro and financial uncertainty, while geopolitical volatility affects most of the precious metals.

The subsample analysis shows that these relations, however, are not persistent over time. Financialization and de-financialization influence linkages of commodities and macroeconomic variables. Generally, we encounter the most Granger causalities during the great recession and the following years (2008–2013), marking the peak of financialization in commodity futures markets. Over the course of de-financialization beginning in 2014, the impact of most macroeconomic variables affecting large subsets of commodity futures during the previous period vanished. Yet, uncertainty measures still affect energy com-

modity prices, while inflation appears to drive futures returns of industrial metals. The time-varying impact of the macroeconomic variables on commodity returns is also corroborated by our out-of-sample trading study that utilizes trading signals from directional MF-VAR return predictions. Despite financialization and co-movement of commodity prices, our results indicate a reasonable degree of commodity market segmentation.

Additionally, by comparing in-sample and out-of-sample results to a standard low-frequency procedure under temporal aggregation of commodity returns, we show that findings do not only depend on the sample period but also on the frequency at which the data is sampled. Linear low-frequency Granger causality tests both fail to detect Granger causalities that are unveiled with mixed-frequency tests and indicate causalities which cannot be confirmed by our mixed-frequency procedure. This is in line with results of Ghysels et al. (2016) and Bevilacqua et al. (2019). The out-of-sample trading results indicate an economic benefit from using higher frequency data to uncover the relationship of monthly economic variables and commodity futures. Trading profits from the mixed-frequency model are significantly higher compared to the low-frequency approach. Thus, temporally aggregating the high-frequency data to circumvent the frequency mismatch between the variables is likely to produce misleading results and might end up in drawing the wrong conclusions.

Our findings on the time-varying relationship between macroeconomic indicators and the broad commodity futures market as well as on the advantageousness of using mixed-frequency data analysis are important to investors and portfolio managers engaged in commodity futures markets as well as for market research outlooks. Moreover, as we highlight the importance of MIDAS techniques for analyzing fundamental commodity return drivers, our results uncover new research opportunities in this field. One limitation of our study is that we only use pairwise Granger causality tests to avoid parameter proliferation and thereby might oversee causality chains, which could be tackled in future research.

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Appendix A. Additional tables and figures

Table A.6: Sample statistics of commodity futures for weekly (5-day) log returns, 1998–2003

	Obs.	Mean	Std.Dev.	Skewn.	Ex.Kurt.	J.B.	ADF	PP	KPSS
Agriculture (Softs)									
Cocoa (ICE)	288	−0.025	5.105	0.659	2.385	0.000	-6.855^{***}	-257.401^{***}	0.244
Coffee (ICE)	288	−0.318	5.832	0.407	1.505	0.000	-7.529^{***}	-328.769^{***}	0.197
Cotton (ICE)	288	0.039	4.100	0.393	0.834	0.000	-7.375^{***}	-263.838^{***}	0.275
Ethanol (CBOT)	–	–	–	–	–	–	–	–	–
Lumber (CME)	288	0.027	4.976	0.100	−0.005	0.786	-6.683^{***}	-271.635^{***}	0.051
Orange Juice (ICE)	288	−0.096	4.267	0.800	4.479	0.000	-7.876^{***}	-292.683^{***}	0.189
Rubber (SGX)	288	0.185	3.553	0.316	1.146	0.000	-6.560^{***}	-211.511^{***}	0.317
Sugar (ICE)	288	−0.267	4.938	0.115	0.342	0.360	-5.399^{***}	-249.190^{***}	0.124
Wool (ASX)	288	0.039	3.378	0.406	1.888	0.000	-5.635^{***}	-261.655^{***}	0.214
Portfolio (Softs)	288	−0.052	1.940	0.251	0.661	0.016	-7.247^{***}	-292.328^{***}	0.404^{*}
Agriculture (Grains)									
Corn (CBOT)	288	−0.023	3.505	0.346	3.288	0.000	-6.435^{***}	-285.508^{***}	0.110
Oats (CBOT)	288	−0.009	5.014	−0.612	2.787	0.000	-6.809^{***}	-293.399^{***}	0.132
Rough Rice (CBOT)	288	−0.076	4.608	1.380	10.065	0.000	-7.047^{***}	-273.884^{***}	0.580^{**}
Soy Bean	288	0.062	3.067	0.332	1.445	0.000	-6.543^{***}	-315.189^{***}	0.430^{*}
Soybean Meal (CBOT)	288	0.067	3.849	0.277	2.983	0.000	-6.824^{***}	-319.332^{***}	0.276
Soybean Oil (CBOT)	288	0.040	3.303	0.523	1.344	0.000	-7.426^{***}	-325.205^{***}	0.429^{*}
Wheat (CBOT)	288	0.045	3.893	0.584	0.928	0.000	-7.731^{***}	-303.609^{***}	0.170
Portfolio (Grains)	288	0.015	2.458	0.576	1.318	0.000	-6.874^{***}	-313.120^{***}	0.592^{**}
Agriculture (Livestock)									
Feeder Cattle (CME)	288	0.018	2.120	−1.692	14.998	0.000	-3.376^{*}	-351.377^{***}	0.082
Lean Hogs (CME)	288	−0.026	6.688	−0.225	3.354	0.000	-7.055^{***}	-312.857^{***}	0.033
Live Cattle (CME)	288	0.060	2.898	−0.513	3.747	0.000	-4.262^{***}	-313.889^{***}	0.031
Pork Bellies (CME)	288	0.183	6.574	−0.788	5.405	0.000	-7.584^{***}	-292.296^{***}	0.030
Portfolio (Livestock)	288	0.059	3.087	−0.469	1.390	0.000	-6.781^{***}	-321.591^{***}	0.042
Energy									
Brent (ICE)	288	0.211	5.283	−0.352	0.957	0.000	-7.306^{***}	-301.422^{***}	0.062
Gasoil (NYMEX)	288	0.207	5.439	−0.649	2.694	0.000	-6.588^{***}	-302.088^{***}	0.066
Gasoline (NYMEX)	–	–	–	–	–	–	–	–	–
Heating Oil (NYMEX)	288	0.213	5.881	−0.454	2.005	0.000	-7.160^{***}	-279.852^{***}	0.065
Natural Gas (NYMEX)	288	0.367	8.210	0.120	0.948	0.003	-6.453^{***}	-282.217^{***}	0.054
WTI (NYMEX)	288	0.217	5.665	−0.334	1.367	0.000	-7.163^{***}	-295.767^{***}	0.061
Portfolio (Energy)	288	0.243	4.834	−0.140	1.172	0.000	-6.609^{***}	-273.501^{***}	0.077
Industrial Metals									
Aluminium (LME)	288	0.012	2.204	0.200	1.180	0.000	-6.616^{***}	-292.664^{***}	0.133
Cobalt (LME)	–	–	–	–	–	–	–	–	–
Copper (LME)	288	0.100	2.615	0.136	0.754	0.021	-6.519^{***}	-230.464^{***}	0.285
Lead (LME)	288	0.091	2.863	0.270	0.426	0.059	-6.898^{***}	-289.457^{***}	0.468^{**}
Nickel (LME)	288	0.353	4.615	−0.474	1.163	0.000	-4.993^{***}	-278.648^{***}	0.386^{*}
Tin (LME)	288	0.068	2.220	−0.211	1.768	0.000	-5.104^{***}	-298.183^{***}	0.386^{*}
Zinc (LME)	288	−0.028	2.553	0.040	−0.103	0.903	-6.929^{***}	-257.349^{***}	0.195
Portfolio (Industrial Metals)	288	0.099	2.106	−0.160	0.770	0.015	-5.576^{***}	-277.776^{***}	0.495^{**}
Precious Metals									
Gold (COMEX)	288	0.126	2.105	0.704	2.929	0.000	-7.210^{***}	-265.649^{***}	0.278
Palladium (NYMEX)	288	−0.009	5.929	0.543	3.392	0.000	-6.749^{***}	-297.035^{***}	0.486^{**}
Platinum (NYMEX)	288	0.274	3.018	−0.043	1.116	0.001	-6.391^{***}	-275.498^{***}	0.109
Silver (COMEX)	288	0.001	3.091	0.164	2.053	0.000	-8.008^{***}	-249.501^{***}	0.247
Portfolio (Precious Metals)	288	0.098	2.367	0.134	0.956	0.003	-6.766^{***}	-296.585^{***}	0.095

Notes: Summary statistics for single futures are provided for non-overlapping 5-day returns calculated as $r_t = 100 \times [\ln(p_t) - \ln(p_{t-5})]$, where $\{p_t\}_{t=1}^{T}$ is the front month continuous futures series which contains daily settlement prices (in USD) of the last 20 trading days of each month. Portfolio log returns are calculated as $n^{-1}\sum_{i=1}^{n} r_{i,t}$, where $i = 1, \ldots, n$ are the futures in the respective portfolio for which returns are available on trading day t. Daily futures data spans the period of 1998:1–2003:12. Asterisks indicate the rejection of the null hypothesis that the time series has a unit root (ADF, PP) or is level stationary (KPSS) at the ***1%, **5%, and *10% level for the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests for stationarity.

Table A.7: Sample statistics of commodity futures for weekly (5-day) log returns, 2004–2007

	Obs.	Mean	Std.Dev.	Skewn.	Ex.Kurt.	J.B.	ADF	PP	KPSS
Agriculture (Softs)									
Cocoa (ICE)	192	0.154	4.596	0.016	2.054	0.000	-6.741^{***}	-183.023^{***}	0.088
Coffee (ICE)	192	0.386	4.320	0.272	0.171	0.272	-6.490^{***}	-178.638^{***}	0.066
Cotton (ICE)	192	−0.051	4.063	−0.177	0.689	0.091	-7.368^{***}	-164.598^{***}	0.303
Ethanol (CBOT)	124	0.532	5.894	−0.654	1.104	0.001	-3.739^{**}	-114.043^{***}	0.202
Lumber (CME)	192	−0.150	4.552	0.398	0.681	0.012	-6.131^{***}	-201.538^{***}	0.092
Orange Juice (ICE)	192	0.448	4.594	0.393	1.670	0.000	-6.213^{***}	-181.191^{***}	0.224
Rubber (SGX)	192	0.366	3.141	−0.408	2.364	0.000	-4.855^{***}	-182.962^{***}	0.084
Sugar (ICE)	192	0.337	4.258	−0.346	1.708	0.000	-5.575^{***}	-181.557^{***}	0.347^{*}
Wool (ASX)	192	0.095	2.507	0.520	3.644	0.000	-6.434^{***}	-203.668^{***}	0.311
Portfolio (Softs)	192	0.222	1.783	−0.246	0.029	0.379	-5.118^{***}	-168.261^{***}	0.065
Agriculture (Grains)									
Corn (CBOT)	192	0.321	4.359	0.336	1.245	0.000	-5.182^{***}	-209.484^{***}	0.247
Oats (CBOT)	192	0.386	5.118	−0.256	0.831	0.022	-6.730^{***}	-200.928^{***}	0.056
Rough Rice (CBOT)	192	0.240	3.548	−1.433	8.941	0.000	-6.271^{***}	-145.016^{***}	0.259
Soy Bean	192	0.218	4.324	−1.918	11.600	0.000	-5.713^{***}	-201.180^{***}	0.435^{*}
Soybean Meal (CBOT)	192	0.164	4.828	−1.429	8.827	0.000	-4.991^{***}	-189.193^{***}	0.313
Soybean Oil (CBOT)	192	0.292	3.545	−0.167	1.384	0.000	-6.912^{***}	-167.982^{***}	0.499^{**}
Wheat (CBOT)	192	0.444	4.338	0.446	0.262	0.032	-7.434^{***}	-166.529^{***}	0.455^{*}
Portfolio (Grains)	192	0.295	2.868	−0.328	1.235	0.000	-5.891^{***}	-185.890^{***}	0.511^{**}
Agriculture (Livestock)									
Feeder Cattle (CME)	192	0.149	2.328	−0.130	1.559	0.000	-5.001^{***}	-210.516^{***}	0.301
Lean Hogs (CME)	192	0.042	4.361	−0.010	3.803	0.000	-6.928^{***}	-165.088^{***}	0.152
Live Cattle (CME)	192	0.115	2.777	−0.249	0.249	0.290	-5.489^{***}	-207.824^{***}	0.043
Pork Bellies (CME)	192	−0.003	5.219	0.428	3.846	0.000	-5.884^{***}	-179.980^{***}	0.044
Portfolio (Livestock)	192	0.076	2.240	−0.204	0.375	0.293	-5.977^{***}	-181.189^{***}	0.159
Energy									
Brent (ICE)	192	0.591	4.326	−0.673	2.374	0.000	-6.852^{***}	-216.799^{***}	0.073
Gasoil (NYMEX)	192	0.587	4.450	−0.051	−0.299	0.670	-6.346^{***}	-205.096^{***}	0.080
Gasoline (NYMEX)	108	0.251	5.608	−0.245	−0.027	0.583	-4.282^{***}	-126.873^{***}	0.089
Heating Oil (NYMEX)	192	0.554	5.024	−0.011	−0.182	0.874	-6.667^{***}	-210.479^{***}	0.071
Natural Gas (NYMEX)	192	0.099	8.373	0.066	0.053	0.922	-6.695^{***}	-205.844^{***}	0.040
WTI (NYMEX)	192	0.564	4.602	−0.651	1.051	0.000	-7.475^{***}	-208.068^{***}	0.073
Portfolio (Energy)	192	0.491	4.479	−0.206	−0.063	0.499	-7.048^{***}	-215.997^{***}	0.062
Industrial Metals									
Aluminium (LME)	192	0.206	3.252	0.253	1.116	0.002	-6.853^{***}	-219.520^{***}	0.161
Cobalt (LME)	–	–	–	–	–	–	–	–	–
Copper (LME)	192	0.551	4.048	−0.261	0.635	0.067	-6.013^{***}	-206.398^{***}	0.157
Lead (LME)	192	0.648	5.329	−0.261	0.670	0.056	-5.472^{***}	-195.711^{***}	0.083
Nickel (LME)	192	0.235	6.472	−0.244	2.226	0.000	-5.197^{***}	-194.598^{***}	0.152
Tin (LME)	192	0.474	4.069	−0.072	2.328	0.000	-5.626^{***}	-186.049^{***}	0.195
Zinc (LME)	192	0.442	5.254	−0.532	1.419	0.000	-5.118^{***}	-214.271^{***}	0.335
Portfolio (Industrial Metals)	192	0.426	3.418	−0.246	0.170	0.339	-6.440^{***}	-185.344^{***}	0.129
Precious Metals									
Gold (COMEX)	192	0.365	2.572	−0.474	0.454	0.012	-7.323^{***}	-195.175^{***}	0.161
Palladium (NYMEX)	192	0.338	4.274	0.017	1.965	0.000	-5.702^{***}	-171.815^{***}	0.071
Platinum (NYMEX)	192	0.330	2.669	−0.247	1.417	0.000	-6.693^{***}	-166.227^{***}	0.082
Silver (COMEX)	192	0.477	4.407	−0.786	1.240	0.000	-6.788^{***}	-180.833^{***}	0.033
Portfolio (Precious Metals)	192	0.378	2.908	−0.628	0.582	0.000	-6.619^{***}	-171.073^{***}	0.067

Notes: Summary statistics for single futures are provided for non-overlapping 5-day returns calculated as $r_t = 100 \times [\ln(p_t) - \ln(p_{t-5})]$, where $\{p_t\}_{t=1}^{T}$ is the front month continuous futures series which contains daily settlement prices (in USD) of the last 20 trading days of each month. Portfolio log returns are calculated as $n^{-1}\sum_{i=1}^{n} r_{i,t}$, where $i = 1, \ldots, n$ are the futures in the respective portfolio for which returns are available on trading day t. Daily futures data spans the period of 2004:1–2007:12 except for Ethanol (2005:6–2007:12) and Gasoline (2005:10–2007:12). Asterisks indicate the rejection of the null hypothesis that the time series has a unit root (ADF, PP) or is level stationary (KPSS) at the ***1%, **5%, and *10% level for the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests for stationarity.

Table A.8: Sample statistics of commodity futures for weekly (5-day) log returns, 2008–2013

	Obs.	Mean	Std.Dev.	Skewn.	Ex.Kurt.	J.B.	ADF	PP	KPSS
Agriculture (Softs)									
Cocoa (ICE)	288	0.099	4.749	−0.302	0.224	0.083	-7.507^{***}	-256.440^{***}	0.090
Coffee (ICE)	288	−0.072	4.192	0.068	0.670	0.060	-7.738^{***}	-239.097^{***}	0.347
Cotton (ICE)	288	0.076	5.294	−0.753	4.829	0.000	-5.987^{***}	-251.528^{***}	0.120
Ethanol (CBOT)	288	−0.074	4.875	−1.228	5.376	0.000	-6.741^{***}	-266.472^{***}	0.086
Lumber (CME)	288	0.149	5.309	0.004	0.929	0.006	-6.459^{***}	-298.668^{***}	0.069
Orange Juice (ICE)	288	−0.018	6.079	0.130	1.835	0.000	-7.413^{***}	-289.414^{***}	0.108
Rubber (SGX)	288	−0.035	5.052	−2.023	11.259	0.000	-4.771^{***}	-230.705^{***}	0.172
Sugar (ICE)	288	0.145	5.507	−0.286	1.392	0.000	-5.442^{***}	-346.980^{***}	0.204
Wool (ASX)	240	0.050	2.784	−0.110	3.030	0.000	-5.419^{***}	-257.313^{***}	0.239
Portfolio (Softs)	288	0.033	2.493	−0.813	4.228	0.000	-5.111^{***}	-286.094^{***}	0.186
Agriculture (Grains)									
Corn (CBOT)	288	−0.027	5.095	−0.745	3.374	0.000	-6.238^{***}	-278.291^{***}	0.150
Oats (CBOT)	288	0.050	5.579	0.330	2.348	0.000	-6.324^{***}	-263.443^{***}	0.073
Rough Rice (CBOT)	288	0.047	4.228	−0.535	1.186	0.000	-6.995^{***}	-247.589^{***}	0.043
Soy Bean	288	0.031	4.133	−0.804	1.812	0.000	-6.154^{***}	-251.803^{***}	0.055
Soybean Meal (CBOT)	288	0.096	4.750	−0.609	1.070	0.000	-6.482^{***}	-236.136^{***}	0.043
Soybean Oil (CBOT)	288	−0.080	3.887	−0.588	2.327	0.000	-5.891^{***}	-259.831^{***}	0.113
Wheat (CBOT)	288	−0.132	5.121	−0.007	0.609	0.108	-6.676^{***}	-290.027^{***}	0.092
Portfolio (Grains)	288	−0.002	3.492	−0.564	1.196	0.000	-5.929^{***}	-249.703^{***}	0.080
Agriculture (Livestock)									
Feeder Cattle (CME)	288	0.160	2.285	−0.252	1.769	0.000	-6.719^{***}	-302.685^{***}	0.107
Lean Hogs (CME)	288	0.135	4.877	−0.430	4.103	0.000	-7.253^{***}	-274.997^{***}	0.042
Live Cattle (CME)	288	0.116	2.369	−0.384	1.408	0.000	-6.550^{***}	-325.126^{***}	0.123
Pork Bellies (CME)	144	0.149	8.182	1.078	9.176	0.000	-5.652^{***}	-129.086^{***}	0.059
Portfolio (Livestock)	288	0.139	2.626	−0.417	2.644	0.000	-7.911^{***}	-245.683^{***}	0.059
Energy									
Brent (ICE)	288	0.058	5.191	−0.901	5.632	0.000	-4.979^{***}	-367.590^{***}	0.093
Gasoil (NYMEX)	288	0.041	4.657	−0.718	2.069	0.000	-4.908^{***}	-322.496^{***}	0.116
Gasoline (NYMEX)	288	0.041	5.729	−0.737	4.907	0.000	-5.495^{***}	-326.229^{***}	0.069
Heating Oil (NYMEX)	288	0.053	4.814	−0.647	4.047	0.000	-5.494^{***}	-305.383^{***}	0.118
Natural Gas (NYMEX)	288	−0.198	6.570	0.440	1.656	0.000	-6.193^{***}	-295.085^{***}	0.131
WTI (NYMEX)	288	0.009	5.646	−0.205	3.760	0.000	-5.084^{***}	-324.391^{***}	0.080
Portfolio (Energy)	288	0.000	4.408	−0.806	4.163	0.000	-4.914^{***}	-321.078^{***}	0.116
Industrial Metals									
Aluminium (LME)	288	−0.102	3.742	−0.127	1.629	0.000	-5.646^{***}	-290.694^{***}	0.085
Cobalt (LME)	184	−0.202	3.705	0.340	1.409	0.000	-6.229^{***}	-218.301^{***}	0.072
Copper (LME)	288	0.036	4.715	−1.306	6.019	0.000	-5.152^{***}	-327.645^{***}	0.083
Lead (LME)	288	−0.052	6.120	−0.303	1.588	0.000	-6.738^{***}	-264.904^{***}	0.088
Nickel (LME)	288	−0.220	5.660	−0.280	2.310	0.000	-6.362^{***}	-289.505^{***}	0.098
Tin (LME)	288	0.109	5.507	−0.681	1.814	0.000	-6.128^{***}	-298.886^{***}	0.068
Zinc (LME)	288	−0.049	4.926	−0.523	1.168	0.000	-6.162^{***}	-275.591^{***}	0.098
Portfolio (Industrial Metals)	288	−0.062	4.019	−0.714	2.510	0.000	-5.545^{***}	-287.536^{***}	0.095
Precious Metals									
Gold (COMEX)	288	0.125	3.039	−0.434	2.670	0.000	-7.477^{***}	-246.733^{***}	0.345
Palladium (NYMEX)	288	0.223	5.590	−0.799	1.825	0.000	-5.385^{***}	-294.113^{***}	0.130
Platinum (NYMEX)	288	−0.038	4.082	−0.963	3.059	0.000	-5.419^{***}	-287.197^{***}	0.069
Silver (COMEX)	288	0.091	5.780	−0.930	4.299	0.000	-5.937^{***}	-259.604^{***}	0.188
Portfolio (Precious Metals)	288	0.100	3.985	−0.910	2.460	0.000	-5.480^{***}	-280.192^{***}	0.153

Notes: Summary statistics for single futures are provided for non-overlapping 5-day returns calculated as $r_t = 100 \times [\ln(p_t) - \ln(p_{t-5})]$, where $\{p_t\}_{t=1}^{T}$ is the front month continuous futures series which contains daily settlement prices (in USD) of the last 20 trading days of each month. Portfolio log returns are calculated as $n^{-1}\sum_{i=1}^{n} r_{i,t}$, where $i = 1, \ldots, n$ are the futures in the respective portfolio for which returns are available on trading day t. Daily futures data spans the period of 2008:1–2013:12 except for Wool (2008:1–2012:12), Pork Bellies (2008:1–2010:12), and Cobalt (2010:3–2013:12). Asterisks indicate the rejection of the null hypothesis that the time series has a unit root (ADF, PP) or is level stationary (KPSS) at the ***1%, **5%, and *10% level for the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests for stationarity.

Table A.9: Sample statistics of commodity futures for weekly (5-day) log returns, 2014–2019

	Obs.	Mean	Std.Dev.	Skewn.	Ex.Kurt.	J.B.	ADF	PP	KPSS
Agriculture (Softs)									
Cocoa (ICE)	288	−0.022	3.629	0.090	0.029	0.820	-6.521^{***}	-245.953^{***}	0.088
Coffee (ICE)	288	0.055	4.687	0.475	0.725	0.000	-7.547^{***}	-258.936^{***}	0.110
Cotton (ICE)	288	−0.071	3.241	−0.531	1.686	0.000	-5.964^{***}	-264.851^{***}	0.112
Ethanol (CBOT)	288	−0.114	4.772	−2.398	22.053	0.000	-7.910^{***}	-263.337^{***}	0.030
Lumber (CME)	288	0.041	4.492	−0.071	2.595	0.000	-6.459^{***}	-259.328^{***}	0.091
Orange Juice (ICE)	288	−0.118	4.559	0.383	0.715	0.001	-6.897^{***}	-258.608^{***}	0.143
Rubber (SGX)	288	−0.155	3.572	−0.007	0.294	0.594	-5.882^{***}	-332.224^{***}	0.159
Sugar (ICE)	288	−0.070	4.160	0.882	2.895	0.000	-6.469^{***}	-244.162^{***}	0.060
Wool (ASX)	–	–	–	–	–	–	–	–	–
Portfolio (Softs)	288	−0.057	1.768	0.066	0.428	0.299	-6.119^{***}	-254.171^{***}	0.066
Agriculture (Grains)									
Corn (CBOT)	288	−0.029	3.264	0.230	1.103	0.000	-6.862^{***}	-318.181^{***}	0.041
Oats (CBOT)	288	−0.067	4.879	−0.249	0.587	0.028	-7.992^{***}	-287.082^{***}	0.141
Rough Rice (CBOT)	288	−0.058	3.292	−0.021	1.311	0.000	-6.699^{***}	-234.482^{***}	0.265
Soy Bean	288	−0.115	3.047	−0.806	3.336	0.000	-6.307^{***}	-329.253^{***}	0.099
Soybean Meal (CBOT)	288	−0.131	3.827	−1.447	12.250	0.000	-7.462^{***}	-284.195^{***}	0.052
Soybean Oil (CBOT)	288	−0.041	2.831	0.144	0.299	0.357	-5.520^{***}	-288.352^{***}	0.159
Wheat (CBOT)	288	−0.028	4.105	0.462	0.533	0.001	-7.475^{***}	-291.078^{***}	0.117
Portfolio (Grains)	288	−0.067	2.233	0.056	0.475	0.239	-7.261^{***}	-288.409^{***}	0.202
Agriculture (Livestock)									
Feeder Cattle (CME)	288	−0.048	2.764	−0.124	2.379	0.000	-6.296^{***}	-303.541^{***}	0.130
Lean Hogs (CME)	288	−0.062	6.298	−0.331	2.651	0.000	-6.625^{***}	-283.262^{***}	0.033
Live Cattle (CME)	288	−0.026	3.140	−0.685	2.083	0.000	-6.185^{***}	-257.943^{***}	0.073
Pork Bellies (CME)	–	–	–	–	–	–	–	–	–
Portfolio (Livestock)	288	−0.045	2.939	−0.341	1.710	0.000	-6.789^{***}	-294.267^{***}	0.061
Energy									
Brent (ICE)	288	−0.180	4.814	0.037	2.822	0.000	-6.001^{***}	-287.978^{***}	0.255
Gasoil (NYMEX)	288	−0.149	4.070	−0.014	1.308	0.000	-6.258^{***}	-241.290^{***}	0.273
Gasoline (NYMEX)	288	−0.172	5.605	0.249	5.787	0.000	-6.102^{***}	-324.090^{***}	0.108
Heating Oil (NYMEX)	288	−0.145	4.367	−0.241	3.789	0.000	-6.801^{***}	-248.443^{***}	0.278
Natural Gas (NYMEX)	288	−0.229	6.628	−0.365	1.581	0.000	-7.833^{***}	-247.975^{***}	0.057
WTI (NYMEX)	288	−0.166	5.057	0.171	2.178	0.000	-5.870^{***}	-279.832^{***}	0.211
Portfolio (Energy)	288	−0.173	3.983	0.023	1.113	0.001	-6.097^{***}	-261.142^{***}	0.244
Industrial Metals									
Aluminium (LME)	288	0.005	2.577	0.529	1.223	0.000	-7.131^{***}	-256.832^{***}	0.099
Cobalt (LME)	288	0.039	3.860	−0.731	4.727	0.000	-5.489^{***}	-273.609^{***}	0.257
Copper (LME)	288	−0.062	2.584	0.310	0.879	0.001	-6.339^{***}	-237.359^{***}	0.196
Lead (LME)	288	−0.047	3.107	0.111	0.487	0.180	-6.877^{***}	-271.483^{***}	0.085
Nickel (LME)	288	0.003	4.094	0.044	0.326	0.505	-5.661^{***}	-314.015^{***}	0.129
Tin (LME)	288	−0.091	2.800	−0.172	1.695	0.000	-5.931^{***}	-292.396^{***}	0.134
Zinc (LME)	288	0.038	3.213	0.021	−0.281	0.617	-5.500^{***}	-281.211^{***}	0.146
Portfolio (Industrial Metals)	288	−0.017	1.938	−0.013	−0.187	0.808	-5.572^{***}	-266.238^{***}	0.194
Precious Metals									
Gold (COMEX)	288	0.082	1.945	0.106	0.436	0.245	-6.439^{***}	-265.846^{***}	0.098
Palladium (NYMEX)	288	0.339	3.742	−0.262	1.427	0.000	-6.938^{***}	-234.223^{***}	0.341
Platinum (NYMEX)	288	−0.120	2.825	−0.009	0.667	0.069	-6.893^{***}	-233.419^{***}	0.154
Silver (COMEX)	288	−0.027	3.233	0.042	0.525	0.183	-7.107^{***}	-260.909^{***}	0.092
Portfolio (Precious Metals)	288	0.069	2.335	−0.105	0.693	0.043	-6.683^{***}	-243.519^{***}	0.233

Notes: Summary statistics for single futures are provided for non-overlapping 5-day returns calculated as $r_t = 100 \times [\ln(p_t) - \ln(p_{t-5})]$, where $\{p_t\}_{t=1}^{T}$ is the front month continuous futures series which contains daily settlement prices (in USD) of the last 20 trading days of each month. Portfolio log returns are calculated as $n^{-1}\sum_{i=1}^{n} r_{i,t}$, where $i = 1, \ldots, n$ are the futures in the respective portfolio for which returns are available on trading day t. Daily futures data spans the period of 2014:1–2019:12. Asterisks indicate the rejection of the null hypothesis that the time series has a unit root (ADF, PP) or is level stationary (KPSS) at the ***1%, **5%, and *10% level for the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests for stationarity.

Table A.10: Sample statistics of commodity futures for monthly log returns, 1998–2019

	Obs.	Mean	Std.Dev.	Skewn.	Ex.Kurt.	J.B.	ADF	PP	KPSS
Agriculture (Softs)									
Cocoa (ICE)	264	0.168	9.052	−0.021	0.677	0.080	-5.551^{***}	-328.455^{***}	0.070
Coffee (ICE)	264	−0.085	9.047	0.559	0.937	0.000	-5.506^{***}	-310.328^{***}	0.128
Cotton (ICE)	264	0.011	8.890	−0.508	2.064	0.000	-5.615^{***}	-306.965^{***}	0.040
Ethanol (CBOT)	174	−0.038	10.847	−0.189	2.168	0.000	-6.562^{***}	-160.434^{***}	0.089
Lumber (CME)	264	0.136	9.362	−0.072	0.441	0.306	-7.770^{***}	-259.913^{***}	0.040
Orange Juice (ICE)	264	0.074	9.229	0.077	−0.014	0.876	-5.386^{***}	-343.617^{***}	0.074
Rubber (SGX)	264	0.260	8.263	−0.351	2.071	0.000	-6.116^{***}	-207.653^{***}	0.140
Sugar (ICE)	264	0.035	9.603	0.026	0.620	0.119	-6.495^{***}	-211.712^{***}	0.067
Wool (ASX)	180	0.227	5.761	0.906	4.147	0.000	-5.244^{***}	-182.685^{***}	0.080
Portfolio (Softs)	264	0.071	4.337	−0.138	0.919	0.006	-5.450^{***}	-270.303^{***}	0.092
Agriculture (Grains)									
Corn (CBOT)	264	0.144	8.336	−0.295	0.776	0.005	-6.798^{***}	-290.894^{***}	0.062
Oats (CBOT)	264	0.253	10.013	−0.013	0.026	0.992	-6.436^{***}	-272.306^{***}	0.044
Rough Rice (CBOT)	264	0.077	8.390	−0.277	1.340	0.000	-5.582^{***}	-357.908^{***}	0.108
Soy Bean	264	0.129	7.799	−0.882	2.654	0.000	-6.767^{***}	-281.934^{***}	0.066
Soybean Meal (CBOT)	264	0.146	9.157	−0.533	2.270	0.000	-7.456^{***}	-278.955^{***}	0.051
Soybean Oil (CBOT)	264	0.125	7.468	−0.422	1.994	0.000	-5.584^{***}	-322.897^{***}	0.075
Wheat (CBOT)	264	0.204	8.837	0.175	0.875	0.008	-6.052^{***}	-284.321^{***}	0.060
Portfolio (Grains)	264	0.154	6.151	−0.412	1.175	0.000	-5.990^{***}	-293.888^{***}	0.085
Agriculture (Livestock)									
Feeder Cattle (CME)	264	0.246	4.478	−0.785	2.746	0.000	-7.528^{***}	-249.138^{***}	0.061
Lean Hogs (CME)	264	0.081	11.419	−0.388	1.460	0.000	-7.761^{***}	-252.442^{***}	0.020
Live Cattle (CME)	264	0.238	5.292	−0.604	2.042	0.000	-8.631^{***}	-263.108^{***}	0.042
Pork Bellies (CME)	156	0.484	11.249	0.058	1.040	0.028	-6.475^{***}	-168.554^{***}	0.036
Portfolio (Livestock)	264	0.220	5.502	−0.273	0.046	0.192	-6.911^{***}	-250.440^{***}	0.054
Energy									
Brent (ICE)	264	0.525	9.280	−0.489	1.695	0.000	-7.232^{***}	-213.706^{***}	0.141
Gasoil (NYMEX)	264	0.534	9.316	−0.437	1.230	0.000	-6.600^{***}	-225.914^{***}	0.126
Gasoline (NYMEX)	170	0.042	11.469	−0.612	2.554	0.000	-7.410^{***}	-131.917^{***}	0.050
Heating Oil (NYMEX)	264	0.537	9.923	−0.335	2.686	0.000	-6.151^{***}	-264.287^{***}	0.125
Natural Gas (NYMEX)	264	−0.013	14.938	−0.056	1.452	0.000	-6.083^{***}	-256.001^{***}	0.120
WTI (NYMEX)	264	0.470	9.562	−0.455	1.091	0.000	-7.233^{***}	-224.763^{***}	0.129
Portfolio (Energy)	264	0.432	8.772	−0.302	1.551	0.000	-6.648^{***}	-231.466^{***}	0.154
Industrial Metals									
Aluminium (LME)	264	0.057	5.590	0.099	0.316	0.466	-6.610^{***}	-289.927^{***}	0.050
Cobalt (LME)	117	−0.282	8.979	−0.858	6.523	0.000	-3.304^{*}	-116.466^{***}	0.122
Copper (LME)	264	0.481	7.247	−0.814	6.066	0.000	-6.539^{***}	-249.400^{***}	0.118
Lead (LME)	264	0.463	8.282	−0.395	1.618	0.000	-5.748^{***}	-278.817^{***}	0.101
Nickel (LME)	264	0.320	10.101	−0.045	0.026	0.952	-5.659^{***}	-268.998^{***}	0.102
Tin (LME)	264	0.439	6.758	0.104	1.133	0.001	-5.970^{***}	-268.828^{***}	0.104
Zinc (LME)	264	0.278	7.665	−0.528	2.803	0.000	-4.810^{***}	-305.990^{***}	0.060
Portfolio (Industrial Metals)	264	0.333	5.673	−0.477	2.685	0.000	-5.460^{***}	-276.180^{***}	0.106
Precious Metals									
Gold (COMEX)	264	0.628	4.755	−0.133	1.078	0.001	-5.830^{***}	-287.672^{***}	0.207
Palladium (NYMEX)	264	0.849	10.178	−0.299	1.926	0.000	-5.565^{***}	-293.673^{***}	0.093
Platinum (NYMEX)	264	0.365	6.484	−1.164	4.945	0.000	-6.577^{***}	-245.558^{***}	0.235
Silver (COMEX)	264	0.415	8.554	−0.317	1.093	0.000	-5.608^{***}	-283.827^{***}	0.136
Portfolio (Precious Metals)	264	0.564	5.971	−0.579	1.435	0.000	-5.914^{***}	-267.241^{***}	0.069

Notes: Summary statistics for single futures are provided for $r_{\tau_L} = 100 \times [\ln(p_{\tau_L}) - \ln(p_{\tau_L - 1})]$, where $\{p_{\tau_L}\}_{\tau_L=1}^{T_L}$ is the front month continuous futures series which contains the last settlement price (in USD) of each month. Portfolio log returns are calculated as $n^{-1} \sum_{i=1}^{n} r_{i,\tau_L}$, where $i = 1, ..., n$ are the futures in the respective portfolio for which returns are available on month τ_L. Daily futures data spans the period of 1998:1–2019:12 except for Ethanol (2005:7–2019:12), Wool (1998:1–2012:12), Pork Bellies (1998:1–2010:12), Gasoline (2005:11–2019:12), and Cobalt (2010:4–2019:12). Asterisks indicate the rejection of the null hypothesis that the time series has a unit root (ADF, PP) or is level stationary (KPSS) at the ***1%, **5%, and *10% level for the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests for stationarity.

Table A.11: Sample statistics of commodity futures for monthly log returns, 1998–2003

	Obs.	Mean	Std.Dev.	Skewn.	Ex.Kurt.	J.B.	ADF	PP	KPSS
Agriculture (Softs)									
Cocoa (ICE)	72	−0.102	10.667	0.273	1.085	0.109	-3.537^{**}	-80.799^{***}	0.262
Coffee (ICE)	72	−1.273	9.879	0.692	0.173	0.054	-4.618^{***}	-76.063^{***}	0.235
Cotton (ICE)	72	0.157	9.177	0.216	−0.393	0.600	-3.673^{**}	-83.693^{***}	0.295
Ethanol (CBOT)	–	–	–	–	–	–	–	–	–
Lumber (CME)	72	0.139	9.829	0.124	−0.085	0.902	-4.249^{***}	-73.240^{***}	0.057
Orange Juice (ICE)	72	−0.382	8.144	0.384	1.027	0.085	-3.806^{**}	-92.160^{***}	0.197
Rubber (SGX)	72	0.736	8.538	0.437	0.556	0.200	-3.572^{**}	-78.275^{***}	0.334
Sugar (ICE)	72	−1.067	10.332	0.277	−0.484	0.444	-4.004^{**}	-74.407^{***}	0.104
Wool (ASX)	72	0.146	6.672	1.041	4.059	0.000	-3.478^{*}	-64.706^{***}	0.203
Portfolio (Softs)	72	−0.206	3.594	0.187	−0.605	0.468	-4.008^{**}	-85.567^{***}	0.424^{*}
Agriculture (Grains)									
Corn (CBOT)	72	−0.103	6.306	0.004	0.430	0.758	-4.899^{***}	-76.912^{***}	0.151
Oats (CBOT)	72	−0.033	9.093	0.073	−0.434	0.730	−3.056	-66.108^{***}	0.145
Rough Rice (CBOT)	72	−0.316	9.624	0.365	0.096	0.443	-3.777^{**}	-104.577^{***}	0.600^{**}
Soy Bean	72	0.226	6.403	0.096	−0.286	0.837	-4.401^{***}	-61.272^{***}	0.517^{**}
Soybean Meal (CBOT)	72	0.238	7.364	0.445	0.543	0.195	-4.733^{***}	-71.886^{***}	0.351^{*}
Soybean Oil (CBOT)	72	0.163	7.339	0.305	1.000	0.128	-3.890^{**}	-70.858^{***}	0.503^{**}
Wheat (CBOT)	72	0.203	7.122	0.280	−0.581	0.376	-4.882^{***}	-84.270^{***}	0.188
Portfolio (Grains)	72	0.054	4.628	0.098	0.110	0.927	-5.107^{***}	-75.425^{***}	0.700^{**}
Agriculture (Livestock)									
Feeder Cattle (CME)	72	0.055	4.124	−2.503	11.884	0.000	-3.500^{**}	-62.822^{***}	0.073
Lean Hogs (CME)	72	−0.107	13.246	−0.764	2.388	0.000	-3.843^{**}	-75.703^{***}	0.045
Live Cattle (CME)	72	0.208	5.819	−0.876	3.859	0.000	-5.098^{***}	-68.088^{***}	0.037
Pork Bellies (CME)	72	0.760	12.227	−0.035	0.734	0.443	-4.119^{***}	-79.577^{***}	0.043
Portfolio (Livestock)	72	0.229	6.287	−0.292	−0.279	0.534	-3.759^{**}	-71.867^{***}	0.053
Energy									
Brent (ICE)	72	0.836	10.500	−0.074	0.754	0.413	-3.409^{*}	-66.354^{***}	0.073
Gasoil (NYMEX)	72	0.827	10.496	−0.058	0.341	0.823	-3.564^{**}	-66.497^{***}	0.076
Gasoline (NYMEX)	–	–	–	–	–	–	–	–	–
Heating Oil (NYMEX)	72	0.862	12.230	−0.197	2.451	0.000	-3.727^{**}	-73.340^{***}	0.074
Natural Gas (NYMEX)	72	1.397	18.549	−0.212	0.657	0.400	-3.335^{*}	-69.370^{***}	0.062
WTI (NYMEX)	72	0.850	10.513	−0.083	0.194	0.907	-3.527^{**}	-71.947^{***}	0.070
Portfolio (Energy)	72	0.954	10.177	0.048	0.910	0.285	−3.137	-66.240^{***}	0.082
Industrial Metals									
Aluminium (LME)	72	0.048	4.648	0.468	0.161	0.258	-3.607^{**}	-82.020^{***}	0.139
Cobalt (LME)	–	–	–	–	–	–	–	–	–
Copper (LME)	72	0.402	5.799	0.536	0.459	0.130	−2.924	-99.427^{***}	0.248
Lead (LME)	72	0.366	5.672	0.697	0.255	0.049	−2.622	-85.527^{***}	0.453^{*}
Nickel (LME)	72	1.411	9.338	0.268	−0.020	0.650	−2.210	-75.007^{***}	0.300
Tin (LME)	72	0.271	4.679	0.191	1.146	0.112	−2.787	-69.637^{***}	0.349^{*}
Zinc (LME)	72	−0.113	5.150	0.305	−0.552	0.362	−2.223	-88.706^{***}	0.206
Portfolio (Industrial Metals)	72	0.397	4.735	0.513	0.341	0.173	−1.813	-93.501^{***}	0.375^{*}
Precious Metals									
Gold (COMEX)	72	0.502	3.972	0.761	1.041	0.006	-4.458^{***}	-65.856^{***}	0.442^{*}
Palladium (NYMEX)	72	−0.039	12.276	0.153	0.571	0.532	−2.994	-71.170^{***}	0.483^{**}
Platinum (NYMEX)	72	1.087	5.297	−0.680	0.509	0.042	−2.883	-65.172^{***}	0.122
Silver (COMEX)	72	−0.005	6.485	−0.246	0.613	0.396	-3.626^{**}	-88.285^{***}	0.320
Portfolio (Precious Metals)	72	0.386	4.899	−0.235	−0.099	0.708	−2.649	-72.569^{***}	0.106

Notes: Summary statistics for single futures are provided for $r_{\tau_L} = 100 \times [\ln(p_{\tau_L}) - \ln(p_{\tau_L - 1})]$, where $\{p_{\tau_L}\}_{\tau_L=1}^{T_L}$ is the front month continuous futures series which contains the last settlement price (in USD) of each month. Portfolio log returns are calculated as $n^{-1} \sum_{i=1}^{n} r_{i,\tau_L}$, where $i = 1, ..., n$ are the futures in the respective portfolio for which returns are available on month τ_L. Daily futures data spans the period of 1998:1–2003:12. Asterisks indicate the rejection of the null hypothesis that the time series has a unit root (ADF, PP) or is level stationary (KPSS) at the $^{***}1\%$, $^{**}5\%$, and $^{*}10\%$ level for the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests for stationarity.

Table A.12: Sample statistics of commodity futures for monthly log returns, 2004–2007

	Obs.	Mean	Std.Dev.	Skewn.	Ex.Kurt.	J.B.	ADF	PP	KPSS
Agriculture (Softs)									
Cocoa (ICE)	48	0.615	7.118	0.333	0.166	0.624	-3.783^{**}	-50.641^{***}	0.190
Coffee (ICE)	48	1.543	8.907	0.594	0.084	0.242	-2.637	-55.544^{***}	0.080
Cotton (ICE)	48	-0.206	9.025	-0.090	-0.002	0.968	-4.465^{***}	-50.573^{***}	0.397^{*}
Ethanol (CBOT)	30	1.589	14.869	-0.200	-0.774	0.622	-3.075	-21.651^{**}	0.124
Lumber (CME)	48	-0.599	8.772	-0.378	0.488	0.445	-4.190^{***}	-43.974^{***}	0.126
Orange Juice (ICE)	48	1.792	8.422	0.171	-0.642	0.589	-3.027	-50.863^{***}	0.235
Rubber (SGX)	48	1.463	6.634	0.600	1.691	0.014	-3.773^{**}	-37.111^{***}	0.083
Sugar (ICE)	48	1.346	8.079	-0.412	0.851	0.246	-2.519	-46.035^{***}	0.273
Wool (ASX)	48	0.381	5.261	1.401	4.917	0.000	-3.559^{**}	-54.730^{***}	0.316
Portfolio (Softs)	48	0.841	3.957	-0.238	-0.642	0.528	-3.466^{*}	-47.922^{***}	0.063
Agriculture (Grains)									
Corn (CBOT)	48	1.283	8.943	-0.190	-0.232	0.821	-3.712^{**}	-45.205^{***}	0.185
Oats (CBOT)	48	1.543	8.917	0.161	-1.030	0.312	-4.809^{***}	-46.618^{***}	0.103
Rough Rice (CBOT)	48	0.962	8.377	-1.585	5.498	0.000	-5.151^{***}	-60.262^{***}	0.267
Soy Bean	48	0.872	9.736	-1.801	5.449	0.000	-4.108^{**}	-62.995^{***}	0.346
Soybean Meal (CBOT)	48	0.656	10.613	-1.267	3.327	0.000	-3.820^{**}	-52.206^{***}	0.261
Soybean Oil (CBOT)	48	1.169	8.741	-0.941	1.799	0.001	-4.154^{**}	-67.704^{***}	0.457^{*}
Wheat (CBOT)	48	1.778	8.056	0.295	-0.511	0.544	-4.192^{***}	-57.390^{***}	0.497^{**}
Portfolio (Grains)	48	1.181	6.674	-1.388	3.786	0.000	-4.721^{***}	-54.464^{***}	0.403^{*}
Agriculture (Livestock)									
Feeder Cattle (CME)	48	0.597	4.284	0.152	-0.563	0.664	-4.146^{**}	-31.078^{***}	0.219
Lean Hogs (CME)	48	0.167	8.306	0.149	-0.590	0.646	-4.442^{***}	-66.460^{***}	0.180
Live Cattle (CME)	48	0.459	4.544	-0.239	0.653	0.520	-5.223^{***}	-48.213^{***}	0.052
Pork Bellies (CME)	48	-0.012	9.812	0.561	1.160	0.074	-4.177^{**}	-54.878^{***}	0.061
Portfolio (Livestock)	48	0.303	4.824	-0.095	-0.715	0.578	-4.404^{***}	-57.361^{***}	0.166
Energy									
Brent (ICE)	48	2.364	7.631	-0.119	-1.242	0.202	-3.658^{**}	-42.344^{***}	0.119
Gasoil (NYMEX)	48	2.347	8.552	0.030	-0.067	0.992	-3.728^{**}	-43.083^{***}	0.109
Gasoline (NYMEX)	26	1.725	12.144	0.115	-0.088	0.968	-2.467	-22.956^{***}	0.067
Heating Oil (NYMEX)	48	2.216	8.664	-0.050	0.120	0.976	-3.820^{**}	-42.964^{***}	0.100
Natural Gas (NYMEX)	48	0.396	16.849	0.114	-0.439	0.783	-3.261^{*}	-41.748^{***}	0.057
WTI (NYMEX)	48	2.255	7.848	-0.150	-1.027	0.318	-3.348^{*}	-47.018^{***}	0.114
Portfolio (Energy)	48	1.982	8.573	-0.052	-0.349	0.876	-3.755^{**}	-40.221^{***}	0.103
Industrial Metals									
Aluminium (LME)	48	0.824	4.632	0.399	-0.387	0.456	-2.862	-48.667^{***}	0.225
Cobalt (LME)	–	–	–	–	–	–	–	–	–
Copper (LME)	48	2.204	7.808	0.494	0.589	0.266	-2.791	-36.086^{***}	0.167
Lead (LME)	48	2.591	9.248	-0.294	-0.161	0.690	-2.446	-38.739^{***}	0.092
Nickel (LME)	48	0.941	11.772	0.003	-0.037	0.999	-3.010	-43.254^{***}	0.143
Tin (LME)	48	1.896	7.087	0.538	0.522	0.239	-3.668^{**}	-45.017^{***}	0.170
Zinc (LME)	48	1.768	9.510	0.083	-0.349	0.861	-2.686	-49.118^{***}	0.281
Portfolio (Industrial Metals)	48	1.704	5.526	0.355	0.241	0.570	-1.540	-52.384^{***}	0.172
Precious Metals									
Gold (COMEX)	48	1.459	4.383	0.115	-0.141	0.930	-2.724	-57.349^{***}	0.207
Palladium (NYMEX)	48	1.354	8.255	0.205	0.105	0.835	-2.994	-54.469^{***}	0.081
Platinum (NYMEX)	48	1.319	4.553	-0.523	1.380	0.050	-3.749^{**}	-53.054^{***}	0.126
Silver (COMEX)	48	1.910	8.962	-0.622	0.678	0.134	-3.188^{*}	-51.525^{***}	0.064
Portfolio (Precious Metals)	48	1.510	5.525	-0.387	0.689	0.342	-2.756	-56.912^{***}	0.099

Notes: Summary statistics for single futures are provided for $r_{\tau_L} = 100 \times [\ln(p_{\tau_L}) - \ln(p_{\tau_L - 1})]$, where $\{p_{\tau_L}\}_{\tau_L=1}^{T_L}$ is the front month continuous futures series which contains the last settlement price (in USD) of each month. Portfolio log returns are calculated as $n^{-1} \sum_{i=1}^{n} r_{i,\tau_L}$, where $i = 1, ..., n$ are the futures in the respective portfolio for which returns are available on month τ_L. Daily futures data spans the period of 2004:1–2007:12 except for Ethanol (2005:7–2007:12) and Gasoline (2005:11–2007:12). Asterisks indicate the rejection of the null hypothesis that the time series has a unit root (ADF, PP) or is level stationary (KPSS) at the ***1%, **5%, and *10% level for the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests for stationarity.

Table A.13: Sample statistics of commodity futures for monthly log returns, 2008–2013

	Obs.	Mean	Std.Dev.	Skewn.	Ex.Kurt.	J.B.	ADF	PP	KPSS
Agriculture (Softs)									
Cocoa (ICE)	72	0.397	9.971	−0.341	−0.275	0.444	-4.537^{***}	-95.490^{***}	0.112
Coffee (ICE)	72	−0.288	8.879	−0.048	0.697	0.476	−2.808	-103.402^{***}	0.340
Cotton (ICE)	72	0.304	10.573	−1.164	3.402	0.000	−2.772	-67.892^{***}	0.103
Ethanol (CBOT)	72	−0.298	8.816	−0.037	−0.472	0.710	-3.913^{**}	-79.841^{***}	0.086
Lumber (CME)	72	0.596	10.155	−0.209	0.486	0.540	-4.377^{***}	-76.718^{***}	0.074
Orange Juice (ICE)	72	−0.071	10.678	−0.004	−0.698	0.481	-3.576^{**}	-89.268^{***}	0.121
Rubber (SGX)	72	−0.138	9.516	−1.273	3.209	0.000	-3.702^{**}	-37.033^{***}	0.119
Sugar (ICE)	72	0.578	11.343	−0.165	0.954	0.217	-4.057^{**}	-43.484^{***}	0.194
Wool (ASX)	60	0.201	5.004	−0.008	0.949	0.324	−2.843	-64.680^{***}	0.200
Portfolio (Softs)	72	0.131	5.583	−0.395	0.952	0.101	−2.981	-69.109^{***}	0.130
Agriculture (Grains)									
Corn (CBOT)	72	−0.106	10.854	−0.496	0.089	0.226	-3.467^{*}	-85.095^{***}	0.140
Oats (CBOT)	72	0.200	11.557	0.102	0.222	0.872	-3.630^{**}	-79.700^{***}	0.069
Rough Rice (CBOT)	72	0.188	8.910	−0.610	0.780	0.043	-4.307^{***}	-80.112^{***}	0.045
Soy Bean	72	0.126	9.008	−0.646	0.218	0.076	-3.933^{**}	-71.134^{***}	0.057
Soybean Meal (CBOT)	72	0.386	10.156	−0.489	0.500	0.163	-4.123^{***}	-76.132^{***}	0.048
Soybean Oil (CBOT)	72	−0.319	8.623	−0.666	1.816	0.000	-3.478^{*}	-75.663^{***}	0.095
Wheat (CBOT)	72	−0.528	10.774	0.199	1.163	0.104	-3.348^{*}	-74.111^{***}	0.122
Portfolio (Grains)	72	−0.008	7.973	−0.235	−0.234	0.661	-3.440^{*}	-75.456^{***}	0.076
Agriculture (Livestock)									
Feeder Cattle (CME)	72	0.641	4.128	−0.051	−0.292	0.867	-4.557^{***}	-72.462^{***}	0.110
Lean Hogs (CME)	72	0.541	8.942	−0.315	0.693	0.269	-4.298^{***}	-81.702^{***}	0.053
Live Cattle (CME)	72	0.465	4.128	−0.559	0.529	0.101	-4.279^{***}	-71.438^{***}	0.134
Pork Bellies (CME)	36	0.595	11.283	−0.218	1.339	0.226	−2.938	-34.267^{***}	0.110
Portfolio (Livestock)	72	0.556	4.366	−0.357	0.328	0.395	-3.651^{**}	-73.188^{***}	0.095
Energy									
Brent (ICE)	72	0.231	9.144	−1.311	4.815	0.000	-4.274^{***}	-40.921^{***}	0.064
Gasoil (NYMEX)	72	0.164	8.995	−1.203	2.851	0.000	-3.794^{**}	-52.678^{***}	0.078
Gasoline (NYMEX)	72	0.164	11.575	−1.499	5.597	0.000	-4.419^{***}	-50.241^{***}	0.052
Heating Oil (NYMEX)	72	0.211	8.636	−1.142	3.270	0.000	-3.990^{**}	-53.916^{***}	0.085
Natural Gas (NYMEX)	72	−0.792	12.710	0.216	2.436	0.000	-3.873^{**}	-64.558^{***}	0.114
WTI (NYMEX)	72	0.035	9.805	−0.996	2.869	0.000	-4.706^{***}	-47.721^{***}	0.057
Portfolio (Energy)	72	0.002	8.328	−1.245	4.021	0.000	-4.378^{***}	-49.424^{***}	0.075
Industrial Metals									
Aluminium (LME)	72	−0.410	7.434	0.041	−0.406	0.774	−3.065	-57.767^{***}	0.064
Cobalt (LME)	45	−0.980	7.276	−0.261	−0.285	0.717	-4.036^{**}	-50.485^{***}	0.172
Copper (LME)	72	0.143	9.596	−1.699	5.729	0.000	-3.389^{*}	-51.815^{***}	0.057
Lead (LME)	72	−0.207	11.108	−0.654	0.707	0.036	−3.126	-72.581^{***}	0.076
Nickel (LME)	72	−0.879	10.957	−0.396	−0.356	0.323	−3.165	-67.568^{***}	0.090
Tin (LME)	72	0.437	9.278	−0.163	−0.190	0.808	-3.800^{**}	-66.106^{***}	0.060
Zinc (LME)	72	−0.196	9.723	−1.200	2.942	0.000	−2.755	-77.013^{***}	0.091
Portfolio (Industrial Metals)	72	−0.246	7.709	−0.878	1.619	0.000	−2.846	-54.200^{***}	0.071
Precious Metals									
Gold (COMEX)	72	0.501	6.332	−0.461	0.345	0.234	-4.166^{***}	-82.212^{***}	0.399^{*}
Palladium (NYMEX)	72	0.891	10.952	−0.791	3.367	0.000	−2.940	-66.238^{***}	0.101
Platinum (NYMEX)	72	−0.151	8.834	−1.289	4.108	0.000	-3.969^{**}	-51.983^{***}	0.052
Silver (COMEX)	72	0.363	11.694	−0.363	0.058	0.452	-3.560^{**}	-71.272^{***}	0.196
Portfolio (Precious Metals)	72	0.401	8.000	−0.667	0.684	0.034	-3.400^{*}	-61.353^{***}	0.129

Notes: Summary statistics for single futures are provided for $r_{\tau_L} = 100 \times [\ln(p_{\tau_L}) - \ln(p_{\tau_L - 1})]$, where $\{p_{\tau_L}\}_{\tau_L=1}^{T_L}$ is the front month continuous futures series which contains the last settlement price (in USD) of each month. Portfolio log returns are calculated as $n^{-1} \sum_{i=1}^{n} r_{i,\tau_L}$, where $i = 1, ..., n$ are the futures in the respective portfolio for which returns are available on month τ_L. Daily futures data spans the period of 2008:1–2013:12 except for Wool (2008:1–2012:12), Pork Bellies (2008:1–2010:12), and Cobalt (2010:4–2013:12). Asterisks indicate the rejection of the null hypothesis that the time series has a unit root (ADF, PP) or is level stationary (KPSS) at the ***1%, **5%, and *10% level for the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests for stationarity.

Table A.14: Sample statistics of commodity futures for monthly log returns, 2014–2019

	Obs.	Mean	Std.Dev.	Skewn.	Ex.Kurt.	J.B.	ADF	PP	KPSS
Agriculture (Softs)									
Cocoa (ICE)	72	−0.089	7.513	−0.251	−0.649	0.364	−3.450*	−97.558***	0.096
Coffee (ICE)	72	0.220	8.418	1.181	3.266	0.000	−3.113	−68.448***	0.115
Cotton (ICE)	72	−0.283	6.527	−0.499	1.409	0.011	−4.234***	−93.718***	0.098
Ethanol (CBOT)	72	−0.457	10.831	−0.422	5.439	0.000	−4.616***	−74.050***	0.047
Lumber (CME)	72	0.164	8.567	0.021	0.836	0.349	−3.561**	−78.370***	0.092
Orange Juice (ICE)	72	−0.471	9.257	−0.011	0.327	0.851	−3.365*	−93.913***	0.146
Rubber (SGX)	72	−0.619	7.627	0.057	−0.277	0.874	−4.576***	−60.560***	0.145
Sugar (ICE)	72	−0.279	7.758	0.416	0.226	0.328	−3.057	−68.920***	0.072
Wool (ASX)	–	–	–	–	–	–	–	–	–
Portfolio (Softs)	72	−0.227	3.830	0.385	−0.202	0.386	−3.381*	−59.745***	0.064
Agriculture (Grains)									
Corn (CBOT)	72	−0.118	6.768	0.189	0.633	0.442	−5.963***	−70.234***	0.060
Oats (CBOT)	72	−0.268	10.050	−0.288	−0.159	0.585	−5.097***	−64.857***	0.217
Rough Rice (CBOT)	72	−0.231	6.440	0.406	0.067	0.370	−3.702**	−83.662***	0.271
Soy Bean	72	−0.459	6.302	−0.383	0.421	0.318	−5.325***	−72.638***	0.096
Soybean Meal (CBOT)	72	−0.525	8.831	−0.345	3.532	0.000	−5.582***	−80.945***	0.058
Soybean Oil (CBOT)	72	−0.164	5.172	0.168	−0.173	0.807	−4.051**	−77.058***	0.162
Wheat (CBOT)	72	−0.111	8.783	0.180	0.087	0.814	−5.951***	−71.846***	0.176
Portfolio (Grains)	72	−0.268	4.976	0.011	−0.161	0.961	−6.318***	−69.680***	0.244
Agriculture (Livestock)									
Feeder Cattle (CME)	72	−0.191	5.254	−0.540	0.510	0.118	−2.898	−76.626***	0.122
Lean Hogs (CME)	72	−0.249	13.474	−0.019	−0.406	0.779	−4.736***	−60.017***	0.042
Live Cattle (CME)	72	−0.105	6.241	−0.346	0.133	0.476	−3.960**	−91.452***	0.069
Pork Bellies (CME)	–	–	–	–	–	–	–	–	–
Portfolio (Livestock)	72	−0.181	6.153	−0.165	−0.137	0.826	−4.444***	−62.636***	0.074
Energy									
Brent (ICE)	72	−0.720	9.085	−0.358	0.266	0.416	−4.472***	−59.171***	0.244
Gasoil (NYMEX)	72	−0.598	8.846	−0.565	1.125	0.022	−4.343***	−56.665***	0.269
Gasoline (NYMEX)	72	−0.688	11.208	0.006	0.417	0.770	−4.190***	−61.256***	0.094
Heating Oil (NYMEX)	72	−0.579	9.356	−0.160	1.613	0.017	−4.317***	−77.919***	0.283
Natural Gas (NYMEX)	72	−0.915	11.377	−0.756	4.044	0.000	−3.630**	−77.171***	0.079
WTI (NYMEX)	72	−0.663	9.353	−0.392	0.335	0.335	−4.276***	−55.434***	0.199
Portfolio (Energy)	72	−0.694	7.748	−0.360	0.403	0.360	−3.968**	−60.278***	0.216
Industrial Metals									
Aluminium (LME)	72	0.022	4.903	0.188	0.034	0.807	−2.547	−85.352***	0.116
Cobalt (LME)	72	0.154	9.920	−1.041	7.161	0.000	−2.253	−60.962***	0.188
Copper (LME)	72	−0.250	5.079	0.260	1.518	0.021	−3.289*	−84.668***	0.217
Lead (LME)	72	−0.190	6.159	0.218	0.415	0.580	−3.646**	−87.018***	0.101
Nickel (LME)	72	0.012	8.713	0.257	−0.484	0.473	−3.996**	−75.440***	0.120
Tin (LME)	72	−0.363	5.081	0.228	0.653	0.386	−3.410*	−87.502***	0.118
Zinc (LME)	72	0.152	5.900	0.180	−0.850	0.278	−3.292*	−70.210***	0.135
Portfolio (Industrial Metals)	72	−0.066	3.923	0.271	−0.700	0.309	−2.139	−75.654***	0.164
Precious Metals									
Gold (COMEX)	72	0.328	3.818	0.217	−0.103	0.742	−3.807**	−71.639***	0.115
Palladium (NYMEX)	72	1.358	8.171	−0.504	0.673	0.110	−3.509**	−90.836***	0.416*
Platinum (NYMEX)	72	−0.479	5.813	−0.266	−0.171	0.627	−4.474***	−89.811***	0.190
Silver (COMEX)	72	−0.108	6.089	0.422	−0.293	0.301	−4.530***	−73.876***	0.104
Portfolio (Precious Metals)	72	0.275	4.807	−0.362	0.395	0.361	−4.135***	−80.329***	0.260

Notes: Summary statistics for single futures are provided for $r_{\tau_L} = 100 \times [\ln(p_{\tau_L}) - \ln(p_{\tau_L - 1})]$, where $\{p_{\tau_L}\}_{\tau_L=1}^{T_L}$ is the front month continuous futures series which contains the last settlement price (in USD) of each month. Portfolio log returns are calculated as $n^{-1} \sum_{i=1}^{n} r_{i,\tau_L}$, where $i = 1, ..., n$ are the futures in the respective portfolio for which returns are available on month τ_L. Daily futures data spans the period of 2014:1–2019:12. Asterisks indicate the rejection of the null hypothesis that the time series has a unit root (ADF, PP) or is level stationary (KPSS) at the ***1%, **5%, and *10% level for the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests for stationarity.

Table A.15: Sample statistics of monthly macroeconomic variables, 1998–2003

	Obs.	Mean	Std.Dev.	Min	Max	Skewn.	Ex.Kurt.	J.B.	ADF	PP	KPSS
Global Economic Activity											
STEEL	72	0.304	4.157	−6.946	13.456	0.986	1.137	0.000	-5.590^{***}	-108.137^{***}	0.093
BDI	72	1.839	9.826	−22.110	52.481	1.753	8.363	0.000	−2.429	-59.221^{***}	0.456^{*}
GECON	72	−0.043	0.335	−1.108	0.636	−0.397	0.151	0.375	−1.193	−15.937	0.368^{*}
WIP	72	0.232	0.513	−1.354	1.112	−0.449	0.065	0.297	−2.041	-95.495^{***}	0.132
Sentiment/Uncertainty											
VIX	72	−0.629	14.208	−34.106	46.550	0.873	1.831	0.000	-4.442^{***}	-50.220^{***}	0.056
CSENTI	72	−0.136	3.780	−11.206	10.278	−0.029	0.382	0.800	-4.175^{***}	-71.103^{***}	0.073
EPU	72	−0.447	17.496	−34.496	70.585	1.079	2.717	0.000	-4.860^{***}	-61.926^{***}	0.054
RUNCERT	72	−0.035	1.877	−5.444	4.528	−0.183	0.557	0.513	-3.922^{**}	-40.107^{***}	0.120
MUNCERT	72	0.107	1.998	−4.560	5.788	−0.150	0.251	0.795	-3.503^{**}	-27.105^{***}	0.219
FUNCERT	72	−0.171	3.466	−7.872	9.035	0.431	0.029	0.327	-4.123^{***}	-36.535^{***}	0.374^{*}
GPR	72	1.266	42.004	−102.940	175.819	0.865	3.122	0.000	-4.797^{***}	-66.433^{***}	0.048
GEOVOL	42	−2.587	46.160	−106.282	92.450	−0.121	−0.448	0.797	-5.639^{***}	-44.053^{***}	0.086
Others											
INFL	72	2.275	0.750	1.064	3.693	0.355	−1.100	0.076	−1.833	−5.257	0.290
INFLE	72	2.597	0.454	0.400	3.200	−2.278	7.810	0.000	−3.020	-24.602^{**}	0.222
USDEER	72	0.023	1.131	−3.586	2.883	−0.290	0.907	0.176	-3.885^{**}	-59.393^{***}	0.480^{**}
TBILL	72	−2.434	6.551	−24.831	11.097	−1.477	2.590	0.000	-3.280^{*}	-43.337^{***}	0.384^{*}
TED	72	−1.376	21.495	−43.413	42.603	0.037	−0.662	0.514	-5.243^{***}	-60.732^{***}	0.076

Notes: Summary statistics are provided for 100× log-differenced data except for GECON, INFL, and INFLE (in levels). Monthly data spans the period of 1998:1–2003:12 except for GEOVOL (2000:7–2003:12). Asterisks indicate the rejection of the null hypothesis that the time series has a unit root (ADF, PP) or is level stationary (KPSS) at the ***1%, **5%, and *10% level for the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests for stationarity.

Table A.16: Sample statistics of monthly macroeconomic variables, 2004–2007

	Obs.	Mean	Std.Dev.	Min	Max	Skewn.	Ex.Kurt.	J.B.	ADF	PP	KPSS
Global Economic Activity											
STEEL	48	0.674	3.769	−7.144	11.216	0.783	1.304	0.016	-6.414^{***}	-63.115^{***}	0.055
BDI	48	1.532	12.943	−28.675	26.404	−0.406	−0.450	0.422	-3.661^{**}	-25.018^{**}	0.326
GECON	48	0.079	0.243	−0.445	0.619	0.073	0.157	0.955	-3.237^{*}	-27.125^{***}	0.542^{**}
WIP	48	0.406	0.348	−0.376	1.296	0.324	0.090	0.652	-3.888^{**}	-68.940^{***}	0.201
Sentiment/Uncertainty											
VIX	48	0.512	13.559	−21.120	37.697	0.686	0.047	0.152	-4.706^{***}	-52.696^{***}	0.226
CSENTI	48	−0.425	5.635	−14.725	11.451	0.179	0.128	0.865	-5.214^{***}	-41.487^{***}	0.084
EPU	48	0.631	15.027	−32.945	35.058	0.133	−0.311	0.846	-5.113^{***}	-49.992^{***}	0.149
RUNCERT	48	0.128	2.168	−3.826	6.828	0.478	0.468	0.322	-4.379^{***}	-28.774^{***}	0.141
MUNCERT	48	0.329	2.031	−3.927	6.333	0.391	0.232	0.514	-3.643^{**}	-22.391^{**}	0.075
FUNCERT	48	0.307	2.310	−3.130	6.366	0.648	−0.281	0.172	−1.315	-31.728^{***}	0.518^{**}
GPR	48	−0.696	29.453	−53.827	63.045	0.164	−0.717	0.537	-5.191^{***}	-51.896^{***}	0.065
GEOVOL	48	0.512	51.400	−164.922	150.359	−0.299	2.052	0.010	-6.278^{***}	-55.049^{***}	0.055
Others											
INFL	48	2.985	0.771	1.397	4.633	0.038	−0.697	0.612	−2.394	−11.892	0.162
INFLE	48	3.185	0.367	2.600	4.600	1.915	4.713	0.000	-3.691^{**}	-23.520^{**}	0.260
USDEER	48	−0.297	1.018	−2.753	1.573	−0.214	−0.727	0.491	−2.946	-37.070^{***}	0.188
TBILL	48	2.525	6.592	−17.972	21.158	−0.324	2.157	0.006	-4.310^{***}	-44.168^{***}	0.948^{***}
TED	48	4.089	23.486	−47.453	86.690	0.533	1.589	0.026	-3.856^{**}	-52.620^{***}	0.238

Notes: Summary statistics are provided for 100× log-differenced data except for GECON, INFL, and INFLE (in levels). Monthly data spans the period of 2004:1–2007:12. Asterisks indicate the rejection of the null hypothesis that the time series has a unit root (ADF, PP) or is level stationary (KPSS) at the ***1%, **5%, and *10% level for the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests for stationarity.

Table A.17: Sample statistics of monthly macroeconomic variables, 2008–2013

	Obs.	Mean	Std.Dev.	Min	Max	Skewn.	Ex.Kurt.	J.B.	ADF	PP	KPSS
Global Economic Activity											
STEEL	72	0.239	5.041	−13.723	12.061	0.282	0.227	0.573	-4.077^{**}	-101.003^{***}	0.058
BDI	72	−2.058	27.386	−101.249	70.348	−0.671	2.087	0.000	-3.989^{**}	-45.040^{***}	0.142
GECON	72	−0.169	0.583	−2.203	0.885	−1.647	3.146	0.000	−2.403	−16.419	0.684^{**}
WIP	72	0.086	0.895	−3.265	1.842	−1.498	3.766	0.000	−2.493	-38.019^{***}	0.203
Sentiment/Uncertainty											
VIX	72	−0.585	18.415	−25.390	71.918	1.839	4.608	0.000	-4.432^{***}	-59.051^{***}	0.063
CSENTI	72	0.123	6.627	−19.925	12.762	−0.614	0.233	0.096	-4.853^{***}	-60.139^{***}	0.096
EPU	72	0.324	18.884	−45.853	54.647	0.202	0.027	0.783	-4.828^{***}	-75.671^{***}	0.057
RUNCERT	72	0.051	2.558	−5.369	7.775	0.308	0.430	0.429	-3.413^{*}	-26.915^{***}	0.169
MUNCERT	72	−0.344	2.773	−5.550	8.284	0.911	1.583	0.000	−3.080	-17.711^{*}	0.168
FUNCERT	72	−0.243	3.939	−9.143	9.933	0.354	0.149	0.456	-3.550^{**}	-23.657^{**}	0.190
GPR	72	−0.027	25.771	−73.343	65.133	−0.201	0.468	0.565	-7.114^{***}	-87.746^{***}	0.031
GEOVOL	72	−0.814	36.099	−73.088	76.899	0.030	−0.684	0.493	-5.657^{***}	-80.276^{***}	0.024
Others											
INFL	72	1.942	1.601	−1.978	5.352	−0.214	−0.048	0.758	−2.910	−9.561	0.135
INFLE	72	3.240	0.726	1.700	5.200	0.871	0.957	0.003	-3.666^{**}	−14.689	0.151
USDEER	72	0.027	1.482	−3.083	6.422	1.155	3.688	0.000	-3.361^{*}	-38.069^{***}	0.058
TBILL	72	−5.288	46.543	−174.392	135.917	−0.007	3.278	0.000	-4.263^{***}	-53.366^{***}	0.162
TED	72	−3.336	24.668	−54.318	69.948	0.377	0.773	0.174	-3.803^{**}	-44.675^{***}	0.121

Notes: Summary statistics are provided for 100× log-differenced data except for GECON, INFL, and INFLE (in levels). Monthly data spans the period of 2008:1–2013:12. Asterisks indicate the rejection of the null hypothesis that the time series has a unit root (ADF, PP) or is level stationary (KPSS) at the ***1%, **5%, and *10% level for the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests for stationarity.

Table A.18: Sample statistics of monthly macroeconomic variables, 2014–2019

	Obs.	Mean	Std.Dev.	Min	Max	Skewn.	Ex.Kurt.	J.B.	ADF	PP	KPSS
Global Economic Activity											
STEEL	72	0.176	4.692	−9.691	13.061	0.635	1.081	0.015	-5.088^{***}	-110.262^{***}	0.038
BDI	72	−0.715	20.785	−53.387	46.504	−0.068	−0.251	0.885	-4.873^{***}	-55.918^{***}	0.136
GECON	72	−0.009	0.229	−0.517	0.351	−0.337	−0.813	0.187	−2.004	-20.407^{**}	0.167
WIP	72	0.145	0.412	−0.973	1.079	0.023	−0.213	0.931	-3.499^{**}	-103.032^{***}	0.097
Sentiment/Uncertainty											
VIX	72	−0.041	18.578	−37.925	70.533	0.780	1.873	0.000	-4.683^{***}	-68.863^{***}	0.034
CSENTI	72	0.257	3.226	−9.146	7.296	−0.177	0.156	0.799	-5.403^{***}	-79.894^{***}	0.059
EPU	72	1.174	18.701	−43.731	60.568	0.532	1.290	0.015	-5.323^{***}	-78.508^{***}	0.046
RUNCERT	72	0.298	1.930	−3.916	6.985	0.725	1.730	0.000	-3.250^{*}	-38.447^{***}	0.403^{*}
MUNCERT	72	0.420	2.090	−4.011	6.436	0.615	0.138	0.100	−2.949	-19.383^{*}	0.205
FUNCERT	72	0.509	3.039	−7.646	9.688	0.096	0.757	0.400	−3.132	-31.277^{***}	0.175
GPR	72	0.322	32.944	−89.791	100.606	0.248	1.276	0.060	-4.909^{***}	-85.482^{***}	0.100
GEOVOL	72	−0.306	53.535	−176.673	138.871	−0.459	1.399	0.015	-6.796^{***}	-90.233^{***}	0.040
Others											
INFL	72	1.550	0.803	−0.230	2.851	−0.674	−0.446	0.049	−2.834	−8.516	0.815^{***}
INFLE	72	2.722	0.239	2.200	3.300	0.542	0.035	0.171	−2.631	-18.984^{*}	0.647^{**}
USDEER	72	0.288	1.143	−2.231	2.777	0.032	−0.670	0.507	−3.033	-38.693^{***}	0.238
TBILL	72	4.354	37.061	−117.198	214.472	2.173	14.265	0.000	−3.141	-56.938^{***}	0.167
TED	72	1.045	17.032	−35.066	45.715	0.183	0.277	0.728	-4.971^{***}	-57.158^{***}	0.062

Notes: Summary statistics are provided for 100× log-differenced data except for GECON, INFL, and INFLE (in levels). Monthly data spans the period of 2014:1–2019:12. Asterisks indicate the rejection of the null hypothesis that the time series has a unit root (ADF, PP) or is level stationary (KPSS) at the ***1%, **5%, and *10% level for the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests for stationarity.

Table A.19: Variable definitions

Variable	Definition	Data source
STEEL	Volume of global crude steel production published by the World Steel Association (log difference)	Refinitiv Datastream
BDI	Baltic Dry Index published by the London Baltic Exchange. Reflects costs in dry bulk cargo shipping	Refinitiv Datastream
GECON	Global Economic Conditions by Baumeister et al. (2020). Based on 16 indicators related to energy demand such as real economic activity, uncertainty, financial indicators, transportation, expectations	https://sites.google.com/site/cjsbaumeister/research
WIP	World Industrial Production by Baumeister & Hamilton (2019). Measures production output generated by the industrial sector in OECD countries and six emerging markets (log difference)	https://sites.google.com/site/cjsbaumeister/research
VIX	Cboe Volatility Index (log difference of monthly averages)	Refinitiv Datastream
CSENTI	Consumer sentiment index published by the University of Michigan (log difference)	http://www.sca.isr.umich.edu
EPU	Economic Policy Uncertainty by Baker et al. (2016). Measures policy-related economic uncertainty based on newspaper coverage frequency (log difference)	https://www.policyuncertainty.com/index.html
RUNCERT, MUNCERT, FUNCERT	Real, Macro, and Financial Uncertainty by Jurado et al. (2015) and Ludvigson et al. (2018). Measures uncertainty based on the predictability of economic and financial indicators (log difference)	https://www.sydneyludvigson.com/
GPR	Geopolitical risk by Caldara & Iacoviello (2018). Measures geopolitical risk based on the number of geopolitical event- or risk-related newspaper articles (log difference)	https://www.matteoiacoviello.com/gpr.htm
GEOVOL	Measure of Geopolitical Volatility from Engle & Campos-Martins (2020). Based on common volatility shocks across different financial assets induced by political, regulatory, and military events as well as terrorism and natural disasters (log difference of monthly averages)	Data kindly provided by Susana Martins and Brian Reis (https://vlab.stern.nyu.edu/)
INFL	YoY log difference in US CPI (seasonally adjusted)	https://www.bls.gov/
INFLE	12 months inflation expectation of consumers published by the University of Michigan	http://www.sca.isr.umich.edu
USDEER	USD effective exchange rate calculated as the geometric weighted average of 60 bilateral exchange rates (log difference)	https://www.bis.org/statistics/
TBILL	3-month USD Treasury Bill rate (log difference of monthly averages)	Refinitiv Datastream
TED	TED spread calculated as the difference of the 3-month USD LIBOR rate and the 3-month USD Treasury Bill rate (log difference of monthly averages)	Refinitiv Datastream

Notes: Definitions and data sources for economic variables used as potential drivers of commodity futures returns in our analysis.

Table A.20: MF Granger causality tests for potential driver (monthly) $\nrightarrow$ commodity (weekly), 1998–2019 (full sample)

	Global Economic Activity				Sentiment/Uncertainty								Others				
	STEEL	BDI	GECON	WIP	VIX	CSENTI	EPU	RUNCERT	MUNCERT	FUNCERT	GPR	GEOVOL	INFL	INFLE	USDEER	TBILL	TED
Cocoa	0.2845	0.0941°	0.6177	0.8985	0.9592	0.3292	0.9279	0.7819	0.6781	0.1906	0.1024	0.6525	0.4251	0.5000	0.2812	0.0341	0.7097
Coffee	0.1599	0.8649	0.5860	0.4552	0.6150	0.9328	0.5120	0.9014	0.2255	0.2032	0.9642	0.4852	0.0212	0.0905°	0.7382	0.2946	0.5894
Cotton	0.6747	0.5621	0.0356	0.0316	0.5720	0.7056	0.5934	0.0965°	0.0666°	0.1380	0.5943	0.4942	0.0200	0.0183	0.1551	0.9522	0.2484
Ethanol	0.7726	0.2156	0.3425	0.1339	0.0596°	0.8698	0.3888	0.2224	0.1145	0.4136	0.0454	0.5283	0.2833	0.5151	0.3114	0.4117	0.7053
Lumber	0.4237	0.3367	0.1924	0.6894	0.6269	0.0462	0.5084	0.3249	0.1097	0.3327	0.8871	0.2628	0.5104	0.3597	0.4100	0.0826°	0.6257
Orange Juice	0.6923	0.0195	0.9819	0.8248	0.1992	0.7524	0.5003	0.4010	0.1218	0.0623°	0.7085	0.4126	0.1602	0.2908	0.6467	0.5359	0.0723°
Rubber	0.4313	0.1063	0.1976	0.0585°	0.0088	0.8432	0.3867	0.0794°	0.0097	0.1336	0.3360	0.4300	0.1334	0.1746	0.3702	0.8877	0.4707
Sugar	0.4190	0.9637	0.0309	0.4665	0.6682	0.8147	0.5481	0.1860	0.8597	0.4497	0.9241	0.7670	0.4932	0.9212	0.0902°	0.7413	0.9886
Wool	0.0480	0.1611	0.4754	0.1814	0.1063	0.3844	0.1350	0.2832	0.1461	0.0537°	0.0561°	0.5452	0.0130	0.2103	0.7597	0.9126	0.8337
Corn	0.1586	0.7240	0.0889°	0.1090	0.5274	0.6621	0.6158	0.1947	0.2081	0.5339	0.7743	0.3070	0.1005	0.1553	0.5158	0.0107	0.3581
Oats	0.8042	0.5839	0.0019	0.0310	0.3743	0.5437	0.7226	0.1590	0.0443	0.9374	0.9874	0.8201	0.7901	0.7007	0.6666	0.6877	0.5229
Rough Rice	0.0862°	0.0830°	0.1557	0.6265	0.4107	0.0773°	0.6090	0.4816	0.4409	0.3641	0.2928	0.6775	0.6938	0.9667	0.0190	0.1550	0.4129
Soy Bean	0.1460	0.7528	0.0245	0.3434	0.0336	0.5565	0.4351	0.0170	0.0367	0.3026	0.4197	0.2294	0.0362	0.1645	0.1789	0.4051	0.8702
Soybean Meal	0.0594°	0.8417	0.4431	0.6421	0.4064	0.7236	0.9314	0.0960°	0.1927	0.4106	0.3101	0.6294	0.0793°	0.7118	0.7679	0.1592	0.6379
Soybean Oil	0.1464	0.5303	0.0259	0.1084	0.0624°	0.4459	0.1473	0.0181	0.0450	0.0076	0.6744	0.3129	0.0655°	0.2986	0.0598°	0.9354	0.9517
Wheat	0.0313	0.7576	0.3791	0.4556	0.5556	0.7393	0.7766	0.2167	0.3812	0.7484	0.5229	0.6519	0.6862	0.4605	0.8282	0.9066	0.7147
Feeder Cattle	0.1547	0.5629	0.5309	0.9682	0.5812	0.3280	0.0150	0.6604	0.6538	0.3806	0.4252	0.2241	0.7711	0.7151	0.9742	0.5509	0.1501
Lean Hogs	0.0041	0.5290	0.5565	0.6246	0.0303	0.5576	0.1893	0.0705°	0.0746°	0.0131	0.9838	0.1363	0.0644°	0.2181	0.1626	0.4878	0.3717
Live Cattle	0.0188	0.3757	0.4581	0.3869	0.1791	0.3355	0.0033	0.7819	0.0577°	0.0843°	0.6858	0.1871	0.4184	0.4261	0.4467	0.4049	0.1898
Pork Bellies	0.0623°	0.0986°	0.0492	0.0374	0.7718	0.6595	0.6740	0.3241	0.8882	0.5605	0.2619	0.7176	0.6705	0.5257	0.5205	0.6720	0.5298
Brent	0.1777	0.2017	0.0956°	0.0009	0.6332	0.4120	0.7739	0.5496	0.0807°	0.6841	0.0769°	0.5066	0.1566	0.2202	0.6815	0.5040	0.4075
Gasoil	0.0772°	0.0817°	0.0233	0.0001	0.8592	0.4049	0.8047	0.9080	0.1928	0.5965	0.0940°	0.4127	0.3797	0.3854	0.5751	0.4457	0.1209
Gasoline	0.0449	0.0012	0.0529°	0.0067	0.8314	0.6730	0.7384	0.2697	0.1643	0.0684°	0.9467	0.2030	0.0202	0.0294	0.3009	0.7630	0.1879
Heating Oil	0.0396	0.0047	0.0102	0.0001	0.7432	0.4469	0.7615	0.5071	0.0734°	0.4783	0.0604°	0.3969	0.5299	0.3004	0.5370	0.4973	0.0268
Natural Gas	0.5722	0.3536	0.0967°	0.1830	0.8705	0.5629	0.9656	0.7506	0.9995	0.5378	0.8073	0.5767	0.6263	0.3121	0.2548	0.5906	0.9020
WTI	0.3487	0.0291	0.0708°	0.0006	0.3562	0.0707°	0.3143	0.6344	0.0594°	0.5804	0.1743	0.3517	0.1089	0.4350	0.8278	0.2805	0.1858
Aluminium	0.0993°	0.3418	0.0019	0.0010	0.1301	0.7762	0.3550	0.1369	0.0978°	0.0437	0.6765	0.5900	0.1562	0.5280	0.1194	0.5658	0.6345
Cobalt	0.9688	0.3670	0.4883	0.4280	0.0364	0.2004	0.0676°	0.2776	0.0755°	0.0938°	0.0055	0.7014	0.4682	0.3359	0.3463	0.8944	0.4801
Copper	0.3337	0.4381	0.1138	0.0031	0.2523	0.9054	0.6770	0.0274	0.0284	0.0472	0.8027	0.2852	0.2305	0.1454	0.1890	0.0685°	0.6934
Lead	0.7039	0.5332	0.0647°	0.0555°	0.1218	0.7566	0.2922	0.1738	0.0241	0.0150	0.7927	0.3197	0.2192	0.2764	0.2885	0.9152	0.2811
Nickel	0.1894	0.6270	0.0003	0.0112	0.7291	0.3701	0.7589	0.0300	0.0054	0.0097	0.5197	0.1755	0.1539	0.0004	0.9934	0.4578	0.5173
Tin	0.5639	0.6675	0.0269	0.0021	0.6345	0.0838°	0.4176	0.2295	0.0175	0.0372	0.3435	0.1791	0.3749	0.3072	0.7990	0.1697	0.6572
Zinc	0.1265	0.8946	0.0249	0.0115	0.4082	0.1763	0.4744	0.0903°	0.0035	0.0144	0.1867	0.0442	0.0204	0.0273	0.8776	0.2597	0.8872
Gold	0.5595	0.9164	0.6121	0.5039	0.6181	0.3747	0.0393	0.7888	0.7107	0.6635	0.1142	0.0232	0.2205	0.5092	0.8513	0.8989	0.4945
Palladium	0.5935	0.6120	0.0590°	0.0813°	0.0542°	0.0238	0.3641	0.7610	0.3862	0.3886	0.4403	0.5114	0.3121	0.0334	0.4497	0.6759	0.3531
Platinum	0.0164	0.9477	0.4128	0.2453	0.0339	0.4448	0.3224	0.8217	0.5283	0.2401	0.3570	0.0443	0.4282	0.1389	0.5876	0.7541	0.9035
Silver	0.1798	0.5453	0.7795	0.3729	0.5941	0.3906	0.4703	0.6174	0.3468	0.0734°	0.4038	0.0010	0.0177	0.2590	0.1462	0.6597	0.9697
Softs	0.4069	0.7742	0.1425	0.0577°	0.1440	0.5073	0.7440	0.4561	0.0799°	0.0274	0.3189	0.6338	0.1745	0.0705°	0.1627	0.2868	0.7384
Grains	0.2890	0.7110	0.0013	0.0163	0.1590	0.7186	0.3625	0.0466	0.0400	0.2120	0.5013	0.4486	0.1106	0.5142	0.1091	0.1151	0.8288
Livestock	0.1926	0.2613	0.0246	0.2719	0.5140	0.2112	0.1837	0.4418	0.2984	0.3115	0.8589	0.5707	0.9194	0.8028	0.5333	0.8162	0.1080
Energy	0.1308	0.0359	0.0561°	0.0001	0.7826	0.3868	0.6944	0.5471	0.1881	0.5176	0.1904	0.2714	0.1353	0.1819	0.7597	0.3409	0.0988°
Industrial Metals	0.0819°	0.5955	0.0006	0.0001	0.1755	0.7912	0.3292	0.0575°	0.0006	0.0007	0.6458	0.0703°	0.1379	0.0322	0.3171	0.7761	0.5798
Precious Metals	0.2933	0.9835	0.4867	0.6785	0.1463	0.0824°	0.2929	0.6322	0.3560	0.2955	0.3708	0.0124	0.1559	0.1308	0.0693°	0.8156	0.8200

Notes: This table shows bootstrapped p-values with $N = 10{,}000$ replications for testing the null hypothesis of non-causality from a potential driver to a commodity at the low-frequency prediction horizon $h = 1$ month ($H_0 : x_L \nrightarrow_h x_H \mid \ell$) based on bivariate MF-VARs with lag order $P = 1$ using monthly (log-differenced) data for the potential driver and weekly log returns for the commodity front-month futures ($m = 4$). Before estimating the MF-VAR models, the data has been demeaned. A highlighted cell (circle) indicates the rejection of non-causality at the 5% (10%) level. The sample spans the period 1998:1–2019:12 where data is available over the full horizon. Commodity futures are grouped by the classes of softs, grains, livestock, energy, industrial metals, and precious metals. The last group consists of equally-weighted commodity portfolios.

Table A.21: MF Granger causality tests for potential driver (monthly) $\nrightarrow$ commodity (weekly), 1998–2003

	Global Economic Activity				Sentiment/Uncertainty								Others				
	STEEL	BDI	GECON	WIP	VIX	CSENTI	EPU	RUNCERT	MUNCERT	FUNCERT	GPR	GEOVOL	INFL	INFLE	USDEER	TBILL	TED
Cocoa	0.0542°	0.3472	0.6201	0.9682	0.9050	0.8462	0.4072	0.7952	0.8784	0.7425	0.0593°	0.9333	0.2668	0.0211	0.4673	0.1080	0.2086
Coffee	0.8632	0.4260	0.2065	0.6017	0.9380	0.7906	0.7800	0.6809	0.4887	0.0729°	0.3019	0.8400	0.1857	0.1004	0.6755	0.9439	0.5789
Cotton	0.2059	0.1826	0.1863	0.3812	0.7342	0.8945	0.1785	0.0691°	0.0234	0.1833	0.5921	0.7114	0.4653	0.4038	0.7248	0.3518	0.8658
Ethanol	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Lumber	0.5063	0.1140	0.7243	0.8916	0.5955	0.5187	0.0527°	0.1286	0.2330	0.1976	0.9212	0.3398	0.0702°	0.0362	0.5139	0.7331	0.3227
Orange Juice	0.7563	0.7408	0.0033	0.1718	0.3562	0.0763°	0.0757°	0.0883°	0.2877	0.1789	0.6517	0.5349	0.1394	0.5486	0.8162	0.1576	0.1198
Rubber	0.3257	0.6175	0.6122	0.2525	0.7789	0.7763	0.1470	0.1612	0.0008	0.2957	0.8510	0.5839	0.2489	0.2357	0.5576	0.9759	0.8856
Sugar	0.3844	0.6063	0.4810	0.7766	0.3318	0.5526	0.0828°	0.8792	0.5746	0.1478	0.0885°	0.7523	0.1074	0.3855	0.9599	0.0602°	0.6876
Wool	0.6337	0.2707	0.2087	0.3721	0.3025	0.1028	0.2377	0.0976°	0.2905	0.6743	0.1838	0.4284	0.0802°	0.1229	0.7483	0.1987	0.3820
Corn	0.0764°	0.5106	0.2154	0.6166	0.5060	0.7705	0.6579	0.2503	0.1133	0.2658	0.2687	0.8542	0.2569	0.4934	0.8071	0.2896	0.0560°
Oats	0.1334	0.1680	0.0897°	0.6533	0.3953	0.9239	0.7021	0.3258	0.0807°	0.8099	0.5408	0.2585	0.0570°	0.7000	0.9678	0.1798	0.3117
Rough Rice	0.2511	0.0219	0.5269	0.1437	0.7147	0.7605	0.2343	0.8135	0.3079	0.2480	0.6889	0.7883	0.5205	0.7841	0.0914°	0.6557	0.4242
Soy Bean	0.5760	0.1266	0.3469	0.3949	0.2197	0.7855	0.4711	0.1307	0.2144	0.3680	0.9537	0.4417	0.3132	0.2326	0.2617	0.6526	0.9473
Soybean Meal	0.2590	0.3701	0.4644	0.7269	0.0262	0.6685	0.5706	0.3072	0.7397	0.8210	0.9089	0.8633	0.2218	0.1781	0.5048	0.5464	0.9877
Soybean Oil	0.6031	0.0455	0.5288	0.3704	0.0941°	0.0235	0.7606	0.5046	0.0747°	0.0445	0.4283	0.4205	0.6053	0.2838	0.2122	0.2343	0.5940
Wheat	0.3769	0.0257	0.3719	0.0876°	0.0378	0.6131	0.4256	0.1459	0.4635	0.3648	0.9449	0.5509	0.6143	0.3850	0.9252	0.5035	0.9761
Feeder Cattle	0.1117	0.0263	0.6337	0.4877	0.1930	0.6612	0.1102	0.4045	0.9552	0.7751	0.3147	0.8990	0.5268	0.2079	0.6634	0.5646	0.5358
Lean Hogs	0.0388	0.5370	0.4259	0.7501	0.3172	0.3262	0.7177	0.5645	0.6475	0.4607	0.2225	0.0790°	0.4190	0.6095	0.4554	0.3659	0.5353
Live Cattle	0.1245	0.0773°	0.9201	0.5951	0.3659	0.7896	0.2599	0.0881°	0.4999	0.1565	0.6237	0.2167	0.2601	0.1101	0.4294	0.3675	0.1895
Pork Bellies	0.3361	0.4466	0.3144	0.9377	0.5255	0.4710	0.6196	0.2065	0.5593	0.3561	0.3775	0.7095	0.5172	0.7765	0.7347	0.1286	0.7571
Brent	0.9134	0.4252	0.2546	0.0382	0.9220	0.2062	0.4541	0.3040	0.2639	0.2200	0.0048	0.6509	0.0037	0.0043	0.7712	0.2875	0.0410
Gasoil	0.7428	0.3410	0.2365	0.2051	0.5656	0.1807	0.6256	0.9635	0.7047	0.7767	0.0157	0.2449	0.2119	0.4394	0.9466	0.0953°	0.0606°
Gasoline	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Heating Oil	0.7267	0.0420	0.0768°	0.0666°	0.5060	0.4293	0.4098	0.9234	0.5125	0.6730	0.0396	0.9834	0.4706	0.1610	0.8125	0.0356	0.0340
Natural Gas	0.8972	0.1886	0.2245	0.3027	0.8204	0.0938°	0.4695	0.8548	0.6655	0.2784	0.0553°	0.8490	0.1665	0.0439	0.4930	0.1528	0.9238
WTI	0.8892	0.2919	0.0544°	0.0300	0.9573	0.0402	0.3712	0.7394	0.6155	0.3300	0.0647°	0.6781	0.0003	0.0026	0.6137	0.1127	0.3320
Aluminium	0.0227	0.0871°	0.4279	0.1419	0.6247	0.8709	0.2381	0.6441	0.2138	0.4602	0.4877	0.9335	0.9115	0.6446	0.3162	0.6817	0.8721
Cobalt	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Copper	0.2727	0.0363	0.3652	0.1962	0.0835°	0.9215	0.0409	0.3059	0.0764°	0.5188	0.5174	0.6100	0.3548	0.5570	0.5163	0.9038	0.6571
Lead	0.7068	0.0324	0.5358	0.9766	0.6093	0.1665	0.1286	0.9618	0.4091	0.4019	0.6677	0.6451	0.1246	0.2690	0.7603	0.6806	0.7830
Nickel	0.2046	0.1449	0.0446	0.3549	0.0552°	0.4046	0.2375	0.8605	0.0555°	0.4691	0.4472	0.5063	0.2207	0.1429	0.8508	0.6454	0.6064
Tin	0.0923°	0.1265	0.5378	0.3195	0.1601	0.1256	0.1057	0.3385	0.1309	0.0938°	0.1209	0.0394	0.0299	0.1038	0.6829	0.9255	0.5141
Zinc	0.2617	0.0946°	0.1703	0.3233	0.2517	0.8859	0.2100	0.6357	0.0105	0.2902	0.1088	0.8696	0.1457	0.5131	0.6047	0.2899	0.5863
Gold	0.4261	0.6667	0.6968	0.8279	0.5700	0.0529°	0.4005	0.6026	0.8583	0.9084	0.0593°	0.0775°	0.5522	0.6299	0.8056	0.7678	0.6671
Palladium	0.1014	0.2579	0.3371	0.5390	0.8729	0.1761	0.9981	0.4298	0.3852	0.2615	0.5058	0.5377	0.1965	0.0694°	0.4885	0.2638	0.2466
Platinum	0.7701	0.2397	0.2891	0.0960°	0.9927	0.3472	0.5938	0.5554	0.6719	0.5425	0.2584	0.5390	0.7344	0.1143	0.3524	0.7547	0.6207
Silver	0.6787	0.1424	0.3426	0.0771°	0.4424	0.3219	0.4432	0.6134	0.1187	0.3552	0.1945	0.2679	0.1667	0.0668°	0.9100	0.9885	0.9299
Softs	0.3933	0.6323	0.5750	0.6857	0.8466	0.2456	0.5891	0.4754	0.1346	0.0614°	0.0184	0.6528	0.0787°	0.0712°	0.6150	0.3946	0.5730
Grains	0.2730	0.2272	0.0674°	0.2518	0.1016	0.5244	0.8863	0.0389	0.1387	0.2385	0.4127	0.6848	0.8508	0.7933	0.6628	0.5399	0.8439
Livestock	0.9147	0.2349	0.4975	0.6531	0.6128	0.6016	0.2235	0.6587	0.7812	0.5004	0.6427	0.2463	0.3095	0.3386	0.7962	0.4838	0.1424
Energy	0.8681	0.1664	0.0784°	0.0156	0.9822	0.2166	0.1978	0.9765	0.8935	0.2669	0.0598°	0.8262	0.1104	0.0502°	0.6991	0.0307	0.0196
Industrial Metals	0.1689	0.1121	0.1619	0.3037	0.0625°	0.9405	0.3032	0.7702	0.0050	0.2088	0.1562	0.9805	0.1264	0.2389	0.9506	0.7767	0.9418
Precious Metals	0.6535	0.2162	0.0421	0.1068	0.5992	0.1845	0.8525	0.0490	0.2349	0.3207	0.6493	0.8600	0.3660	0.5558	0.5063	0.6440	0.4733

Notes: This table shows bootstrapped p-values with $N = 10{,}000$ replications for testing the null hypothesis of non-causality from a potential driver to a commodity at the low-frequency prediction horizon $h = 1$ month ($H_0 : x_L \nrightarrow_h x_H \mid \ell$) based on bivariate MF-VARs with lag order $P = 1$ using monthly (log-differenced) data for the potential driver and weekly log returns for the commodity front-month futures ($m = 4$). Before estimating the MF-VAR models, the data has been demeaned. A highlighted cell (circle) indicates the rejection of non-causality at the 5% (10%) level. The sample spans the period 1998:1–2003:12 where data is available over the full horizon. Commodity futures are grouped by the classes of softs, grains, livestock, energy, industrial metals, and precious metals. The last group consists of equally-weighted commodity portfolios.

Table A.22: MF Granger causality tests for potential driver (monthly) $\nrightarrow$ commodity (weekly), 2004–2007

	Global Economic Activity				Sentiment/Uncertainty								Others				
	STEEL	BDI	GECON	WIP	VIX	CSENTI	EPU	RUNCERT	MUNCERT	FUNCERT	GPR	GEOVOL	INFL	INFLE	USDEER	TBILL	TED
Cocoa	0.3599	0.5273	0.0002	0.1570	0.3251	0.1501	0.4214	0.2827	0.4683	0.2130	0.7885	0.7047	0.2663	0.0775°	0.5350	0.9364	0.5673
Coffee	0.4812	0.2475	0.1916	0.7303	0.6283	0.3009	0.8988	0.5709	0.8336	0.3020	0.0966°	0.4533	0.6632	0.2515	0.0399	0.8821	0.0243
Cotton	0.2434	0.3724	0.6895	0.4678	0.7687	0.3081	0.7984	0.4565	0.9252	0.4587	0.4624	0.5455	0.1671	0.1145	0.5092	0.0165	0.1534
Ethanol	0.7171	0.3202	0.8002	0.9313	0.2566	0.2666	0.8126	0.0274	0.1044	0.1730	0.6000	0.7321	0.1990	0.1829	0.4350	0.0078	0.1294
Lumber	0.1742	0.6635	0.0803°	0.6869	0.2651	0.2973	0.4001	0.3454	0.2388	0.1615	0.4704	0.0536°	0.3126	0.1772	0.1742	0.5143	0.9140
Orange Juice	0.6689	0.9901	0.0778°	0.8461	0.0320	0.5327	0.7869	0.0817°	0.0518°	0.6692	0.2638	0.2301	0.0214	0.6030	0.0795°	0.6629	0.8877
Rubber	0.9514	0.0425	0.5633	0.7951	0.8564	0.2254	0.1425	0.3059	0.5854	0.5650	0.5440	0.9633	0.0160	0.1642	0.7070	0.5449	0.8013
Sugar	0.9151	0.0633°	0.7027	0.0244	0.1087	0.5215	0.9135	0.4844	0.2767	0.9077	0.9490	0.3824	0.5312	0.2808	0.5832	0.0361	0.4833
Wool	0.1211	0.6875	0.5762	0.8091	0.2377	0.3020	0.4337	0.8867	0.8900	0.6454	0.6464	0.9471	0.5796	0.0417	0.5731	0.5415	0.2294
Corn	0.6918	0.6099	0.4152	0.1157	0.7562	0.6580	0.7583	0.9726	0.2379	0.5740	0.2928	0.5492	0.8534	0.8317	0.8790	0.3119	0.5453
Oats	0.2966	0.2069	0.4974	0.4105	0.9718	0.4953	0.4299	0.1829	0.1993	0.8287	0.3128	0.9297	0.9155	0.3437	0.1262	0.0641°	0.6916
Rough Rice	0.7560	0.1200	0.5584	0.3580	0.2750	0.8889	0.1273	0.9263	0.4549	0.9708	0.3708	0.6310	0.3476	0.7978	0.7604	0.3237	0.9310
Soy Bean	0.1842	0.7215	0.2002	0.4056	0.2063	0.7583	0.5591	0.5562	0.3301	0.2778	0.3062	0.2908	0.0654°	0.0650°	0.9805	0.0326	0.1170
Soybean Meal	0.1436	0.7434	0.6099	0.1593	0.5064	0.4573	0.5284	0.8085	0.7474	0.0551°	0.2455	0.1076	0.3780	0.1192	0.6030	0.1793	0.1640
Soybean Oil	0.3785	0.7859	0.8457	0.6985	0.3849	0.2504	0.3406	0.0251	0.0362	0.9249	0.1933	0.7726	0.7628	0.0261	0.3790	0.0125	0.5362
Wheat	0.9172	0.7953	0.7375	0.0839°	0.5420	0.8766	0.7160	0.2146	0.2908	0.2746	0.6421	0.1545	0.6617	0.3723	0.1450	0.6909	0.7734
Feeder Cattle	0.5459	0.1410	0.2170	0.4941	0.2228	0.1603	0.4918	0.6264	0.2838	0.3798	0.0628°	0.7132	0.4064	0.2286	0.7398	0.0100	0.0154
Lean Hogs	0.0946°	0.9888	0.6392	0.3366	0.1794	0.8187	0.9615	0.3039	0.2466	0.4906	0.8646	0.7613	0.9518	0.0723°	0.9298	0.0805°	0.4692
Live Cattle	0.3251	0.3228	0.3254	0.3805	0.3319	0.5112	0.7271	0.1628	0.0978°	0.9049	0.7341	0.9363	0.7825	0.5887	0.5329	0.1310	0.6697
Pork Bellies	0.5260	0.4325	0.4519	0.9339	0.9236	0.8175	0.9948	0.1744	0.0496	0.2936	0.5542	0.7042	0.6753	0.0089	0.4920	0.0895°	0.0871°
Brent	0.6916	0.0952°	0.0708°	0.5038	0.1394	0.0300	0.9092	0.0404	0.2979	0.8620	0.9004	0.8950	0.0397	0.0057	0.2204	0.9918	0.1180
Gasoil	0.5695	0.0214	0.7265	0.4630	0.2765	0.3150	0.6759	0.4931	0.8560	0.4695	0.3997	0.9981	0.0213	0.0078	0.1740	0.8153	0.0631°
Gasoline	0.6566	0.4431	0.0572°	0.7467	0.1476	0.6820	0.5370	0.0583°	0.2586	0.8332	0.8227	0.0482	0.3234	0.4671	0.8373	0.1893	0.1967
Heating Oil	0.5565	0.0768°	0.1905	0.5823	0.1927	0.0615°	0.9320	0.7391	0.9436	0.8431	0.7603	0.5669	0.0064	0.0004	0.2987	0.6652	0.2444
Natural Gas	0.5802	0.2585	0.3436	0.4027	0.5518	0.0400	0.9465	0.8554	0.5058	0.1237	0.9865	0.8860	0.0310	0.0704°	0.1371	0.6062	0.8144
WTI	0.6299	0.1240	0.3790	0.8483	0.1696	0.2404	0.9663	0.1039	0.3158	0.8559	0.4291	0.7302	0.0696°	0.0137	0.4003	0.9307	0.2887
Aluminium	0.8718	0.3446	0.7887	0.7811	0.4786	0.4828	0.9547	0.7918	0.7099	0.2386	0.1142	0.7633	0.4162	0.1030	0.2930	0.8619	0.9276
Cobalt	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Copper	0.9050	0.4474	0.0326	0.4330	0.5171	0.7196	0.0918°	0.2545	0.2256	0.4751	0.1664	0.0588°	0.4274	0.2039	0.5242	0.4826	0.6425
Lead	0.7742	0.1066	0.9649	0.1493	0.1378	0.6525	0.7469	0.6619	0.6075	0.3935	0.8868	0.1763	0.2589	0.5747	0.9624	0.6207	0.7653
Nickel	0.7842	0.1269	0.6014	0.7995	0.0309	0.4492	0.6997	0.3497	0.6142	0.4811	0.5162	0.1736	0.4163	0.4569	0.1649	0.4563	0.4081
Tin	0.3366	0.7473	0.0859°	0.1640	0.2645	0.0465	0.7558	0.3572	0.1907	0.5025	0.1326	0.4700	0.0060	0.1528	0.2556	0.1560	0.5624
Zinc	0.7514	0.9973	0.5850	0.0982°	0.1086	0.7346	0.5602	0.6793	0.7735	0.0671°	0.6638	0.4559	0.2396	0.4090	0.7989	0.1852	0.5600
Gold	0.0417	0.9550	0.8386	0.1219	0.6401	0.8637	0.7266	0.6049	0.4597	0.5605	0.2696	0.1388	0.9385	0.7928	0.8689	0.2760	0.3544
Palladium	0.7416	0.8448	0.2113	0.6860	0.7907	0.3329	0.3390	0.9812	0.9480	0.5096	0.5000	0.6788	0.4427	0.5145	0.5785	0.2030	0.7409
Platinum	0.6367	0.4258	0.6645	0.4094	0.7328	0.9133	0.9676	0.6792	0.7480	0.7907	0.7165	0.1470	0.9532	0.6497	0.8575	0.1820	0.2192
Silver	0.0396	0.8616	0.6540	0.3938	0.5791	0.7217	0.5646	0.2853	0.0684°	0.0744°	0.7431	0.0156	0.9565	0.6666	0.8264	0.1496	0.1324
Softs	0.4125	0.5739	0.7771	0.7204	0.5112	0.4417	0.8173	0.9871	0.9060	0.2179	0.9026	0.4578	0.0103	0.4870	0.3557	0.8817	0.0765°
Grains	0.1097	0.8168	0.4553	0.2987	0.3934	0.5222	0.7792	0.2526	0.5135	0.8366	0.2364	0.6001	0.4313	0.6649	0.4377	0.0888°	0.3630
Livestock	0.8743	0.6135	0.3418	0.5043	0.5397	0.7624	0.9974	0.2062	0.5423	0.8162	0.8334	0.9335	0.6814	0.1803	0.7852	0.0244	0.0654°
Energy	0.5165	0.2079	0.1694	0.8300	0.1570	0.3404	0.8642	0.4514	0.5761	0.6577	0.5705	0.6965	0.0169	0.0082	0.2526	0.9249	0.2727
Industrial Metals	0.9941	0.8814	0.2760	0.7775	0.3588	0.4722	0.1352	0.3513	0.2222	0.0676°	0.3883	0.0567°	0.4647	0.1301	0.8328	0.5788	0.4757
Precious Metals	0.4342	0.9376	0.8935	0.4199	0.8391	0.8125	0.9383	0.8724	0.7186	0.1805	0.4541	0.0681°	0.9902	0.9855	0.6940	0.1676	0.2109

Notes: This table shows bootstrapped p-values with $N = 10{,}000$ replications for testing the null hypothesis of non-causality from a potential driver to a commodity at the low-frequency prediction horizon $h = 1$ month ($H_0 : x_L \nrightarrow_h x_H \mid \ell$) based on bivariate MF-VARs with lag order $P = 1$ using monthly (log-differenced) data for the potential driver and weekly log returns for the commodity front-month futures ($m = 4$). Before estimating the MF-VAR models, the data has been demeaned. A highlighted cell (circle) indicates the rejection of non-causality at the 5% (10%) level. The sample spans the period 2004:1–2007:12 where data is available over the full horizon. Commodity futures are grouped by the classes of softs, grains, livestock, energy, industrial metals, and precious metals. The last group consists of equally-weighted commodity portfolios.

Table A.23: MF Granger causality tests for potential driver (monthly) $\nrightarrow$ commodity (weekly), 2008–2013

	Global Economic Activity				Sentiment/Uncertainty								Others				
	STEEL	BDI	GECON	WIP	VIX	CSENTI	EPU	RUNCERT	MUNCERT	FUNCERT	GPR	GEOVOL	INFL	INFLE	USDEER	TBILL	TED
Cocoa	0.3962	0.5176	0.1126	0.7347	0.3125	0.0343	0.1608	0.3241	0.0625°	0.0492	0.9059	0.0675°	0.0002	0.1493	0.6197	0.1991	0.5549
Coffee	0.1685	0.6050	0.3371	0.6145	0.0604°	0.2298	0.5160	0.5891	0.0368	0.0976°	0.4350	0.4906	0.0116	0.0200	0.4644	0.4549	0.7701
Cotton	0.5759	0.4547	0.0946°	0.1305	0.8780	0.8072	0.9452	0.1273	0.1275	0.0206	0.6127	0.9189	0.0021	0.0196	0.4511	0.7410	0.5779
Ethanol	0.4100	0.0481	0.0864°	0.1614	0.0222	0.5741	0.5868	0.0188	0.1871	0.0538°	0.0238	0.0859°	0.0907°	0.4465	0.0841°	0.9891	0.4195
Lumber	0.1991	0.3122	0.1348	0.0774°	0.5039	0.1143	0.5953	0.6439	0.5783	0.0841°	0.9103	0.9629	0.3903	0.1744	0.1424	0.0539°	0.8863
Orange Juice	0.3443	0.0144	0.2210	0.0301	0.4873	0.0226	0.2692	0.0166	0.0108	0.2255	0.9659	0.6696	0.0044	0.0561°	0.9308	0.4925	0.2999
Rubber	0.2666	0.3768	0.0301	0.0960°	0.1665	0.7915	0.7702	0.0004	0.0028	0.0048	0.1027	0.5837	0.0016	0.2042	0.1554	0.5481	0.4808
Sugar	0.6322	0.2369	0.0338	0.3372	0.1861	0.2118	0.8548	0.0313	0.0396	0.1266	0.5058	0.7648	0.3410	0.3479	0.0829°	0.5484	0.9389
Wool	0.3724	0.2777	0.3055	0.2661	0.2936	0.7825	0.1569	0.3187	0.1224	0.1583	0.8228	0.2695	0.0025	0.0815°	0.9795	0.7752	0.1938
Corn	0.3727	0.0762°	0.1390	0.2635	0.1176	0.0356	0.4389	0.1979	0.0700°	0.0481	0.6478	0.1627	0.1390	0.5476	0.2112	0.7631	0.3452
Oats	0.2814	0.9604	0.1108	0.1128	0.1653	0.9087	0.8261	0.2403	0.0265	0.4366	0.3228	0.5397	0.0941°	0.4227	0.4575	0.9461	0.6537
Rough Rice	0.0920°	0.1047	0.1934	0.9257	0.4729	0.1065	0.9139	0.0625°	0.3771	0.5421	0.1657	0.5004	0.0858°	0.3637	0.2114	0.7607	0.0115
Soy Bean	0.2046	0.0674°	0.1433	0.5062	0.1461	0.6800	0.7263	0.4369	0.5381	0.0110	0.1110	0.4218	0.0174	0.4167	0.2349	0.8511	0.8319
Soybean Meal	0.0970°	0.1558	0.6910	0.8186	0.0727°	0.9358	0.7203	0.2729	0.1362	0.0375	0.0655°	0.3265	0.0022	0.2725	0.3103	0.7784	0.9019
Soybean Oil	0.2997	0.1243	0.0369	0.1316	0.0912°	0.3880	0.4227	0.3444	0.0441	0.0292	0.1984	0.6860	0.0431	0.2194	0.1401	0.4478	0.8949
Wheat	0.1634	0.4793	0.1167	0.7163	0.1948	0.0961°	0.6920	0.3728	0.3029	0.0837°	0.1721	0.1904	0.5729	0.3394	0.1624	0.9861	0.1622
Feeder Cattle	0.4954	0.2487	0.4522	0.2713	0.6304	0.4310	0.5325	0.2680	0.3643	0.2676	0.2356	0.6237	0.8514	0.2827	0.4554	0.2316	0.4237
Lean Hogs	0.2964	0.3824	0.5330	0.2573	0.3646	0.5612	0.2785	0.1411	0.0382	0.1124	0.2707	0.4143	0.1021	0.1710	0.3782	0.4144	0.4128
Live Cattle	0.6818	0.3025	0.0116	0.0066	0.2243	0.3060	0.5692	0.9066	0.0890°	0.0310	0.7879	0.0379	0.2623	0.2102	0.1715	0.2217	0.2851
Pork Bellies	0.5289	0.1750	0.1406	0.0210	0.3106	0.6232	0.6171	0.1047	0.1538	0.8913	0.6569	0.7739	0.1418	0.5004	0.0239	0.8201	0.7352
Brent	0.5569	0.6531	0.6436	0.0048	0.2117	0.9408	0.3979	0.2047	0.2920	0.4168	0.0019	0.3349	0.0056	0.0154	0.6107	0.5102	0.5743
Gasoil	0.6395	0.4024	0.0154	0.0005	0.4570	0.9774	0.6548	0.5249	0.2105	0.5617	0.0282	0.3314	0.0892°	0.0363	0.1393	0.3202	0.6174
Gasoline	0.0584°	0.1615	0.1960	0.0038	0.2864	0.9028	0.0416	0.1138	0.0190	0.1066	0.2662	0.2746	0.0134	0.1042	0.1607	0.7690	0.4957
Heating Oil	0.5609	0.4245	0.0717°	0.0002	0.0794°	0.9614	0.2921	0.7532	0.4582	0.1305	0.0083	0.0693°	0.2363	0.1551	0.4857	0.2046	0.5094
Natural Gas	0.5272	0.4340	0.0403	0.2752	0.5251	0.7978	0.7439	0.6303	0.3576	0.8966	0.1794	0.9093	0.1352	0.4947	0.5915	0.4690	0.9964
WTI	0.8749	0.2291	0.4964	0.0178	0.0630°	0.6071	0.1266	0.6027	0.1485	0.4644	0.1875	0.1012	0.0253	0.0228	0.6970	0.3089	0.5044
Aluminium	0.3465	0.0245	0.2065	0.0034	0.0944°	0.8440	0.6492	0.3405	0.0722°	0.2521	0.3292	0.7340	0.0420	0.0421	0.0131	0.9663	0.6810
Cobalt	0.6918	0.1147	0.9938	0.6409	0.0487	0.1362	0.2135	0.1556	0.3628	0.1066	0.2671	0.6793	0.1247	0.2839	0.1914	0.0852°	0.8558
Copper	0.0412	0.3902	0.0091	0.0056	0.2333	0.9513	0.7238	0.0272	0.0010	0.1531	0.5629	0.1949	0.0118	0.1193	0.0154	0.9691	0.2501
Lead	0.3046	0.6572	0.0772°	0.0293	0.5642	0.4967	0.8100	0.1096	0.0683°	0.1664	0.3225	0.5814	0.0062	0.0017	0.0742°	0.3367	0.1380
Nickel	0.3908	0.1233	0.0186	0.0126	0.1882	0.1608	0.3791	0.1359	0.0039	0.0074	0.3468	0.6803	0.0130	0.0030	0.6628	0.1264	0.0184
Tin	0.3972	0.2806	0.0759°	0.0496	0.1770	0.0934°	0.5957	0.4495	0.0268	0.0729°	0.6783	0.1323	0.1150	0.0348	0.2496	0.5626	0.4059
Zinc	0.0735°	0.3566	0.3022	0.2941	0.1239	0.1806	0.6660	0.0192	0.0027	0.2145	0.5852	0.4800	0.0005	0.0104	0.5257	0.9592	0.2081
Gold	0.5860	0.5645	0.1143	0.4972	0.4270	0.1541	0.4787	0.9005	0.8440	0.6814	0.2392	0.1871	0.1919	0.5154	0.2032	0.9107	0.3404
Palladium	0.1730	0.2015	0.0745°	0.1612	0.0129	0.0184	0.2484	0.1937	0.0388	0.0408	0.6919	0.2850	0.0080	0.0103	0.1344	0.4936	0.3501
Platinum	0.0357	0.1959	0.2145	0.3218	0.0067	0.3893	0.4150	0.7200	0.3361	0.4672	0.8051	0.2571	0.0750°	0.0513°	0.1891	0.3301	0.2643
Silver	0.4879	0.0672°	0.0537°	0.7746	0.2700	0.1642	0.1208	0.6307	0.1870	0.2405	0.0295	0.5766	0.0196	0.1893	0.1256	0.7928	0.2398
Softs	0.2880	0.7561	0.1248	0.1321	0.1074	0.3266	0.4116	0.0819°	0.2245	0.0246	0.7233	0.4807	0.0006	0.1136	0.6115	0.9738	0.7428
Grains	0.3060	0.0772°	0.0453	0.3021	0.0527°	0.1428	0.8439	0.2657	0.0698°	0.0208	0.1090	0.2496	0.0709°	0.2791	0.1205	0.9384	0.7423
Livestock	0.7246	0.7474	0.0087	0.0020	0.3383	0.2386	0.9355	0.1041	0.2472	0.6891	0.2917	0.4282	0.8038	0.4492	0.4492	0.8751	0.5055
Energy	0.7981	0.4939	0.4788	0.0016	0.0220	0.9555	0.2824	0.1294	0.2338	0.1712	0.0210	0.1627	0.0398	0.1267	0.5203	0.7846	0.3436
Industrial Metals	0.0847°	0.0671°	0.0226	0.0084	0.2155	0.4270	0.6986	0.0203	0.0038	0.0799°	0.3269	0.3934	0.0035	0.0048	0.0497	0.5536	0.4367
Precious Metals	0.2516	0.2481	0.3500	0.8959	0.0277	0.0037	0.3862	0.6136	0.3266	0.2066	0.2653	0.3662	0.0164	0.0894°	0.1145	0.6250	0.1283

Notes: This table shows bootstrapped p-values with $N = 10{,}000$ replications for testing the null hypothesis of non-causality from a potential driver to a commodity at the low-frequency prediction horizon $h = 1$ month ($H_0 : x_L \nrightarrow_h x_H \mid \ell$) based on bivariate MF-VARs with lag order $P = 1$ using monthly (log-differenced) data for the potential driver and weekly log returns for the commodity front-month futures ($m = 4$). Before estimating the MF-VAR models, the data has been demeaned. A highlighted cell (circle) indicates the rejection of non-causality at the 5% (10%) level. The sample spans the period 2008:1–2013:12 where data is available over the full horizon. Commodity futures are grouped by the classes of softs, grains, livestock, energy, industrial metals, and precious metals. The last group consists of equally-weighted commodity portfolios.

Table A.24: MF Granger causality tests for potential driver (monthly) $\nrightarrow$ commodity (weekly), 2014–2019

	Global Economic Activity				Sentiment/Uncertainty								Others				
	STEEL	BDI	GECON	WIP	VIX	CSENTI	EPU	RUNCERT	MUNCERT	FUNCERT	GPR	GEOVOL	INFL	INFLE	USDEER	TBILL	TED
Cocoa	0.8444	0.1429	0.3419	0.3007	0.3225	0.3679	0.9882	0.4594	0.7122	0.4149	0.1644	0.5386	0.4335	0.3617	0.0134	0.2275	0.1841
Coffee	0.2249	0.6771	0.9738	0.5911	0.2059	0.8866	0.1429	0.5904	0.9625	0.9547	0.9224	0.0265	0.0434	0.2958	0.9056	0.5378	0.7370
Cotton	0.2037	0.2563	0.1713	0.2238	0.0464	0.3195	0.4700	0.1119	0.0224	0.0215	0.8169	0.8684	0.4747	0.0711°	0.1794	0.7160	0.3155
Ethanol	0.5225	0.7634	0.6771	0.8322	0.5790	0.0844°	0.1712	0.9970	0.6049	0.7621	0.3902	0.7175	0.0608°	0.1491	0.8341	0.5290	0.5194
Lumber	0.8147	0.9467	0.6754	0.7294	0.8564	0.1920	0.7068	0.1828	0.5975	0.9736	0.6824	0.3126	0.2109	0.2626	0.0510°	0.3224	0.2336
Orange Juice	0.8658	0.2268	0.6306	0.2209	0.3737	0.2156	0.8108	0.9747	0.3210	0.7279	0.4896	0.8345	0.1569	0.5487	0.2562	0.4727	0.3133
Rubber	0.1697	0.1942	0.4166	0.8606	0.0842°	0.2684	0.7707	0.5603	0.5530	0.4149	0.8931	0.6014	0.7680	0.0580°	0.6944	0.2151	0.4098
Sugar	0.9502	0.2901	0.1438	0.9749	0.4046	0.1677	0.0361	0.7785	0.2008	0.1721	0.7031	0.6082	0.0045	0.6768	0.5122	0.4754	0.7539
Wool	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Corn	0.4947	0.1997	0.0058	0.8955	0.7766	0.0899°	0.4668	0.7707	0.2833	0.0952°	0.8720	0.7555	0.0573°	0.0722°	0.7197	0.0499	0.6846
Oats	0.3708	0.6505	0.0681°	0.4974	0.0432	0.4770	0.4645	0.7766	0.6673	0.3573	0.9724	0.6079	0.1193	0.0814°	0.9107	0.0443	0.6387
Rough Rice	0.9839	0.1533	0.8833	0.3950	0.5290	0.7028	0.0226	0.9280	0.1831	0.0623°	0.1902	0.5557	0.1508	0.5735	0.1776	0.0066	0.9704
Soy Bean	0.7220	0.1241	0.7447	0.7863	0.1468	0.5403	0.1859	0.0035	0.0242	0.8439	0.5329	0.9212	0.1077	0.0215	0.6995	0.5029	0.4379
Soybean Meal	0.0409	0.3962	0.5618	0.4355	0.4256	0.8908	0.2536	0.0634°	0.1705	0.6700	0.3413	0.6704	0.8127	0.0150	0.2073	0.2844	0.2411
Soybean Oil	0.0915°	0.7408	0.2020	0.7781	0.5099	0.3312	0.4012	0.4570	0.4301	0.0799°	0.5772	0.7365	0.0037	0.4583	0.9264	0.8633	0.3896
Wheat	0.1398	0.9098	0.5262	0.2793	0.7001	0.7063	0.1034	0.5313	0.4343	0.1389	0.3476	0.8274	0.0104	0.3577	0.8891	0.0098	0.3369
Feeder Cattle	0.6264	0.7522	0.1650	0.1265	0.9444	0.3489	0.2369	0.5743	0.7107	0.1612	0.9701	0.1106	0.3024	0.0662°	0.3634	0.0742°	0.9194
Lean Hogs	0.0505°	0.3482	0.5474	0.7544	0.0116	0.7335	0.7072	0.3342	0.6577	0.6124	0.7663	0.7161	0.0051	0.6600	0.0705°	0.8566	0.1197
Live Cattle	0.5927	0.9330	0.9439	0.9352	0.6708	0.6180	0.0128	0.1196	0.0156	0.3068	0.0371	0.4864	0.0380	0.2547	0.2104	0.2173	0.8382
Pork Bellies	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Brent	0.4784	0.9477	0.6751	0.8484	0.5266	0.3020	0.0318	0.4183	0.8100	0.0048	0.9861	0.0124	0.4180	0.6488	0.7576	0.0939°	0.9096
Gasoil	0.3136	0.3575	0.5696	0.4177	0.6038	0.2478	0.1134	0.6202	0.2572	0.0050	0.8162	0.0328	0.8570	0.5723	0.4004	0.0901°	0.5054
Gasoline	0.3064	0.0341	0.4894	0.7064	0.8919	0.1940	0.6599	0.3365	0.4201	0.0133	0.8805	0.0777°	0.5145	0.9799	0.7912	0.9918	0.4301
Heating Oil	0.8142	0.5754	0.3322	0.3964	0.5708	0.2538	0.0644°	0.2752	0.4585	0.0212	0.9145	0.1693	0.4426	0.4624	0.3777	0.2601	0.8812
Natural Gas	0.5902	0.0082	0.7359	0.6047	0.4049	0.9623	0.1985	0.0143	0.0663°	0.0764°	0.7681	0.0517°	0.6669	0.8949	0.7579	0.6892	0.0716°
WTI	0.5350	0.9759	0.9075	0.7987	0.3499	0.1617	0.1780	0.5851	0.1499	0.0007	0.9844	0.0102	0.5819	0.5664	0.5675	0.0973°	0.7950
Aluminium	0.0818°	0.9739	0.0821°	0.0507°	0.5548	0.7774	0.0411	0.8064	0.8780	0.0564°	0.4320	0.1738	0.0037	0.8825	0.4517	0.4087	0.4678
Cobalt	0.8936	0.8190	0.0297	0.6357	0.4396	0.7121	0.2480	0.2273	0.0034	0.0319	0.0491	0.4939	0.0932°	0.2645	0.7698	0.1709	0.5434
Copper	0.6500	0.9641	0.3709	0.2346	0.3682	0.4917	0.3437	0.0122	0.2875	0.3567	0.5170	0.1378	0.0140	0.3989	0.0555°	0.3516	0.9089
Lead	0.4279	0.8670	0.2872	0.6192	0.1555	0.1147	0.0820°	0.7421	0.2939	0.6278	0.9228	0.9464	0.0022	0.4558	0.0092	0.1570	0.6392
Nickel	0.6835	0.4585	0.9596	0.2876	0.8333	0.2187	0.1322	0.7373	0.4582	0.7105	0.1870	0.2012	0.0173	0.7919	0.2262	0.3471	0.7722
Tin	0.4194	0.0869°	0.0727°	0.7950	0.6166	0.2712	0.2554	0.2532	0.7414	0.8830	0.3714	0.9760	0.6778	0.4115	0.2329	0.0526°	0.4216
Zinc	0.3119	0.5396	0.0511°	0.4924	0.4226	0.4440	0.0463	0.7167	0.9855	0.2169	0.6394	0.5727	0.0001	0.7173	0.0218	0.0182	0.9914
Gold	0.0799°	0.5733	0.4320	0.7089	0.3457	0.6418	0.1650	0.7726	0.7322	0.7491	0.9647	0.2898	0.1472	0.1030	0.2812	0.1464	0.8255
Palladium	0.1906	0.0497	0.5849	0.2354	0.4078	0.0781°	0.2556	0.2617	0.9539	0.2022	0.8002	0.9343	0.1327	0.6691	0.1280	0.3858	0.9724
Platinum	0.2940	0.0447	0.3952	0.9496	0.1411	0.6424	0.0666°	0.3085	0.6988	0.1274	0.9790	0.2835	0.0109	0.4317	0.3353	0.6945	0.5853
Silver	0.5542	0.2694	0.2264	0.6597	0.3173	0.4530	0.1466	0.8356	0.6029	0.5459	0.9957	0.4821	0.1534	0.1681	0.0768°	0.9793	0.2259
Softs	0.9845	0.0078	0.4625	0.6372	0.1588	0.1723	0.5242	0.0842°	0.6852	0.4115	0.5498	0.5212	0.1858	0.4199	0.2915	0.1794	0.1248
Grains	0.1812	0.1429	0.3209	0.8413	0.2060	0.3704	0.1871	0.3295	0.2184	0.3221	0.4539	0.7142	0.1290	0.0030	0.7804	0.1553	0.3722
Livestock	0.3715	0.2856	0.2894	0.3095	0.7514	0.9957	0.3826	0.3517	0.3701	0.7160	0.9008	0.4199	0.0699°	0.7254	0.2195	0.5539	0.3896
Energy	0.4721	0.7148	0.7238	0.7014	0.7335	0.3089	0.0168	0.1911	0.0975°	0.0317	0.7342	0.0026	0.3053	0.7422	0.5529	0.0879°	0.7347
Industrial Metals	0.2251	0.6656	0.2533	0.0208	0.2831	0.5359	0.0021	0.3172	0.2881	0.3816	0.2868	0.4040	0.0026	0.3855	0.0477	0.0703°	0.5053
Precious Metals	0.2033	0.0284	0.3376	0.4331	0.8264	0.5035	0.1825	0.6267	0.7300	0.8884	0.9869	0.3537	0.0983°	0.2168	0.1698	0.5897	0.8659

Notes: This table shows bootstrapped p-values with $N = 10{,}000$ replications for testing the null hypothesis of non-causality from a potential driver to a commodity at the low-frequency prediction horizon $h = 1$ month ($H_0 : x_L \nrightarrow_h x_H \mid \ell$) based on bivariate MF-VARs with lag order $P = 1$ using monthly (log-differenced) data for the potential driver and weekly log returns for the commodity front-month futures ($m = 4$). Before estimating the MF-VAR models, the data has been demeaned. A highlighted cell (circle) indicates the rejection of non-causality at the 5% (10%) level. The sample spans the period 2014:1–2019:12 where data is available over the full horizon. Commodity futures are grouped by the classes of softs, grains, livestock, energy, industrial metals, and precious metals. The last group consists of equally-weighted commodity portfolios.

Table A.25: LF Granger causality tests for potential driver (monthly) $\nrightarrow$ commodity (monthly), 1998–2019 (full sample)

	Global Economic Activity				Sentiment/Uncertainty								Others				
	STEEL	BDI	GECON	WIP	VIX	CSENTI	EPU	RUNCERT	MUNCERT	FUNCERT	GPR	GEOVOL	INFL	INFLE	USDEER	TBILL	TED
Cocoa	0.3711	0.1908	0.4526	0.4420	0.9370	0.7949	0.7738	0.5872	0.3839	0.3100	0.9842	0.0448	0.1465	0.5963	0.0211	0.0313	0.3464
Coffee	0.9143	0.8584	0.3611	0.2778	0.9950	0.9732	0.5863	0.4327	0.0409	0.2247	0.8370	0.9328	0.0856°	0.3317	0.3200	0.9000	0.1906
Cotton	0.7496	0.4731	0.0839°	0.0081	0.5923	0.3081	0.2595	0.3574	0.0146	0.0356	0.8626	0.3157	0.0014	0.0027	0.1119	0.8054	0.4488
Ethanol	0.9794	0.3334	0.4083	0.0880°	0.3929	0.5303	0.2192	0.3191	0.0546°	0.5594	0.0902°	0.4260	0.0658°	0.1206	0.0059	0.5276	0.3461
Lumber	0.6225	0.1801	0.0917°	0.1836	0.0567°	0.0893°	0.1406	0.1751	0.0914°	0.0149	0.9733	0.8288	0.1135	0.0363	0.0659°	0.3557	0.9981
Orange Juice	0.9457	0.0094	0.8110	0.4401	0.8450	0.8529	0.7803	0.5333	0.0912°	0.2754	0.8604	0.8240	0.1524	0.5056	0.2062	0.2563	0.1872
Rubber	0.5789	0.7267	0.1884	0.0084	0.0008	0.8724	0.0828°	0.1898	0.0285	0.0180	0.0929°	0.0334	0.0174	0.0106	0.2081	0.6543	0.3266
Sugar	0.5547	0.8150	0.1818	0.4348	0.5391	0.2849	0.2319	0.2829	0.3530	0.6979	0.5641	0.6074	0.2557	0.4547	0.5651	0.3857	0.9141
Wool	0.1384	0.8619	0.2216	0.2119	0.0726°	0.1380	0.0132	0.1726	0.0238	0.0080	0.0907°	0.5177	0.0022	0.0463	0.8556	0.8116	0.8833
Corn	0.6718	0.5057	0.2502	0.0118	0.5029	0.9546	0.8774	0.0718°	0.1186	0.3696	0.2402	0.0925°	0.3606	0.2851	0.2762	0.4127	0.2963
Oats	0.3222	0.2250	0.3426	0.0032	0.4868	0.6852	0.9443	0.3495	0.2054	0.5630	0.8525	0.6025	0.5098	0.4754	0.3291	0.4083	0.3901
Rough Rice	0.5017	0.0424	0.1635	0.2564	0.4607	0.1126	0.1563	0.1084	0.0579°	0.1147	0.3207	0.3684	0.8117	0.8768	0.0015	0.7160	0.2063
Soy Bean	0.0192	0.1316	0.4183	0.0218	0.7861	0.7996	0.8546	0.0231	0.0167	0.1585	0.0270	0.8672	0.1748	0.2715	0.1110	0.2531	0.9897
Soybean Meal	0.0192	0.2325	0.5591	0.1530	0.6643	0.7673	0.6783	0.0731°	0.0993°	0.0594°	0.0199	0.9121	0.4138	0.6721	0.0987°	0.1084	0.6435
Soybean Oil	0.1306	0.2632	0.4325	0.0169	0.2075	0.4446	0.7342	0.0583°	0.0768°	0.4541	0.6495	0.4121	0.0777°	0.0689°	0.0314	0.9233	0.7717
Wheat	0.0511°	0.5662	0.2642	0.1785	0.3443	0.7043	0.5259	0.0171	0.1161	0.8206	0.8699	0.7716	0.4128	0.0927°	0.9893	0.5329	0.8926
Feeder Cattle	0.8586	0.4539	0.1988	0.4860	0.5947	0.2849	0.4718	0.3565	0.2678	0.4153	0.2073	0.0321	0.5412	0.7085	0.5798	0.5837	0.8374
Lean Hogs	0.0195	0.5221	0.1217	0.1581	0.1316	0.4933	0.6682	0.8511	0.4085	0.1212	0.8761	0.8486	0.7181	0.5975	0.4156	0.3038	0.1902
Live Cattle	0.0335	0.1621	0.0617°	0.3528	0.7813	0.3296	0.0216	0.5137	0.2503	0.6681	0.6807	0.0831°	0.3143	0.8888	0.9214	0.8369	0.4756
Pork Bellies	0.7684	0.2146	0.0969°	0.0851°	0.2430	0.3746	0.6639	0.0852°	0.3293	0.7898	0.5768	0.3167	0.8291	0.9058	0.9930	0.3120	0.6404
Brent	0.0445	0.2574	0.0621°	0.0129	0.1552	0.0892°	0.1568	0.5773	0.0298	0.1649	0.4066	0.3522	0.0671°	0.0878°	0.3582	0.7439	0.8199
Gasoil	0.0492	0.3051	0.0146	0.0102	0.3525	0.0831°	0.2441	0.4596	0.0152	0.1874	0.4170	0.4276	0.1516	0.0926°	0.1995	0.8923	0.5140
Gasoline	0.8657	0.9032	0.7533	0.4219	0.3946	0.9964	0.2651	0.2077	0.0399	0.0039	0.4564	0.8936	0.0552°	0.0864°	0.0153	0.6402	0.0251
Heating Oil	0.0855°	0.1115	0.0014	0.0020	0.1548	0.1015	0.2818	0.4500	0.0207	0.1959	0.8690	0.2257	0.1252	0.1809	0.1821	0.8107	0.2435
Natural Gas	0.1035	0.0235	0.0923°	0.1302	0.2733	0.4460	0.5584	0.8441	0.9975	0.8365	0.6262	0.6055	0.2615	0.9629	0.4447	0.3731	0.7697
WTI	0.1699	0.1637	0.0520°	0.0325	0.1297	0.0401	0.0479	0.5590	0.0232	0.2103	0.5394	0.4805	0.0531°	0.1210	0.4694	0.4090	0.7228
Aluminium	0.0123	0.0188	0.0098	0.0001	0.0111	0.4386	0.4257	0.1602	0.0615°	0.0013	0.6220	0.1147	0.2250	0.3419	0.3444	0.1007	0.4544
Cobalt	0.6454	0.4905	0.1075	0.0381	0.3660	0.5482	0.2988	0.9313	0.2914	0.0064	0.0038	0.7454	0.6134	0.1089	0.7656	0.9066	0.3223
Copper	0.0225	0.0799°	0.3151	0.0042	0.1022	0.7804	0.3398	0.0398	0.0087	0.0022	0.7602	0.3176	0.1120	0.0489	0.5174	0.0249	0.2259
Lead	0.2327	0.1710	0.1535	0.0363	0.0565°	0.2078	0.2268	0.0180	0.0290	0.0201	0.5784	0.1432	0.0296	0.1808	0.2971	0.5728	0.7587
Nickel	0.0496	0.1514	0.1228	0.0078	0.3301	0.0537°	0.5025	0.0280	0.0014	0.0002	0.2179	0.0636°	0.1325	0.0002	0.5971	0.7592	0.1503
Tin	0.2635	0.3541	0.0694°	0.0191	0.1882	0.1384	0.1122	0.1634	0.0078	0.0063	0.9599	0.1148	0.0548°	0.0340	0.2689	0.8026	0.9648
Zinc	0.0370	0.6111	0.1797	0.0018	0.0543°	0.7795	0.2265	0.0150	0.0074	0.0008	0.3605	0.5582	0.0567°	0.0910°	0.9082	0.1325	0.2921
Gold	0.2450	0.5560	0.4216	0.6078	0.9741	0.7547	0.9888	0.6333	0.6432	0.4026	0.2117	0.1541	0.6528	0.3655	0.8812	0.7158	0.7847
Palladium	0.7934	0.3260	0.0122	0.0259	0.3331	0.5008	0.7803	0.3702	0.0627°	0.1429	0.3204	0.1560	0.0470	0.0140	0.3766	0.2036	0.4835
Platinum	0.1041	0.9637	0.5111	0.2492	0.4802	0.5959	0.9208	0.3191	0.0422	0.0264	0.1672	0.3977	0.2270	0.0225	0.3505	0.9038	0.9400
Silver	0.5345	0.4255	0.6547	0.2330	0.1134	0.9424	0.4775	0.2215	0.0545°	0.0080	0.6154	0.0113	0.1568	0.0852°	0.4488	0.8169	0.4061
Softs	0.9674	0.8232	0.2756	0.0050	0.3421	0.3749	0.2124	0.2202	0.0088	0.0058	0.3365	0.1646	0.0054	0.0316	0.0083	0.4042	0.8138
Grains	0.2953	0.2126	0.2766	0.0077	0.6345	0.8299	0.8832	0.0348	0.0566°	0.1460	0.1496	0.4796	0.2554	0.2699	0.0528°	0.2753	0.6130
Livestock	0.0438	0.9219	0.0272	0.0263	0.3551	0.6541	0.6615	0.4472	0.9303	0.1888	0.4535	0.4769	0.4431	0.9721	0.6819	0.4348	0.3253
Energy	0.0830°	0.2391	0.0229	0.0118	0.4027	0.0666°	0.1714	0.5037	0.0404	0.1784	0.6531	0.6194	0.0602°	0.1792	0.4445	0.6914	0.3758
Industrial Metals	0.0291	0.1382	0.0552°	0.0010	0.0374	0.2818	0.2039	0.0167	0.0078	0.0001	0.2860	0.0902°	0.0162	0.0076	0.4686	0.1691	0.3147
Precious Metals	0.2850	0.9677	0.2741	0.1212	0.3479	0.7986	0.8459	0.3054	0.0602°	0.0217	0.2211	0.0561°	0.1619	0.0296	0.5161	0.8098	0.5508

Notes: This table shows bootstrapped p-values with $N = 10{,}000$ replications for testing the null hypothesis of non-causality from a potential driver to a commodity at the low-frequency prediction horizon $h = 1$ month ($H_0 : x_L \nrightarrow_h x_H \mid \ell$) based on bivariate MF-VARs with lag order $P = 1$ using monthly (log-differenced) data for the potential driver and monthly log returns for the commodity front-month futures ($m = 1$). Before estimating the MF-VAR models, the data has been demeaned. A highlighted cell (circle) indicates the rejection of non-causality at the 5% (10%) level. The sample spans the period 1998:1–2019:12 where data is available over the full horizon. Commodity futures are grouped by the classes of softs, grains, livestock, energy, industrial metals, and precious metals. The last group consists of equally-weighted commodity portfolios.

Table A.26: LF Granger causality tests for potential driver (monthly) $\nrightarrow$ commodity (monthly), 1998–2003

	Global Economic Activity				Sentiment/Uncertainty								Others				
	STEEL	BDI	GECON	WIP	VIX	CSENTI	EPU	RUNCERT	MUNCERT	FUNCERT	GPR	GEOVOL	INFL	INFLE	USDEER	TBILL	TED
Cocoa	0.6977	0.2141	0.0508°	0.8147	0.5722	0.8619	0.6498	0.1337	0.8453	0.8174	0.2096	0.5226	0.9995	0.1241	0.3254	0.0417	0.2659
Coffee	0.5676	0.1896	0.6816	0.2335	0.9252	0.3141	0.3853	0.2347	0.0590°	0.1604	0.3481	0.4149	0.1414	0.0852°	0.9279	0.8091	0.2867
Cotton	0.1588	0.8291	0.0114	0.4118	0.8924	0.3863	0.0148	0.7349	0.1572	0.7305	0.9430	0.7530	0.1870	0.2159	0.6021	0.7423	0.5253
Ethanol	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Lumber	0.2478	0.0119	0.8205	0.7845	0.1574	0.0501°	0.2520	0.0031	0.0164	0.0044	0.6175	0.2450	0.2586	0.0349	0.8085	0.5303	0.4624
Orange Juice	0.7306	0.6001	0.0154	0.2574	0.1682	0.0681°	0.0232	0.8915	0.5083	0.4276	0.6752	0.0663°	0.5191	0.9442	0.9304	0.3222	0.0015
Rubber	0.2362	0.5370	0.3872	0.0933°	0.9182	0.9960	0.0153	0.2081	0.0232	0.3616	0.8610	0.9508	0.1436	0.0440	0.6001	0.5839	0.3464
Sugar	0.9907	0.0982°	0.6096	0.5932	0.2833	0.6836	0.1270	0.6860	0.9194	0.0819°	0.1593	0.9413	0.2957	0.5903	0.8203	0.3092	0.4430
Wool	0.4692	0.5043	0.7605	0.5708	0.2684	0.0173	0.0656°	0.1172	0.0431	0.0713°	0.0784°	0.1761	0.3996	0.0303	0.3150	0.1589	0.4795
Corn	0.0260	0.7213	0.5940	0.6789	0.0650°	0.4631	0.7119	0.0863°	0.2472	0.6736	0.8150	0.2620	0.9543	0.9436	0.7012	0.1760	0.0469
Oats	0.0509°	0.1048	0.3550	0.9871	0.4006	0.9594	0.8035	0.7500	0.4476	0.7757	0.0728°	0.9797	0.2421	0.8881	0.8051	0.2783	0.0307
Rough Rice	0.8494	0.0001	0.4976	0.5754	0.9512	0.2371	0.0515°	0.3034	0.1648	0.2050	0.7919	0.8497	0.6619	0.6792	0.1126	0.5246	0.8024
Soy Bean	0.3239	0.2753	0.7436	0.6563	0.2846	0.7385	0.1735	0.0633°	0.0823°	0.4386	0.8359	0.7588	0.8984	0.2970	0.9815	0.4818	0.7692
Soybean Meal	0.0958°	0.1807	0.2040	0.2712	0.1643	0.5227	0.9597	0.1072	0.1881	0.3053	0.5186	0.2809	0.5264	0.0386	0.5775	0.1768	0.7685
Soybean Oil	0.8924	0.0108	0.4334	0.6624	0.7583	0.0129	0.3978	0.3906	0.2560	0.4374	0.0563°	0.7500	0.9735	0.6887	0.4605	0.6949	0.7768
Wheat	0.0375	0.9213	0.2897	0.7327	0.0018	0.9648	0.6985	0.1601	0.3884	0.4793	0.7131	0.2463	0.3107	0.5128	0.5034	0.6818	0.6563
Feeder Cattle	0.3781	0.8104	0.5114	0.1749	0.1871	0.3964	0.0414	0.0532°	0.7159	0.8424	0.3478	0.4917	0.1887	0.9382	0.7741	0.7429	0.5887
Lean Hogs	0.2948	0.6421	0.6464	0.7275	0.1390	0.4057	0.3328	0.9477	0.9136	0.4599	0.6056	0.0056	0.3786	0.9088	0.4099	0.6913	0.4706
Live Cattle	0.2819	0.2550	0.7565	0.3264	0.2864	0.1907	0.0921°	0.2350	0.8463	0.6160	0.8081	0.0496	0.6767	0.0833°	0.8391	0.2761	0.3994
Pork Bellies	0.6698	0.9800	0.7478	0.7028	0.0655°	0.2515	0.3644	0.4464	0.8165	0.8651	0.6253	0.0072	0.8704	0.6032	0.6230	0.8686	0.9649
Brent	0.9237	0.3793	0.0292	0.7947	0.8161	0.0221	0.1023	0.2118	0.6461	0.9845	0.0118	0.4131	0.0934°	0.4420	0.5042	0.2297	0.8314
Gasoil	0.4391	0.3277	0.0088	0.4643	0.9244	0.0042	0.1279	0.6772	0.3161	0.8687	0.0642°	0.8570	0.1751	0.9318	0.6416	0.1142	0.5386
Gasoline	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Heating Oil	0.7559	0.0849°	0.0049	0.0646°	0.8572	0.1281	0.1260	0.5484	0.3914	0.9359	0.2454	0.9413	0.1303	0.9653	0.5345	0.0453	0.4567
Natural Gas	0.6302	0.2217	0.5601	0.0493	0.1903	0.4578	0.3602	0.6842	0.6550	0.4307	0.5504	0.8142	0.5282	0.2665	0.0776°	0.2069	0.9320
WTI	0.9647	0.3090	0.0047	0.4158	0.8363	0.0021	0.0282	0.2217	0.7475	0.8695	0.0505°	0.3219	0.0520°	0.6697	0.4218	0.2739	0.8550
Aluminium	0.0324	0.0255	0.4269	0.0497	0.4434	0.6021	0.7837	0.6913	0.6404	0.1911	0.3175	0.8114	0.5418	0.7413	0.4332	0.8260	0.4375
Cobalt	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Copper	0.1987	0.0102	0.0983°	0.0246	0.1706	0.5148	0.1297	0.6740	0.0241	0.1243	0.2993	0.9592	0.2763	0.1295	0.9361	0.5631	0.4755
Lead	0.6691	0.5563	0.8434	0.9813	0.2864	0.4147	0.3533	0.8420	0.9217	0.1150	0.1367	0.6672	0.8850	0.3237	0.7791	0.7541	0.4475
Nickel	0.0097	0.0944°	0.0960°	0.1790	0.6871	0.0602°	0.0677°	0.2348	0.0143	0.0582°	0.3431	0.9457	0.0419	0.0171	0.9698	0.6711	0.6628
Tin	0.0028	0.0163	0.1902	0.0386	0.8932	0.3023	0.8966	0.8566	0.5265	0.0393	0.4603	0.9274	0.0327	0.5983	0.4515	0.7753	0.3341
Zinc	0.0347	0.0449	0.0541°	0.0182	0.2168	0.7814	0.0750°	0.2230	0.0065	0.0203	0.1263	0.8714	0.0374	0.2783	0.1540	0.5157	0.6553
Gold	0.2074	0.1229	0.4205	0.4800	0.9775	0.0192	0.5168	0.5154	0.6322	0.4917	0.1844	0.2614	0.1839	0.2951	0.8311	0.8102	0.9810
Palladium	0.1442	0.6883	0.0259	0.9723	0.3312	0.1066	0.9798	0.3792	0.9861	0.6515	0.1056	0.5343	0.2990	0.0353	0.7593	0.1372	0.4667
Platinum	0.7638	0.0704°	0.0923°	0.1856	0.9752	0.0847°	0.1597	0.6373	0.5477	0.4783	0.0592°	0.9604	0.2458	0.0843°	0.3466	0.9083	0.1512
Silver	0.9862	0.8946	0.3038	0.0079	0.4679	0.1784	0.1573	0.2487	0.0254	0.1195	0.9505	0.1720	0.2219	0.1160	0.7831	0.9254	0.5864
Softs	0.3394	0.5225	0.5401	0.8119	0.9641	0.8079	0.1252	0.0289	0.0003	0.0032	0.5646	0.9464	0.1325	0.0005	0.6623	0.0859°	0.2047
Grains	0.4782	0.1213	0.8937	0.7238	0.0190	0.4170	0.4753	0.1184	0.2536	0.7025	0.1781	0.1895	0.7218	0.6950	0.8126	0.7272	0.3223
Livestock	0.5716	0.6796	0.8485	0.8663	0.0999°	0.5370	0.6635	0.7970	0.8783	0.4825	0.5902	0.0193	0.3287	0.5583	0.8052	0.9627	0.6411
Energy	0.7103	0.1849	0.0032	0.1231	0.6697	0.0079	0.2552	0.4600	0.7154	0.8036	0.2218	0.7825	0.1402	0.9080	0.2913	0.0629°	0.6704
Industrial Metals	0.0431	0.0125	0.1337	0.0186	0.2687	0.4286	0.1008	0.5121	0.0150	0.0520°	0.4707	0.9039	0.0313	0.1694	0.7952	0.6938	0.5531
Precious Metals	0.6374	0.4493	0.0042	0.0729°	0.4716	0.0233	0.4722	0.6012	0.4053	0.6722	0.1526	0.4585	0.1486	0.0095	0.7602	0.3946	0.5079

Notes: This table shows bootstrapped p-values with $N = 10{,}000$ replications for testing the null hypothesis of non-causality from a potential driver to a commodity at the low-frequency prediction horizon $h = 1$ month ($H_0 : x_L \nrightarrow_h x_H \mid \ell$) based on bivariate MF-VARs with lag order $P = 1$ using monthly (log-differenced) data for the potential driver and monthly log returns for the commodity front-month futures ($m = 1$). Before estimating the MF-VAR models, the data has been demeaned. A highlighted cell (circle) indicates the rejection of non-causality at the 5% (10%) level. The sample spans the period 1998:1–2003:12 where data is available over the full horizon. Commodity futures are grouped by the classes of softs, grains, livestock, energy, industrial metals, and precious metals. The last group consists of equally-weighted commodity portfolios.

Table A.27: LF Granger causality tests for potential driver (monthly) $\nrightarrow$ commodity (monthly), 2004–2007

	Global Economic Activity				Sentiment/Uncertainty								Others				
	STEEL	BDI	GECON	WIP	VIX	CSENTI	EPU	RUNCERT	MUNCERT	FUNCERT	GPR	GEOVOL	INFL	INFLE	USDEER	TBILL	TED
Cocoa	0.1112	0.7164	0.9770	0.0269	0.6692	0.9716	0.0847°	0.4704	0.7343	0.2469	0.4274	0.7953	0.4296	0.4059	0.1884	0.7172	0.1961
Coffee	0.0617°	0.1255	0.7288	0.1363	0.6911	0.4928	0.8163	0.3177	0.3911	0.1847	0.9429	0.5712	0.6716	0.5960	0.4027	0.4120	0.2025
Cotton	0.2457	0.5187	0.3444	0.6660	0.7868	0.3739	0.8431	0.1328	0.2838	0.1955	0.8495	0.9799	0.6701	0.8259	0.3423	0.0054	0.0739°
Ethanol	0.5961	0.0565°	0.9255	0.9870	0.1504	0.2298	0.4539	0.7859	0.8316	0.8035	0.7515	0.6692	0.3037	0.0013	0.8590	0.5428	0.8055
Lumber	0.3652	0.5804	0.0082	0.6292	0.0244	0.1243	0.0990°	0.6745	0.8020	0.3203	0.7821	0.4027	0.4305	0.7736	0.3113	0.5498	0.9433
Orange Juice	0.0935°	0.5783	0.0931°	0.4020	0.9174	0.1710	0.5389	0.5400	0.5768	0.3167	0.4361	0.9542	0.0347	0.6017	0.5312	0.3160	0.5501
Rubber	0.5395	0.1716	0.1955	0.1735	0.5548	0.5928	0.4470	0.5505	0.8310	0.6389	0.1259	0.6713	0.3923	0.0788°	0.4105	0.0698°	0.2360
Sugar	0.5540	0.0106	0.8955	0.9876	0.6791	0.4986	0.8439	0.7918	0.8368	0.9684	0.4243	0.8867	0.6677	0.1454	0.2179	0.9658	0.3681
Wool	0.0431	0.7353	0.9230	0.7495	0.4564	0.4558	0.2384	0.4714	0.4792	0.8860	0.6232	0.9572	0.5201	0.5938	0.5099	0.0287	0.3269
Corn	0.2561	0.2826	0.6081	0.1147	0.9195	0.3060	0.0566°	0.6478	0.9786	0.9776	0.0530°	0.7659	0.4458	0.3625	0.9449	0.0039	0.6054
Oats	0.9016	0.3212	0.9591	0.2010	0.5958	0.2978	0.6843	0.7164	0.5839	0.2651	0.1022	0.8905	0.5220	0.2096	0.6830	0.0012	0.0765°
Rough Rice	0.7314	0.1558	0.1312	0.1673	0.1189	0.5872	0.3452	0.6107	0.6165	0.8457	0.1842	0.3193	0.5316	0.7951	0.7980	0.0511°	0.8046
Soy Bean	0.6864	0.1370	0.5909	0.0894°	0.2955	0.9708	0.0754°	0.3406	0.8183	0.4519	0.1011	0.3583	0.0487	0.3937	0.9470	0.0132	0.4393
Soybean Meal	0.8705	0.1021	0.7811	0.0304	0.4278	0.5611	0.1844	0.8063	0.6458	0.7161	0.0428	0.4106	0.1198	0.8449	0.6516	0.0101	0.5143
Soybean Oil	0.2312	0.4728	0.6459	0.8169	0.3080	0.5564	0.1144	0.1358	0.2331	0.3352	0.0149	0.6183	0.1711	0.0414	0.3034	0.0241	0.3447
Wheat	0.4613	0.4563	0.3810	0.0815°	0.3134	0.7354	0.2549	0.0425	0.6163	0.1902	0.2191	0.3047	0.4581	0.7475	0.6343	0.0082	0.8533
Feeder Cattle	0.3106	0.0568°	0.8346	0.7312	0.9705	0.2919	0.4875	0.9973	0.5477	0.8404	0.0022	0.4392	0.4542	0.6705	0.4166	0.1025	0.0897°
Lean Hogs	0.0089	0.6271	0.1055	0.7941	0.4100	0.8183	0.6090	0.4582	0.5624	0.7334	0.6479	0.6612	0.6757	0.1460	0.8186	0.5681	0.2031
Live Cattle	0.3520	0.9637	0.8296	0.2814	0.0149	0.6785	0.9572	0.0529°	0.0332	0.6626	0.5092	0.9725	0.7818	0.3645	0.6518	0.4814	0.8419
Pork Bellies	0.8750	0.7032	0.0840°	0.7928	0.8897	0.8195	0.8234	0.0157	0.0475	0.0653°	0.3320	0.5655	0.3226	0.5969	0.5696	0.8968	0.0598°
Brent	0.5073	0.0074	0.9424	0.1549	0.4591	0.0074	0.5416	0.0209	0.1572	0.6093	0.3025	0.5686	0.0118	0.0094	0.1694	0.7618	0.2298
Gasoil	0.4015	0.0017	0.9431	0.1320	0.9496	0.1825	0.4969	0.1471	0.3337	0.5632	0.2250	0.9055	0.0084	0.0035	0.1430	0.9175	0.6847
Gasoline	0.7820	0.7446	0.3866	0.3661	0.3853	0.7638	0.7700	0.2963	0.5156	0.8492	0.4310	0.4073	0.2625	0.2315	0.1299	0.6879	0.9702
Heating Oil	0.4454	0.0029	0.7329	0.1970	0.7084	0.0348	0.6661	0.1720	0.3811	0.7845	0.0730°	0.9996	0.0369	0.0125	0.0388	0.9403	0.6544
Natural Gas	0.5481	0.2948	0.2301	0.3233	0.6431	0.9629	0.5966	0.3472	0.1817	0.0106	0.9611	0.5246	0.0129	0.0924°	0.0068	0.5239	0.2223
WTI	0.2378	0.0043	0.9900	0.5154	0.7103	0.0212	0.6372	0.0102	0.1782	0.7667	0.2981	0.7935	0.0181	0.0129	0.1890	0.6664	0.1292
Aluminium	0.8455	0.6872	0.7215	0.4584	0.0466	0.4163	0.9065	0.7719	0.8119	0.0120	0.2401	0.3887	0.7636	0.7785	0.1892	0.4671	0.8183
Cobalt	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Copper	0.7967	0.4283	0.2098	0.2583	0.5074	0.3965	0.6167	0.1044	0.3449	0.0874°	0.6006	0.8893	0.4481	0.6957	0.2034	0.5772	0.0705°
Lead	0.5311	0.4558	0.8750	0.7945	0.5580	0.1266	0.9480	0.0792°	0.2842	0.4939	0.8100	0.1953	0.4925	0.1464	0.5356	0.7285	0.0752°
Nickel	0.9904	0.5534	0.2582	0.6089	0.2162	0.1969	0.3736	0.3571	0.1572	0.0623°	0.9752	0.6267	0.5721	0.5397	0.0313	0.7244	0.5503
Tin	0.4232	0.8130	0.0530°	0.0169	0.0863°	0.1195	0.6240	0.1055	0.0255	0.1060	0.7983	0.3988	0.0035	0.0407	0.0875°	0.1599	0.4514
Zinc	0.5623	0.7073	0.8089	0.7042	0.4732	0.1201	0.6410	0.6289	0.6615	0.0023	0.7648	0.9218	0.4615	0.8713	0.1410	0.0994°	0.3910
Gold	0.5631	0.6567	0.3137	0.3716	0.2969	0.8928	0.3203	0.3020	0.7420	0.9501	0.0300	0.8805	0.9062	0.6412	0.5237	0.1843	0.0488
Palladium	0.6229	0.2819	0.6664	0.1369	0.8291	0.6290	0.7187	0.3683	0.5633	0.0652°	0.8417	0.3895	0.7216	0.9572	0.3848	0.0173	0.4120
Platinum	0.7266	0.8274	0.2658	0.6243	0.3441	0.5158	0.2034	0.2632	0.3950	0.6553	0.6685	0.8894	0.7990	0.8433	0.3387	0.0668°	0.0028
Silver	0.7311	0.5786	0.5932	0.3076	0.7477	0.6318	0.4560	0.2290	0.3371	0.1161	0.1003	0.1865	0.9414	0.5659	0.3979	0.7209	0.0289
Softs	0.0284	0.5069	0.6932	0.2652	0.2957	0.2903	0.9156	0.7287	0.8864	0.4816	0.4848	0.6567	0.7471	0.4319	0.2346	0.3184	0.2036
Grains	0.9761	0.1253	0.3689	0.0554°	0.3789	0.9830	0.1067	0.1970	0.8705	0.5700	0.0271	0.4798	0.0496	0.7317	0.8290	0.0125	0.3958
Livestock	0.1861	0.3873	0.1315	0.9179	0.2013	0.5611	0.9820	0.0557°	0.4074	0.3188	0.7917	0.6173	0.5362	0.7224	0.8482	0.5571	0.0339
Energy	0.5852	0.0112	0.5622	0.2898	0.9631	0.0850°	0.7646	0.3846	0.7536	0.3554	0.4533	0.8478	0.0050	0.0009	0.0321	0.8143	0.4230
Industrial Metals	0.7561	0.9569	0.8375	0.8789	0.3935	0.0441	0.4300	0.1135	0.0966°	0.0060	0.7405	0.1225	0.8468	0.5771	0.1497	0.6799	0.3887
Precious Metals	0.9844	0.4110	0.3377	0.2185	0.8611	0.8790	0.4111	0.3475	0.4540	0.2435	0.3324	0.3389	0.8325	0.7800	0.5400	0.1025	0.0541°

Notes: This table shows bootstrapped p-values with $N = 10{,}000$ replications for testing the null hypothesis of non-causality from a potential driver to a commodity at the low-frequency prediction horizon $h = 1$ month ($H_0 : x_L \nrightarrow_h x_H \mid \ell$) based on bivariate MF-VARs with lag order $P = 1$ using monthly (log-differenced) data for the potential driver and monthly log returns for the commodity front-month futures ($m = 1$). Before estimating the MF-VAR models, the data has been demeaned. A highlighted cell (circle) indicates the rejection of non-causality at the 5% (10%) level. The sample spans the period 2004:1–2007:12 where data is available over the full horizon. Commodity futures are grouped by the classes of softs, grains, livestock, energy, industrial metals, and precious metals. The last group consists of equally-weighted commodity portfolios.

Table A.28: LF Granger causality tests for potential driver (monthly) $\nrightarrow$ commodity (monthly), 2008–2013

	Global Economic Activity				Sentiment/Uncertainty								Others				
	STEEL	BDI	GECON	WIP	VIX	CSENTI	EPU	RUNCERT	MUNCERT	FUNCERT	GPR	GEOVOL	INFL	INFLE	USDEER	TBILL	TED
Cocoa	0.1785	0.9479	0.9801	0.4777	0.2024	0.9322	0.8126	0.7736	0.2937	0.1171	0.1851	0.0062	0.0098	0.4292	0.4676	0.4271	0.0386
Coffee	0.2740	0.8476	0.4489	0.0752°	0.8918	0.9850	0.7067	0.1708	0.0741°	0.3992	0.7935	0.6725	0.0060	0.0853°	0.5376	0.9444	0.7118
Cotton	0.3987	0.6194	0.1699	0.0492	0.4590	0.8474	0.4950	0.3852	0.0561°	0.0229	0.8058	0.4554	0.0006	0.0016	0.5562	0.8400	0.0507°
Ethanol	0.0358	0.8719	0.3183	0.0222	0.0159	0.3878	0.4064	0.0051	0.0090	0.2367	0.0735°	0.0128	0.0169	0.1449	0.0206	0.3348	0.0321
Lumber	0.7404	0.3667	0.0036	0.0306	0.0789°	0.1522	0.1786	0.1063	0.2077	0.0852°	0.7225	0.9627	0.2250	0.1915	0.3215	0.0922°	0.1171
Orange Juice	0.0328	0.0055	0.0414	0.0514°	0.2119	0.1092	0.5287	0.0313	0.0004	0.0763°	0.5915	0.0616°	0.0001	0.0280	0.6496	0.7972	0.6354
Rubber	0.1727	0.4450	0.4575	0.2266	0.0054	0.7572	0.3844	0.1978	0.0125	0.0060	0.0234	0.1641	0.0010	0.0305	0.0702°	0.3743	0.0735°
Sugar	0.3287	0.1981	0.8071	0.6735	0.9350	0.1682	0.6716	0.2463	0.2147	0.6012	0.3316	0.7033	0.0200	0.6622	0.6398	0.3908	0.6399
Wool	0.5486	0.8491	0.1113	0.2033	0.3691	0.6311	0.0764°	0.0897°	0.0376	0.0253	0.8886	0.7866	0.0017	0.0648°	0.8672	0.8446	0.6374
Corn	0.4692	0.8822	0.4549	0.1489	0.0243	0.4850	0.5184	0.1466	0.0501°	0.0834°	0.0212	0.0148	0.1589	0.0758°	0.3683	0.8609	0.1657
Oats	0.4789	0.4912	0.0942°	0.0295	0.4002	0.4439	0.6620	0.0221	0.0103	0.4112	0.1587	0.2839	0.0162	0.1146	0.3946	0.6612	0.3627
Rough Rice	0.6105	0.6225	0.2347	0.4516	0.1072	0.6114	0.6891	0.0159	0.1299	0.2857	0.0623°	0.1373	0.2893	0.6575	0.0155	0.4563	0.0009
Soy Bean	0.1672	0.5590	0.5993	0.1407	0.0810°	0.4666	0.7735	0.0818°	0.0371	0.0524°	0.0119	0.1752	0.1248	0.1479	0.3428	0.8800	0.3638
Soybean Meal	0.3349	0.7465	0.8084	0.9685	0.0827°	0.6688	0.6551	0.2495	0.2055	0.0680°	0.0005	0.1766	0.1905	0.2440	0.5688	0.8734	0.5898
Soybean Oil	0.3268	0.4341	0.1457	0.0254	0.0492	0.9195	0.6933	0.0655°	0.0098	0.0419	0.4205	0.0772°	0.0477	0.0580°	0.0814°	0.9863	0.2693
Wheat	0.2493	0.4420	0.4330	0.3636	0.3015	0.9039	0.8603	0.0538°	0.0202	0.1132	0.2859	0.0235	0.0885°	0.0391	0.8023	0.8069	0.7027
Feeder Cattle	0.1238	0.0464	0.0517°	0.1026	0.9035	0.2827	0.4802	0.6382	0.2161	0.3888	0.2336	0.1345	0.8562	0.2083	0.3688	0.8583	0.6848
Lean Hogs	0.2774	0.7911	0.1784	0.1594	0.6558	0.7553	0.8180	0.4846	0.2745	0.7637	0.2971	0.7568	0.9087	0.7545	0.8546	0.3769	0.8183
Live Cattle	0.3119	0.0665°	0.0495	0.0074	0.9229	0.8761	0.9129	0.7338	0.7701	0.4057	0.6259	0.0592°	0.8798	0.5493	0.4092	0.1882	0.6266
Pork Bellies	0.8789	0.4735	0.2779	0.0243	0.5252	0.7879	0.4612	0.5654	0.7148	0.5993	0.5238	0.7181	0.9267	0.2170	0.4789	0.1685	0.3619
Brent	0.2445	0.1146	0.1051	0.0725°	0.1257	0.5987	0.3475	0.2460	0.0456	0.0647°	0.7622	0.1798	0.0225	0.0378	0.3052	0.8787	0.3495
Gasoil	0.1614	0.0966°	0.0261	0.0006	0.1205	0.6662	0.5705	0.3229	0.0409	0.0891°	0.7793	0.1262	0.0610°	0.0289	0.0196	0.7452	0.1882
Gasoline	0.9834	0.2568	0.5901	0.4631	0.2101	0.6198	0.1615	0.3051	0.0575°	0.0141	0.9029	0.3344	0.0428	0.0324	0.0271	0.7117	0.1953
Heating Oil	0.1448	0.0455	0.0172	0.0037	0.0723°	0.6715	0.3567	0.2644	0.0655°	0.0574°	0.9938	0.1079	0.0472	0.0613°	0.0384	0.9218	0.1279
Natural Gas	0.1244	0.3342	0.0049	0.1025	0.6985	0.5960	0.4340	0.4536	0.4848	0.6559	0.6991	0.9779	0.2719	0.9397	0.2689	0.6429	0.7495
WTI	0.0888°	0.0420	0.1498	0.0732°	0.2004	0.2481	0.0702°	0.2860	0.0271	0.1330	0.4433	0.3812	0.0366	0.0428	0.3678	0.0154	0.1646
Aluminium	0.0406	0.0035	0.0221	0.0021	0.1215	0.4858	0.4896	0.0370	0.0013	0.0328	0.7747	0.9722	0.0071	0.1023	0.2177	0.2938	0.0838°
Cobalt	0.7332	0.0072	0.7332	0.2571	0.0092	0.7582	0.0592°	0.6681	0.9418	0.1089	0.0951°	0.3659	0.0384	0.4794	0.9666	0.7062	0.8112
Copper	0.2281	0.0206	0.4184	0.2803	0.0846°	0.7645	0.3433	0.0395	0.0010	0.0366	0.8637	0.1667	0.0022	0.0034	0.2719	0.0596°	0.0656°
Lead	0.4652	0.2711	0.0995°	0.0225	0.1340	0.0955°	0.6139	0.0107	0.0010	0.0101	0.3746	0.4685	0.0003	0.0022	0.1012	0.9959	0.0026
Nickel	0.7422	0.3136	0.1752	0.0707°	0.1467	0.0878°	0.2740	0.1084	0.0112	0.0020	0.9857	0.3914	0.0040	0.0016	0.3193	0.1936	0.0132
Tin	0.4893	0.1948	0.0652°	0.1985	0.1132	0.6173	0.3269	0.1920	0.0186	0.0162	0.8123	0.2014	0.0176	0.0077	0.1830	0.7649	0.2642
Zinc	0.3967	0.2144	0.2449	0.0212	0.0841°	0.9218	0.1808	0.0231	0.0005	0.0381	0.3110	0.7039	0.0001	0.0003	0.8626	0.2516	0.0221
Gold	0.9546	0.4549	0.5027	0.9680	0.4899	0.2594	0.4683	0.3744	0.3407	0.7074	0.7365	0.1431	0.1025	0.2435	0.8063	0.5129	0.0903°
Palladium	0.4296	0.0577°	0.0800°	0.1117	0.5036	0.2453	0.6899	0.0339	0.0009	0.0002	0.5117	0.5103	0.0012	0.0008	0.0463	0.7408	0.0581°
Platinum	0.5132	0.9371	0.8082	0.5473	0.8042	0.8725	0.5951	0.1321	0.0343	0.0296	0.6313	0.2496	0.0084	0.0059	0.8830	0.6132	0.1580
Silver	0.5805	0.6145	0.6757	0.4791	0.3346	0.6758	0.3053	0.3436	0.0606°	0.0496	0.9527	0.0562°	0.0058	0.0403	0.2832	0.8260	0.0306
Softs	0.1518	0.1895	0.0896°	0.0290	0.1899	0.3937	0.7082	0.0867°	0.0068	0.0306	0.7447	0.0791°	0.0001	0.0257	0.2565	0.8645	0.0771°
Grains	0.5105	0.6954	0.2670	0.0469	0.0570°	0.8823	0.7265	0.0451	0.0075	0.0745°	0.0043	0.0278	0.0483	0.1024	0.3315	0.9017	0.1719
Livestock	0.2403	0.3816	0.0006	0.0006	0.5951	0.7109	0.9737	0.6826	0.4509	0.8095	0.2529	0.4300	0.8015	0.7694	0.9186	0.6945	0.6065
Energy	0.0778°	0.0146	0.0171	0.0118	0.1914	0.4718	0.3095	0.2077	0.0303	0.0615°	0.8470	0.2481	0.0370	0.0819°	0.0476	0.7532	0.2471
Industrial Metals	0.2462	0.0102	0.1311	0.0465	0.0968°	0.4042	0.3388	0.0107	0.0005	0.0039	0.3631	0.4530	0.0004	0.0006	0.3192	0.7880	0.0163
Precious Metals	0.5507	0.8889	0.5551	0.2311	0.5194	0.9261	0.5385	0.0535°	0.0172	0.0600°	0.8240	0.1812	0.0013	0.0082	0.5763	0.7026	0.0122

Notes: This table shows bootstrapped p-values with $N = 10{,}000$ replications for testing the null hypothesis of non-causality from a potential driver to a commodity at the low-frequency prediction horizon $h = 1$ month ($H_0 : x_L \nrightarrow_h x_H \mid \ell$) based on bivariate MF-VARs with lag order $P = 1$ using monthly (log-differenced) data for the potential driver and monthly log returns for the commodity front-month futures ($m = 1$). Before estimating the MF-VAR models, the data has been demeaned. A highlighted cell (circle) indicates the rejection of non-causality at the 5% (10%) level. The sample spans the period 2008:1–2013:12 where data is available over the full horizon. Commodity futures are grouped by the classes of softs, grains, livestock, energy, industrial metals, and precious metals. The last group consists of equally-weighted commodity portfolios.

Table A.29: LF Granger causality tests for potential driver (monthly) $\nrightarrow$ commodity (monthly), 2014–2019

	Global Economic Activity				Sentiment/Uncertainty								Others				
	STEEL	BDI	GECON	WIP	VIX	CSENTI	EPU	RUNCERT	MUNCERT	FUNCERT	GPR	GEOVOL	INFL	INFLE	USDEER	TBILL	TED
Cocoa	0.5194	0.0360	0.8063	0.2095	0.5933	0.8389	0.6126	0.1891	0.6926	0.9630	0.1500	0.6038	0.4147	0.2402	0.0006	0.1187	0.0734°
Coffee	0.8798	0.2034	0.7602	0.3220	0.7215	0.7761	0.0156	0.1157	0.8908	0.5625	0.2093	0.1780	0.5680	0.8756	0.7882	0.9156	0.5130
Cotton	0.4814	0.3493	0.8728	0.0139	0.8381	0.9948	0.2254	0.2527	0.7525	0.0063	0.8681	0.5877	0.1360	0.0567°	0.5991	0.5422	0.4805
Ethanol	0.6009	0.2758	0.6855	0.6270	0.2306	0.0041	0.1534	0.5704	0.5466	0.9302	0.3248	0.7187	0.2072	0.9718	0.0632°	0.0289	0.0015
Lumber	0.7740	0.9442	0.2922	0.3777	0.3360	0.2617	0.3808	0.1880	0.5332	0.5371	0.5281	0.3828	0.7660	0.2862	0.0013	0.7398	0.0089
Orange Juice	0.3504	0.7473	0.6889	0.0497	0.8192	0.6432	0.2293	0.8304	0.1201	0.7060	0.2078	0.4355	0.1221	0.6823	0.0411	0.2085	0.0782°
Rubber	0.6286	0.1705	0.2344	0.6192	0.0182	0.3705	0.7080	0.1846	0.5072	0.5878	0.6084	0.1691	0.3593	0.0047	0.3404	0.4740	0.9547
Sugar	0.4420	0.4258	0.0179	0.9667	0.7239	0.7189	0.9160	0.5851	0.6945	0.7894	0.2235	0.3377	0.1638	0.8152	0.9772	0.7072	0.9742
Wool	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Corn	0.8057	0.7495	0.8305	0.3085	0.2137	0.4675	0.8824	0.8210	0.4359	0.7559	0.4977	0.4870	0.7975	0.4852	0.4708	0.2449	0.0057
Oats	0.0380	0.1471	0.4415	0.1110	0.1882	0.4546	0.5385	0.4200	0.8496	0.9476	0.7821	0.9002	0.0207	0.0279	0.6698	0.0105	0.8764
Rough Rice	0.9539	0.5528	0.9885	0.0458	0.9879	0.9034	0.0114	0.4424	0.5339	0.9896	0.4717	0.2794	0.9122	0.0399	0.0719°	0.8534	0.4178
Soy Bean	0.0799°	0.9357	0.9655	0.2266	0.7630	0.8660	0.4435	0.9039	0.6999	0.6813	0.9733	0.4243	0.2606	0.2201	0.2267	0.2907	0.0816°
Soybean Meal	0.0586°	0.7865	0.1688	0.1904	0.9684	0.7712	0.9698	0.9897	0.3087	0.3508	0.8660	0.6388	0.9781	0.2621	0.0411	0.0711°	0.0115
Soybean Oil	0.8179	0.8320	0.1435	0.7363	0.4965	0.0764°	0.4499	0.0859°	0.4270	0.8748	0.7340	0.5082	0.1641	0.1364	0.2892	0.8922	0.6196
Wheat	0.9829	0.7586	0.5823	0.9818	0.4702	0.5649	0.9315	0.5296	0.5637	0.8301	0.2419	0.4471	0.1870	0.7273	0.7144	0.4911	0.0379
Feeder Cattle	0.5671	0.9127	0.3030	0.3618	0.9947	0.0385	0.2942	0.6897	0.9373	0.5541	0.4369	0.1438	0.0216	0.0014	0.9959	0.4310	0.8690
Lean Hogs	0.5156	0.3916	0.6940	0.8184	0.0483	0.8098	0.9518	0.3246	0.9741	0.2224	0.1961	0.1910	0.6339	0.5983	0.5680	0.0526°	0.4308
Live Cattle	0.4297	0.9872	0.3964	0.7010	0.6856	0.9922	0.0336	0.0316	0.0063	0.1834	0.1747	0.4746	0.0103	0.3280	0.1450	0.6429	0.6147
Pork Bellies	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Brent	0.1826	0.5358	0.6505	0.4671	0.6842	0.4161	0.4236	0.4654	0.3493	0.7922	0.6698	0.3053	0.8719	0.1245	0.2617	0.7442	0.2913
Gasoil	0.0451	0.5198	0.5603	0.6408	0.9079	0.3512	0.4978	0.8679	0.2559	0.9717	0.7496	0.6095	0.7124	0.0838°	0.2277	0.5684	0.2205
Gasoline	0.9471	0.0138	0.6409	0.6954	0.7444	0.1153	0.9750	0.7638	0.2381	0.1717	0.7454	0.6049	0.4213	0.4644	0.1069	0.2116	0.3338
Heating Oil	0.0349	0.2325	0.8314	0.5752	0.7298	0.4789	0.5267	0.7922	0.1063	0.7087	0.9267	0.2383	0.4138	0.0407	0.0745°	0.5592	0.8255
Natural Gas	0.1223	0.0023	0.8548	0.3416	0.6578	0.6794	0.8831	0.1100	0.0326	0.7429	0.9404	0.3743	0.5169	0.8630	0.2805	0.2048	0.0759°
WTI	0.0810°	0.6622	0.4196	0.8233	0.5624	0.4397	0.6455	0.4396	0.4075	0.6877	0.7811	0.1091	0.9692	0.4086	0.3478	0.8075	0.5014
Aluminium	0.1382	0.4206	0.0591°	0.0970°	0.3071	0.5480	0.5196	0.4839	0.5454	0.1778	0.2829	0.0594°	0.0952°	0.8799	0.3758	0.1225	0.3771
Cobalt	0.4345	0.9724	0.0765°	0.0571°	0.7938	0.5487	0.7486	0.7577	0.1609	0.0127	0.0249	0.8085	0.5824	0.1066	0.4328	0.8230	0.1239
Copper	0.1878	0.2945	0.6945	0.0390	0.5650	0.0632°	0.9011	0.4817	0.8335	0.9483	0.6712	0.2790	0.2052	0.1008	0.5853	0.2619	0.5517
Lead	0.1506	0.8953	0.0696°	0.7816	0.5062	0.0144	0.1900	0.9416	0.8819	0.4137	0.3216	0.3877	0.5295	0.6868	0.9696	0.0357	0.2015
Nickel	0.1621	0.8188	0.7594	0.1567	0.9092	0.0391	0.9467	0.5332	0.1717	0.2265	0.3068	0.1338	0.2340	0.8427	0.0310	0.6095	0.8961
Tin	0.6824	0.1008	0.3258	0.2307	0.3299	0.5405	0.5722	0.3887	0.4722	0.3762	0.9612	0.9393	0.6051	0.1872	0.2585	0.8803	0.0255
Zinc	0.4133	0.1896	0.5700	0.0482	0.9982	0.0342	0.7337	0.9446	0.8295	0.4154	0.5444	0.6567	0.9471	0.7974	0.8625	0.4168	0.9711
Gold	0.0325	0.5558	0.1932	0.7788	0.3831	0.7979	0.2689	0.1612	0.4840	0.3030	0.8604	0.8389	0.3030	0.3958	0.7671	0.4888	0.5439
Palladium	0.0770°	0.7466	0.3186	0.0621°	0.7657	0.0720°	0.3901	0.1814	0.6013	0.8418	0.3344	0.4758	0.0212	0.7155	0.3051	0.9085	0.7850
Platinum	0.2284	0.1057	0.4421	0.5637	0.4695	0.7177	0.1411	0.1669	0.8012	0.0456	0.7044	0.7204	0.3776	0.1791	0.3249	0.9162	0.9226
Silver	0.6693	0.3014	0.0938°	0.4898	0.8083	0.6954	0.5051	0.2681	0.7379	0.0976°	0.9172	0.2893	0.9316	0.2314	0.9898	0.6579	0.1537
Softs	0.8638	0.0247	0.2041	0.9544	0.3281	0.2477	0.3747	0.0199	0.9501	0.4280	0.6319	0.8778	0.1510	0.3007	0.0708°	0.2313	0.0173
Grains	0.0867°	0.6576	0.6869	0.4185	0.9105	0.8471	0.6513	0.4185	0.9781	0.7998	0.5498	0.6257	0.7482	0.0856°	0.1450	0.1684	0.0208
Livestock	0.4612	0.5746	0.4475	0.9324	0.2967	0.6265	0.2713	0.2423	0.5336	0.4826	0.9043	0.1775	0.0816°	0.5575	0.3892	0.4709	0.7111
Energy	0.1649	0.6359	0.6352	0.9947	0.9727	0.2572	0.5998	0.9908	0.1306	0.7378	0.9352	0.4931	0.9398	0.2116	0.1013	0.7610	0.7011
Industrial Metals	0.2023	0.4158	0.3914	0.0131	0.6810	0.0328	0.4243	0.8046	0.2485	0.0309	0.4433	0.1520	0.4384	0.3014	0.3383	0.1969	0.9613
Precious Metals	0.0850°	0.3363	0.1580	0.2676	0.9075	0.4490	0.2918	0.1293	0.6276	0.2473	0.7785	0.5622	0.1755	0.3254	0.5769	0.7864	0.6780

Notes: This table shows bootstrapped p-values with $N = 10{,}000$ replications for testing the null hypothesis of non-causality from a potential driver to a commodity at the low-frequency prediction horizon $h = 1$ month ($H_0 : x_L \nrightarrow_h x_H \mid \ell$) based on bivariate MF-VARs with lag order $P = 1$ using monthly (log-differenced) data for the potential driver and monthly log returns for the commodity front-month futures ($m = 1$). Before estimating the MF-VAR models, the data has been demeaned. A highlighted cell (circle) indicates the rejection of non-causality at the 5% (10%) level. The sample spans the period 2014:1–2019:12 where data is available over the full horizon. Commodity futures are grouped by the classes of softs, grains, livestock, energy, industrial metals, and precious metals. The last group consists of equally-weighted commodity portfolios.

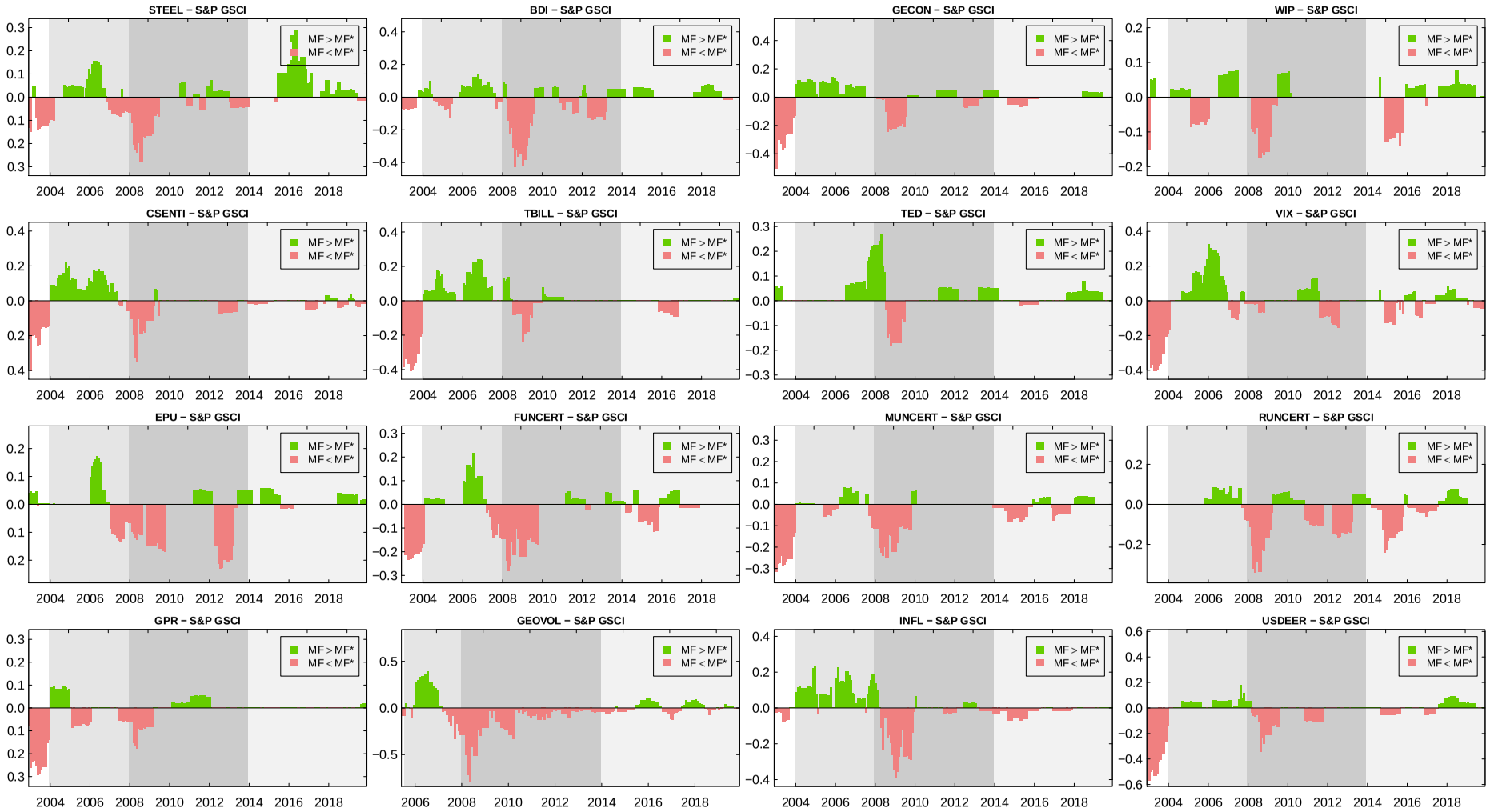

Figure A.10: 12-month rolling excess returns of MF-VAR ($m = 4$) over MF-VAR ($m = 4$) without including a driver (MF-VAR*) on a monthly basis. The trading period runs from the end of 2002:2 (2004:8 for GEOVOL) to 2019:12. Shadings indicate the following periods: pre-financialization, emerging financialization, global financial crisis, de-financialization. INFLE is omitted.